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Mihai Nadin *Editor*

Anticipation Across Disciplines

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The German Science Foundation (DFG), the Hanse Wissenschaftskolleg/Institute for Advanced Study, and the University of Texas at Dallas/antÉ—Institute for Research in Anticipatory Systems provided funding for an international conference of 30 scientists, who have in common an interest in anticipatory systems. They work in a variety of disciplines (from neuroscience to art and architecture, engineering, political science, computer science and artificial intelligence, mathematical biology, and quantum theory). Nevertheless, they were able to sustain a lively conversation on how anticipation is expressed within their respective fields of interest. This volume deviates slightly from the program (peer-review stringency explains the deviation) and from what are usually considered conference proceedings. It is representative of the variety of perspectives pursued in anticipation research today.

Dr. David Daniel, until recently president, and Dr. B. Hobson Wildenthal, currently president *ad interim*, honored the commitment of the University of Texas at Dallas to excellence in research by granting Dr. Nadin an exceptional Special Faculty Development Assignment in support of the Study Group in Anticipation. Dr. Reto Weiler, Rector of the Hanse Wissenschaftskolleg/Institute for Advanced Study, and the entire team of the Institute deserve recognition for their support of the project. Springer—Applied Sciences and Engineering, which assisted in the editorial and production effort beyond the peer review phase, also deserves acknowledgment. Asma Naz, herself a distinguished participant in the conference, helped in the laborious preparation of the volume.

Contents

The (Almost) Impossible Task of Interdisciplinarity

Mihai Nadin

Abstract While physics and physics-based disciplines adequately describe the non-living, there is a need for a complementary perspective that captures the essence of life. Biology and neuroscience could provide such a perspective, provided that they are not practiced as yet another form of physics. Of course, an authentic and effective complementary perspective can only reaffirm materiality and the associated dynamics that physics, or for that matter biology, explores. But it has to also account for the specific causality characteristic of life by integrating past, present, and *future*. Experimental evidence and empirical knowledge attest that there is no intentionality in the realm covered by physics and physics-associated disciplines. In contradistinction, the living is always characterized by what an observer could only describe as goal-oriented behavior. Current biology and neuroscience either end up explaining this behavior in terms specific to physical determinism, or simply leave anticipation out of the larger picture.

A large body of empirical evidence of goal-oriented activity is already available. Observations of finality—a concept cavalierly dismissed or sneered at—ranging from anecdotal to systematic recordings and experiments, associated with data and validation criteria, have been accumulated through time immemorial. Classic texts (of philosophic intent at the beginning, later of scientific focus, mainly in medicine, biology, zoology, botany, etc.) make reference to goal-driven performance. By association, such descriptions relate to anticipatory processes. However, until the beginning of the 20th century, few attempts were made to articulate hypotheses inspired by such observations and to verify them experimentally. (The exception is Renaissance science, in particular Leonardo's experiments—a subject worth more than a parenthesis.) This state of affairs started to change when scientists such as Nikolai Bernstein, Ivan Beritashvili, and Dimitri Uznadze, living in the Soviet

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Union, dedicated themselves to a science challenging the "official" views, i.e., the dogma of "dialectic materialism" that sanctified the cause-and-effect sequence. Their contributions were documented at an international conference (September 1–3, 2014, Hanse Institute for Advanced Study, Delmenhorst, Germany) and in the volume dedicated to them (*Learning from the Past: Soviet/Russian Contributions to a Science of Anticipation* [1]). Let us make note here of the fact that such scientists effected change within a system that actually vilified their efforts. In defying the official dogma, they became suspect of advocating an ideological deviation. Consequently, their work was never properly discussed. Science, of course, cannot evolve without the freedom to research and to freely exchange new ideas. Outside the Soviet Union and the countries influenced by the superpower of those days, one would expect openness to original ideas. The language barrier partially explains the deaf ear on which the work of Soviet colleagues fell. However, most relevant even for our days is the fact that the attempt of those scientists to suggest a new epistemological horizon was regarded with suspicion since it challenged views dominant even in the science of the "free world."

The publication (over 20–30 years later) of Robert Rosen's *Anticipatory Systems* [2] and Mihai Nadin's *Mind – Anticipation and Chaos* [3] resulted in a similar situation in the science of the "free" world. Outside the echo chamber of "official" science (as sanctioned by funding agencies), there is little a scientist can do in order to ascertain new ideas and concepts. Robert Rosen was already a "thorn" in the side of the "high priests" of a science of the living aligned with determinism—the sacrosanct dogma. As a newcomer, I earned the complicit indifference of those whose views were challenged by my work. Nevertheless, there is currently a rapidly growing interest in understanding how anticipatory processes take place, and what the practical implications of this understanding might be. Not surprisingly, some researchers are rushing in the direction of institutionalizing this interest in the hope of making it theirs, even in terms of institutionalized support. When cats and athletes teach robots how to fall, and when a patent protects the technology that guides the falling of the iPhone on its display, anticipation starts making a difference. Moreover, predictive computation is making inroads, creating an interactive environment that facilitates anticipatory behavior (Nadin [4]).

The Hanse Institute for Advanced Study hosted my research (during the 2011–2012 academic year), acknowledging early contributions I made to the foundations of the discipline. The Institute for Research in Anticipatory Systems at the University of Texas at Dallas cooperated in the undertaking, and so did Dr. Otthein Herzog (Director, Technical Center for Informatics, University of Bremen; professor, Visual Information Technologies, Jacobs University) and Dr. Christian Freksa (professor, Computer Science, and Director, Cognitive Systems Group—CoSy, University of Bremen). I took note of the genuine desire of other Fellows at Hanse, and of scientists who participated in seminars and colloquia, to have the opportunity to learn more about the science of anticipation. Where there is thirst for knowledge, one has to provide for satisfying it.

As the subject of anticipation claims its legitimate place in current scientific and technological inquiry, researchers from various disciplines realize the need to integrate an anticipatory perspective in their research. Therefore, I suggested to Hanse that a Study Group be established, and assured the long-term cooperation of the Institute for Research in Anticipatory Systems. The volume you have in your hands (or read on your eBook device) is but one outcome of the activity of this Study Group.

1 What Is at Stake?

Indeed, the need for a proactive approach to matters of energy, sustainability, and public health is almost unanimously accepted. In defining a Research Agenda for the 21st Century, the National Science Foundation stated: "It is no overstatement to suggest that humanity's future will be shaped by its capacity to anticipate…." The Study Group, recognizing the validity of the assertion, has emerged as a virtual association centered on the subject of anticipation across disciplines. The Hanse Wissenschaftskolleg/Hanse Institute for Advanced Study and those associated with the antÉ Institute could profit from this virtual institutional affiliation by hosting scientists of high quality for short study sessions. The Hanse will also enjoy the rewards of cross-pollination of ideas and skills. Among other activities, the Study Group planned three international conferences:

1. Learning from the Past: Soviet/Russian Contributions to a Science of Anticipation
2. Anticipation Across Disciplines
3. Anticipation and Medicine

The first two have already taken place. The third is, at the time of this writing, in the advanced stages of preparation (it will take place September 28–30, 2015).

2 Interdisciplinary Perspective

Cross-modal validation is of extreme importance in science. If anticipation were only a tempting theoretic perspective, chances are that it would not continue to attract researchers or justify the support of society. But this is clearly not the case. The major crises of the last ten years (financial, ecological, social, medical, and even moral) illustrate the urgent need for an anticipatory perspective. We cannot afford to ignore, for example, the questions pertinent to sustainability—a major global challenge. Leading scholars in economics, energy research, oceanography, engineering, and behavioral sciences worked with us in preparing a two-and-one-half-day-long conference. We provided a forum for 22 researchers to exchange experiences in respect to particular aspects of anticipation. Doctoral candidates and post-doctoral scientists were also present. The hope is to trigger future work on the subject by having well-defined projects carried out by scientists working in the defining spirit of interdisciplinarity implied by anticipation.

During the conference, a distinguished researcher (Dr. Johann Hoffmann, emeritus, Würzburg University) made note of the fact that I was able to engage scholars usually focused on their own tightly defined area of interest (the “specialization” syndrome) in an interdisciplinary effort without precedent: “I’ve never experienced such a successful interdisciplinary effort.” A compliment like this would go unmentioned were it not for the fact that if anticipation, as a subject in its own right, should eventually succeed, it will be on account of cross- and interdisciplinarity. The conference occasioned an exchange of knowledge and data of a very large scope: from an art event (documented in this book) to experiments in neuroscience, design of power networks, anticipatory expression in plants, anticipation in politics, and anticipatory computing. Contrary to stereotype, I shall not summarize contributions made within the conference. Rather, I am taking advantage of the opportunity to suggest a number of applications in the hope that they will eventually become part of the new anticipation-endowed reality.

3 Computers and the Ability to Anticipate

For over 300 years—since Descartes’ major elaborations (*Discourse on Method*, 1637 and *Principles of Philosophy*, 1644) and Newton’s *Principia* (1687)—science has advanced the understanding of the reactive characteristic of the physical world, expressed in the cause-and-effect sequence. The corresponding reductionist viewpoint states that a machine can represent the functional characteristics of reality, including the functioning of the human being. The assumption of homogeneity (“All electrons are the same,” someone once said) is implicit in physics. In the living there is no such identity.

Computer programs (“soft machines”) are descriptions that capture details of a homogenous reality that has escaped all previous machines. Programs express these details in many ways: from visualizations of data to intelligence-like inferences, to procedures for automating the execution of complicated, yet well-defined, tasks (the domain of robotics, for instance). However, in describing the living, regardless of its complexity—from monocell to the whole human being—descriptions based on the deterministic understanding of the world and the corresponding reductionist model fail to capture the defining characteristic of life: the ability to anticipate. The living is infinitely heterogenous (there are no identical cells, not to say identical neurons) and variable.

In the age of computation, it becomes unavoidable to ask whether computers can anticipate or enhance anticipation in the living. Arguing from a formal system (the Turing machine, the von Neumann sequential computer, algorithmic or non-algorithmic computation, quantum computation, neural networks, etc.) to reality is quite different from arguing from a characteristic of the living (in particular, brain functioning) to formalism. Libet’s [5] readiness potential (i.e., the time before an action, signaled through neurological activity, actually takes place) is an expression of anticipation. It was and continues to be quantified in various cognitive studies and in brain research. The area of inquiry extends from the anticipation of moving stimuli (vision) to synchronization mechanisms, medicine, genetics, motion planning, and design, among others. A very rapidly increasing amount of data was and continues to be generated in connection to such specific knowledge domains. Inferring from this very rapidly increasing body of data to an integrated understanding of change, and its possible anticipation, assumes that we know how anticipation is defined. Short of this, questions regarding computation are meaningless. Two distinct formal definitions of anticipatory systems originate from Robert Rosen's work:

1. An anticipatory system is a system whose current state depends not only upon a previous state, but also upon a future state.
2. An anticipatory system is a system that contains a model of itself that unfolds in faster than real time.

My own definition deviates a bit from Rosen's:

3. The current state of an anticipatory system depends not only on a previous state, but also upon possible future states.

Please take note of the possibilistic dimension introduced through this definition. The process through which anticipations are generated might indeed rely upon faster-than-real-life unfolding models, but alternate possibilities, similar to quantum entanglement, should also be considered. Of course, we have to address a critical question: can such definitions serve as a basis for conceiving, designing and implementing anticipatory computing?

4 Constraints, Programming, and Knowing Before Knowing

The more constrained a mechanism, the more programmable it is. Reaction can be programmed, even without computers. Although there is anticipation of a sort in the airbag and the anti-lock braking system in cars, these remain expressions of pre-defined reactions to extreme situations. In programming reaction, we infer from probabilities (a shock will deploy the airbag, sometimes without cause) always defined after the fact (collisions result in mechanical shock). They capture what different experiences have in common, i.e., the degree of homogeneity. Proactive behavior can to some extent be modeled or simulated. If we want to support proactive behavior—prevention, for instance—we need to define a space of possibilities and to deal with variability. We need to afford interpretations (e.g., an accidental shock that does not require the airbag should be distinguished from a collision). To infer from the combined possibility-probability mapping of the information process describing the dynamics of reality to anticipation means to acknowledge that deterministic and non-deterministic processes are complementary. This is especially relevant to information security (and to security in general) since it is not in the nature of the computer—a homogenous physical entity—to cause security breakdowns. Rather, it is in the nature of those involved in the ever-expanding network of human interactions—a heterogenous entity of extreme variability—to express themselves in a manner that can be qualified as destructive. Hacking, for example, can be demonized or seen as an expression of creativity. Anticipation can have many explanations.

Given the nature of computation it is possible either

1. to achieve effective pseudo-anticipation performance (since only the living authentically expresses itself in anticipation) within the forms of computation currently practiced; or
2. to develop hybrid computational mechanisms that integrate physical and living components, with the aim of achieving effective anticipatory properties.

These are two distinct research themes within the emerging notion of anticipatory computing. (More on this subject in my presentation in this volume, "Anticipation and Computation. Is Anticipatory Computation Possible?")

Information Security and Assurance will become an ever more elusive target within the reactive mode of computation in which it is practiced today. Every step towards higher security and assurance only prompts the escalation of the problem that gave rise to such steps in the first place. In order to break this cycle, one has to conceive, design, implement, and deploy anticipatory computing that replaces the reactive model (such as virus detection) with a dynamic stealth ubiquitous proactive process distributed over networks. Anticipatory computation, inspired by anticipation processes in the living, implies a self-repair component. It also involves learning, not only in reaction to a problem, but as a goal- action-oriented activity. The human immune system, which is anticipatory in nature, is a good analogy for what has to be done—but it also shows how difficult the task is. In some ways, anticipatory processes are reverse computations. Therefore, an area of anticipatory computing research will involve experiments with reverse computation (limited, of course, by the physical substratum of the computation process, i.e., by the laws of thermodynamics), either through quantum computation implementations or through hybrid computers (with a living component).

Anticipatory computing is indeed a grand challenge. The ALife community could not deliver a comprehensive view of change because it failed to acknowledge the role of anticipation. The swarm metaphor was a step in the right direction, but not pursued by any relevant research. The current efforts of leading scientists and research centers (e.g., Intel's involvement in proactive computing, the work of the Department of Energy's Sandia Laboratory, IBM's efforts) support the claims I made in 1998—anticipation is the new frontier in science—and in 2000—anticipation is the second Cartesian revolution. This work, of extreme significance, is dedicated to the description of complex forms of causality characteristic of the living, rather than those associated with determinism and reductionism (the domain of the Cartesian model of the world).

Most research in our days, which I wish to acknowledge (and which is often spectacular), is frequently carried out with no understanding of the fundamentals of anticipation. The technical aspects of anticipatory computing extend well beyond the subject of the "predictive devices" that "know" when you have a flight (because you booked it through one of your devices) and order a taxi for you so that you can arrive at the airport on time. It might well be that in addressing information security, we simultaneously address the fundamentals of current computation, intrinsically unsecure.

Climate changes, variations in the financial markets, shifts of all kind in ecosystems, and even the state of the human body are preceded by various signals. The problem is that most of the time we have no idea what such signals are. And even if we have some intuition as to what they might mean, we do not have consistent ways to infer from such signals to the future. Indeed, anticipation is not some kind of symptom, it is rather an encompassing expression, most of the time very close to the event we would prefer to know about in advance. Obviously, it would be beneficial to foresee transitions. This is notoriously difficult but within the scope of anticipation studies. The conference approached this applied research perspective.

5 Living in a World of Fast-Expanding Vulnerability

Science and technology continue to impact our existence. To be blind to what has changed in the world in recent years, and how such changes are shaping a new human being is almost impossible. Blindness itself is in the process of being overcome through technology. But there is another form of blindness that is actually not decreasing: blindness to the consequences of change. Today we have a better understanding of atomic energy than we did in the early 1950s, but many forget about the time when it was fashionable to wear a heart implant driven by an atomic battery. Without any desire to demonize any of the new opportunities, we still have the obligation to understand their short- and long-term consequences. This is not the place to dignify the daily scare messages associated with what it means to stare at a monitor, to be dependent on a cellular phone, to experience the loss of privacy, to face the medical consequences of trading physical activity for the passivity of uninterrupted entertainment. The conference took note of the fact that from a reaction-based perspective, more data ("Big Data") makes sense and promises many revelations. From an anticipatory perspective, it is probably meaningful to minimize data to what is necessary and sufficient in order to describe a process. To derive banality from *big data* is quite different from deriving meaning from *significant data*.

The conference documented in this book took note of the fact the reactive approach to virus prevention, whether in immunopathology (e.g., Ebola, West Nile virus, avian flu) or in computer malware (e.g., Conficker, nVir, Stoned), is extremely expensive and marginally efficient. Self-inflicted vulnerabilities are the expression of the lack of anticipatory awareness. This extends to social and political life. In view of such observations, this was a good conference. Discussions, not recorded for this or any other publication, occasioned exchanges of ideas which will, I am sure, benefit all participants.

Acknowledgments The entire support structure in place at the Hanse Wissenschaftskolleg/ Institute for Advanced Study functioned error free. Dr. Dorothe Poggel, at times overwhelmed by the scale of the event, made sure that the program was flawlessly executed. Dr. Monica Meyer-Bohlen and Wolfgang Stenzel, working with Lada Nakonechna offered the opportunity of opening up the discussion in the domain of aesthetic activity.

For their contributions to this publication, gratitude is owed to Asma Naz—she herself a much appreciated contributor to the conference. Elvira Nadin, also a contributor, worked hard in the organization of the session as well as in the preparation of the manuscript for this book. Last but not least, the Deutsche Forschungs Gemeinschaft, Hanse Institute for Advanced Study, antÉ—Institute for Research in Anticipatory Systems, the University of Texas at Dallas, and the Political Anticipation Network provided funding and other support, without which neither the conference nor this volume would have been possible.

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Part I
Theoretical and General Aspects of Anticipation

Anticipation of Random Future Events

Patrizio Tressoldi

Abstract I will present the evidence, albeit apparently paradoxical, that some seconds before the perception of random events of different arousal levels (e.g. a pleasant or an unpleasant sound), our neuro- and psychophysiological systems, show a reaction correlated with them. In this chapter I will describe the phenomenon, review the available evidenceand I'll try to explain this phenomenon and the possible practical applications.

Keywords Anticipation · Random · Prediction · Probability · Psychophysiology

1 Physiological Anticipation of Future Events

The study of anticipation is now a multidisciplinary theme and there is a significant body of evidence in psychology and neurobiology, indicating the presence of several anticipatory mechanisms in the brain and our psychophysiological system. Soon, Brass, Heinze, and Haynes [1] and a review by van Boxtel and Böcker [2], highlight the crucial role of anticipation in a large array of cognitive functions such as vision, motor control, learning, and motivational and emotional dynamics.

If a sequence of events follows a rule, then the autonomic and neurophysiological systems can learn this rule before the person can discover it overtly that is, with a conscious awareness. An important characteristic of this phenomenon is that the anticipation of future events is a completely unconscious process because these anticipatory responses are too weak for participants to be detected using introspective cognitive means. This implicit learning capacity of the human autonomic and neural systems has a clear adaptive value that allows us to prepare our behavioral and cognitive responses, depending on whether future events may be dangerous or useful [3].

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What happens however if events do not follow a rule and instead occur at random? In this case, implicit learning is not possible and only more or less sophisticated guessing strategies can be employed, such as the "Gambler's Fallacy" strategy [4].

Since the late 1990s, some authors have attempted to discern whether anticipatory responses can be observed, even when implicit learning is not possible. If such anticipatory responses could be observed, this would demonstrate that our autonomic and neurophysiological systems possess a more sophisticated capacity to predict future events than was previously thought and consequently, are set up to help us predict events that are generally thought to be intrinsically unpredictable.

1.1 The Phenomenon

Imagine an individual must open one of two doors. Behind one door there is a safe event, behind the other, a dangerous one. The individual has no way of knowing which door opens to which event and cannot use his or her previous experiences for guidance. It is a sort of roulette game with your life to play for (Fig. 1).

Is this choice a real 50–50 bet? Only if we cannot change this probability, that is, if we cannot anticipate the future event at least partially. As strange as it may appears, a consistent evidence has been accumulated supporting this possibility. In the following paragraphs we will summarize the psychophysical and behavioral evidence accumulated to date, supporting the possibility that it is possible to increase the probability of anticipating future random events beyond the expected chance.

1.2 Neuro- and Psychophysiological Evidence

There is evidence that our neuro- and psychophysiological systems can react differently before the perception of two classes of events presented randomly,

Fig. 1 A crucial task: if you open one door you are safe or dead

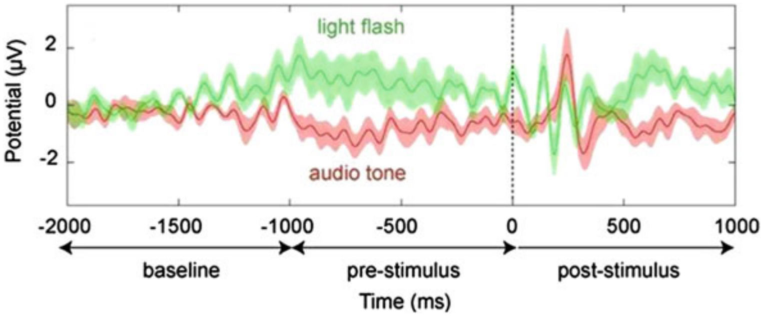

Fig. 2 Example of an EEG anticipation activity related to two different stimulations before (pre-stimulus) their perception (post-stimulus)

characterized by different strength of reactions (i.e. heart rate, electro-dermal response, EEG activity, etc.), that is before their perception, as presented in Fig. 2.

In a meta-analysis covering all available studies published up to 2010, Mossbridge, Tressoldi and Utts [5] estimated a weighted effect size $d = 0.21$; 95 % Confidence Intervals = 0.15 to 0.27, from a pool of 26 experiments selected because they possessed sufficient information related to the similarities between the pre-stimulus and post-stimulus effects. After excluding methodological and statistical artifacts and the expectancy effect,[1] as being the cause of this result, the authors summarized these finding as follows: "*In sum, the results of this meta-analysis indicate a clear effect, but we are not at all clear about what explains it*".

If real, this phenomenon could be a demonstration that this anticipatory predictive ability is an important adaptive tool that is always at our disposal. Even though it operates at an unconscious level, it may be sufficient to prepare our defense or avoidance reactions.

In an attempt to estimate the prediction accuracy of these effects, Tressoldi and collaborators [6–8], devised a series of experiments to study the percentage of correct prediction of two different events by analyzing the anticipatory reactions of pupil dilation and heart rate. Figure 3, demonstrates an example of pupil dilation prediction accuracy related to two different events, a smile and a gun associated with a shot audio clip, with respect to the expected chance of 50 %.

The overall prediction accuracy of both the anticipatory pupil dilation and heart rate observed by Tressoldi et al. [6–8], ranged from 4 to 15 % above the expected chance of 50 %.

[1]Expectation bias arises when a random sequence including multiple repetitions of the same stimulus type (e.g. five non-arousing stimuli) produces an expectation in the participant that the next stimulus should be of another type (e.g. an arousing stimulus). Expectation bias can also arise when experimenters use non-equiprobable stimuli in an attempt to account for known emotional adaptation effects (e.g. a 2:1 ratio of calm to emotional images).

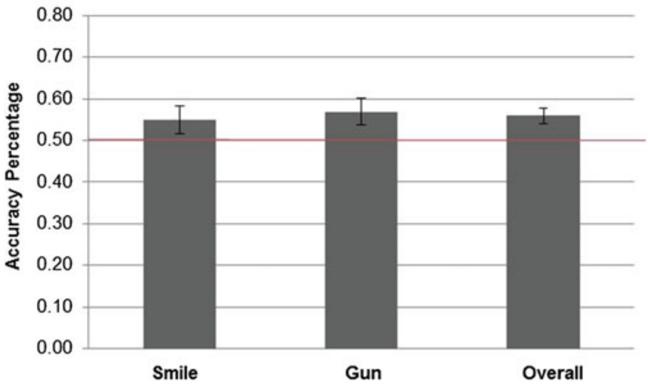

Fig. 3 Prediction accuracy of anticipatory pupil dilation related two different events

1.3 Behavioral Evidence

In the paper titled *Feeling the future: Experimental Evidence for Anomalous Retroactive Influences on Cognition and Affect* published in 2011, Daryl Bem [9], directed the scientific attention towards a counterintuitive phenomenon, that is, that future perceptions, cognitive or behavioral experiences have an implicit "retro-causal" influence on behavioral decisions. For example, it was demonstrated that participants can chose above chance the side behind which an emotional picture was presented randomly or that presenting a congruent priming after a picture (i.e. a smiling girl followed by the word "smile"), reduced the reaction times in the detection of a pleasant versus unpleasant picture with respect to an incongruent post-priming (i.e. a smiling girl followed by the word "sad"). As expected these findings aroused a huge number of comments and methodological, statistical and theoretical criticisms. Although the results of some experiments were not replicated [10], in a meta-analysis of all retrievable studies related to these effects, Bem et al. [11], supported Bem's [9] evidence even if the purported retrocausal or anticipatory effects, were moderated by the type of tasks (i.e. priming, reinforcement, practice, etc.).

It is important to point out that similarly to the psychophysiological effects, these behavioral effects are very moderate. In term of standardized effect sizes. The higher values are d = 0.14; 95 % Confidence Intervals = 0.08–0.21.

2 Tentative Interpretations

Are these phenomena caused by anticipation, retrocausation or entanglement in time? In relation to the neuro- and psychophysiological effects, the term "anticipation of future events" was used whereas for the behavioral effects, the term "retro-causal". However what all these effects have in common is that they are correlations between events measured in two different time frames. How is it possible that events (physiological, perceptual or behavioral) can be correlated in time? In quantum physics it has been theoretically defined [12] and empirically demonstrated [13] how, by entangling two photons that exist at separate times, the time at which quantum measurements are taken and their order has no effect on the outcome of a quantum mechanical experiment.

Is such a type of entanglement also possible between mental events? This possibility is under investigation and there is already some support for it [14, 15]. Our provisional theoretical interpretations of all phenomena described above is that what we measure, both psychophysiological and behavioral variables at time-1 and what we measure at time-2, can be correlated because they are entangled in time. This entanglement is due to the shared, complementary relationship between the events at time-1 and events at time-2 (e.g. heart rate and future emotion). Further theoretical interpretations are presented by Maier and Buchner [16]

3 Practical Applications

It may be possible to exploit these correlations between events separately in time for practical applications? For example is it possible to detect the neuro-psychophysiological reactions measured at time-1, to avoid negative events

Fig. 4 Image of the CardioAlert prototype. On *top left*, the heart rate recorder that receives the changes in the hemoglobin detected by a led sensor connected to an individual's finger. This signal is filtered, amplified and elaborated to obtain the heart rate by using an Arduino microcontroller. On *bottom left*, is the smartphone which receives the data from the microcontroller by a bluetooth connection

at time-2? Mossbridge et al. [17] and Bierman [18] discuss this possibility from a theoretically point of view and it is under investigation by Tressoldi et al. [19]. These last authors for example, have devised a portable apparatus, named CardioAlert, to measure heart rate connected via Bluetooth with a smartphone that can be tailored to individual differences, to produce an alert when a potential random negative event is going to happen. An image of this apparatus is presented in Fig. 4.

After measuring of the heart rate baseline, the operator can set the level of the alarm (a sound), by changing the CardioAlert software installed in the smartphone. In a pilot study, Tressoldi et al. [19] used as the alarm threshold a change in the baseline heart rate above or below 1.5 the value of the standard deviation of beat-to-beat intervals. The choice of this parameter is particularly delicate because it is necessary to find the optimal value to reduce false alarms and the false negative responses to a minimum.

4 Final Comments

The naïve idea that random events are unpredictable must be corrected. Some seconds before a future emotion, even if triggered by a random event, it is possible to detect an anticipation of its psycho- and neurophysiological correlates. Even if this anticipation is of a smaller level than its future manifestation preventing its conscious awareness, it can easily be detected by electronic apparatuses and exploited to devise experimental and practical applications by the integration of bioengineering and neuro- and psychophysiological skills.

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The Birth Defect of the Information Processing Approach

Joachim Hoffmann

Abstract Academic psychology is dominated by the information processing approach (IPA) since about six decades. According to the IPA mental activities, i.e. cognition, serve the processing of stimuli in order to reconstruct a representation of the environment. It is argued that this notion is misleading: Mental activities primarily serve the control of voluntary behaviour. In this function, they are striving for anticipations of achievable states. Accordingly, cognition does not refer to the processing but to the anticipation of achievable desired stimuli or states. Two 'ancient' conceptions in psychology already emphasized the crucial role of behaviourally guided anticipations: the reafference—and the ideomotor principle, the former dealing with the basics of perception and the latter dealing with the basics of behavioural control. Speculations are discussed, about how both principles might work together for the control of voluntary behaviour creating by this the mental structure of the perceived world.

Keywords Anticipation · Behavioural control · Reafference · Ideomotor · Action-effect learning

1 Introduction

In the first half of the last century academic psychology was dominated by behaviourism. John B. Watson, one of the most prominent maintainer of behaviourism, proclaimed psychology as being *"… a purely objective experimental branch of natural science. Its theoretical goal is the prediction and control of behavior…"* [1, p. 158]. At this time only stimuli and responses could be objectively measured. Consequently, behaviourism exclusively explored the formation and structure of stimulus-response relations. The mediating mental processes were

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excluded from analyses, so that behaviourism often has been ironically named 'black-box psychology'.

However, beginning with the forties of the last century developments in different disciplines heralded a new look: In 1949, Claude Elwood Shannon and Warren Weaver published a thin book entitled 'The mathematical theory of communication' which provided the mathematics for a measurement of information. One year before Norbert Wiener argued that control and communication can be likewise studied in the animal and the machine. Allan M. Turing discussed in 1950 'intelligence' as being a feature of computing machines and John von Neumann delivered the architecture of such intelligent machines [2–5].

All these developments strongly influenced academic psychology and when William Edmund Hick from Cambridge reported that the reaction time (RT) linear increased with the information (the entropy) of the presented stimuli [6], the strong belief emerged that the processes which mediate between stimuli and responses can be explored as information processing. The arising hope, that human information processing can finally be understood by its simulation in computers was confirmed, only 9 years later, by Alan Newell and Herb Simon from Carnegie Mellon University [7]. They implemented a computer program, the so called 'General Problem Solver', which was able to solve simple problems like the tower of Hanoi. The information processing approach was born and Ulric Neisser gave the new movement its name by his seminal book "Cognitive Psychology" [8]. Neisser defined *cognition* as referring *"…to all the processes by which sensory input is transformed, reduced, elaborated, stored, recovered, and used."* [8, p. 4]. Accordingly, from this time on up to today academic psychology analyses all these processes, i.e. perception, attention, memory, language, thinking, learning etc.

I experienced these new developments as a student and I shared of course the enthusiasm for the information processing view at this time. It was a good feeling, to be part of a breakup, by which light was shed into the black box of the behaviourist and it was probably due to this enthusiasm that it took me a long time until I started to suspect that the information processing approach might be basically wrong. I have in particular two reasons for my skepticism.

2 The Fault of the Information Processing Approach

First, the information processing approach suggests that there is one and only world which delivers the information for its mental representation via stimulation. However there is no one and only world. I will take a very simple example for demonstration. Figure 1 presents an elementary sensory input which we typically perceive or represent as being two squares. However there are likewise eight triangles or the shape of a house with some extra brackets, or an octagon with extra brackets etc. As it is in this simple example, it is always the case that there are various alternative interpretations of the environment around us from which we typically realize only one in every moment. Accordingly, the critical question is not

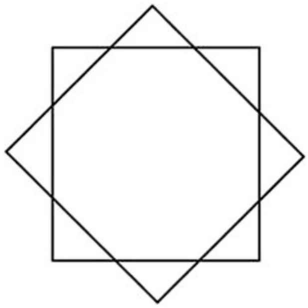

Fig. 1 Two *squares*, but also eight *triangles*, the shape of house or an *octagon* with some extra brackets

how we process the "given" information but rather what determines the selection of the particular information, we are processing, what is a complete different affair.

Second and even more important: Any action, as simple as it may be, produces changes of the sensory input. Whether we move our finger, our eyes and even if we just talk, in any case we produce some new sensory input for ourselves. Thus, our mind continuously has to distinguish what of the sensory input has been induced by ourselves, and what has been caused otherwise. Without distinguishing self-induced sensory effects from other sensory input, no valid perception would be possible. Accordingly, organisms have to learn what the sensory effects of their actions are, i.e. not stimulus-response relations but action-effect relations are crucial for behavioural control.

To sum up: The information processing approach fortunately overcame the black box of the behaviourism but unfortunately it inherited the disastrous fixation on stimulus-response relations: All cognition, so again the credo, starts with the impact of stimuli. However organisms and above all human beings typically do not respond on stimuli but they almost always act in order to create stimulations or situations they are striving for. To have overlooked this goal-oriented character of almost all behaviour, I call the 'birth defect' of the information processing approach. In order to overcome Behaviourism academic psychology would has been better focused not on the processing of incoming stimulation but on the generation of desired stimulations—especially as the importance of behaviourally guided anticipations of action-effects has been emphasized already in several conceptions before. The most prominent are the Reafference Principle and the Ideomotor Principle.

3 The Reafference Principle: Control of Perception by Anticipation

The Reafference Principle (henceforth RP) has been first discussed by Erich von Holst and Horst Mittelstaedt in a paper published 1950. In the introduction the authors explain their concern as follows [9, p. 464]:

> We do not ask for the relation between an afference and the resulting efference i.e. the reflex but rather depart with the efference and ask what happens in the CNS with the afference which has been caused by it, which we call the reafference (translated by the author).

Figure 2 presents a schematic illustration of what von Holst and Mittelstaedt assumed to happen with the 'reafference'. According to the RP any efferent motor command causes via corresponding neuronal networks some action in an effector (e.g. an eye movement). Additionally changes in the environment may happen. The immediate sensory consequences of the action are called reafferences and the sensory input from other sources are called exafferences. Both are fed back via corresponding neuronal networks for perception. So far it is a matter of course. The critical assumptions of the RP concern two points: (1) Any efferent motor command goes along with a corollary discharge—the so called efference copy and (2) The efference copy and the reafference cancel each other out. As a result, only the ex-afferences are transmitted for perception.

There are many observations which confirm the validity of the RP [cf. 9]: For example, in patients suffering from Polyneuritis the kinaesthetic feedback from the muscles is generally reduced. If these patients are pressing a hand against a wall they report a feeling as if the wall would be flexible like rubber. According to the RP the phenomenon appears because the kinaesthetic reafference is less strong than the efference copy so that the difference between the copy and the reafference becomes positive what corresponds to a situation in which the wall would move a little bit away, exactly what is perceived.

Or imagine an experiment conducted by the physician Kornmüller. Kornmüller paralysed eye muscles by an injection of curare but gave nevertheless the order to move the gaze to the right. Trying to look to the right, participants reported to see a short flip of the whole environment to the right. Again, the reason is that the shift of the retinal image which typically goes along with a gaze shift fails to appear what

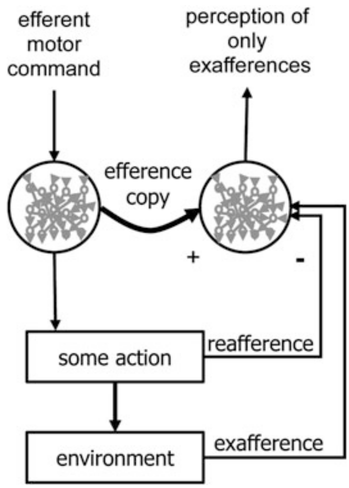

Fig. 2 A simplified schematic outline of the reafference principle

corresponds to a situation in which the environment would move with the gaze shift, exactly what the participants have seen in these experiments.

The RP is also responsible for that it is difficult to tickle oneself, what has been very nicely experimentally demonstrated [10]. The reason is that if we tickle ourselves the efference copies of our movement commands cancel the resulting sensations (the reafference) out so that their tickling effect vanishes or is at least reduced.

Despite all this convincing evidence, there remains a problem: Motor commands and sensations are incommensurable to each other. Consider for example an eye movement. The motor command for an eye movement refers to the contraction of at least three pairs of muscles whereas the resulting shift of the retinal image refers to spatially distributed signals from the retina. That is, the efference copy cannot be a pure copy of a motor command but must somehow contain anticipations of the expected reafference—otherwise it's impossible to see how the "copy" might cancel out the arriving reafference. Thus, the gist of the RP is: Motor commands go along with *anticipations* of their effects which are charged against the sensory input.

4 The Ideomotor Principle: Control of Behaviour by Anticipation

The other theoretical conception which already emphasized the central role of action-effect relations is the ideo-motor principle (henceforth IMP). The IMP has British and German roots. In Britain Thomas Laycock and William Carpenter and in Germany Johan Friedrich Herbart, Hermann Lotze and Emil Harless already propagated the idea that the motor outcome influences retroactively the motor control [cf. 11]. William James finally tied together the ideas of all these scholars to the Ideo-Motor Principle in his seminal Book *Principles of Psychology* published more than 120 years ago [12]. Figure 3 presents a schematic illustration of the basic ideas, reduced to the fewest possible terms.

In the beginning we have some external stimulation 'S' which triggers a motor command 'M' causing via corresponding neuronal networks some action and changes in the environment, which are fed back by what has been called by James resident and remote effects 'K'. Furthermore, James assumed that by repetition new connections are formed between neuronal representations of 'K' and 'M' (Fig. 3, left side). These new connections, he assumed, change the flow of activation in the following way [12, p. 586]:

> K may be aroused in any way whatsoever (not as before from S or from without) and still it will tend to discharge into M; or, to express it in psychic terms, the idea of the movement M's sensory effects will have become an immediately antecedent condition to the production of the movement itself. …Here, then, we have the answer to our original question of how a sensory process which, the first time it occurred, was the effect of a movement, can later figure as the movement's cause.

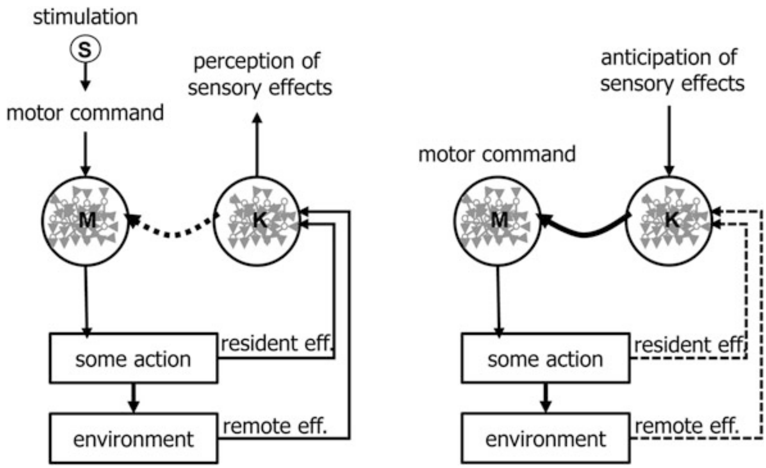

Fig. 3 A simplified schematic outline of the ideomotor principle

The gist of the IMP is that actions become connected to their sensory consequences so that anticipations (the idea) of such consequences gain the power to trigger the movements that formerly brought them about. In other words: voluntary movements or actions become determined by anticipations of their own sensory consequences (cf. Fig. 3, right side).

The IMP was widely acknowledged in the beginning of the last century. However, for the upcoming behaviourism the assumption that behaviour is determined by something unobservable like an idea was a sacrilege so that behaviourists rejected the IMP in total. For example: Edward Thorndike mocked the IMP in his presidential lecture at the APA Congress in 1913, by saying [13, p. 101]:

> Shocking as it may seem, it can be shown that the orthodox belief of modern psychologists, that an idea of a movement tend to produce the movement which is like it, is a true child of primitive man´s belief that if you sprinkle water in a proper way your mimicry tends to produce rain.

Thus it happened that the IMP remained almost without any significant influence on academic psychology for decades. However in the last years the IMP experienced a renaissance especially in experimental psychology. For example, Shin, Proctor, and Capaldi noticed 2010 in a comprehensive review that PsycINFO listed 134 entries with ‘ideomotor/ideo-motor’ in the titles and 517 results with it as a keyword [14, p. 943].

5 An Experimental Demonstration of the IMP

Many of the experimental demonstrations of the IMP follow a methodological proposal made by Anthony Greenwald more than 40 years ago [15]: In a typical choice reaction time experiment the response alternatives are to be connected with different but distinctive sensory consequences so that a possible impact of the sensory consequences on the responses, they are the result of, can be examined. The following example is taken from a paper published by Kunde et al. [16].

The authors came from the stimulus-response-compatibility phenomenon: If there is a dimensional overlap between stimuli and responses in terms of space, time or intensity, compatible stimulus-response assignments are accomplished faster than incompatible assignments [cf. 17]. For example, if participants have to respond to quiet or loud tones with a strong or a soft keystroke, they respond faster if the strong keystroke is assigned to the loud tones and the soft keystroke is assigned to the quiet tones than if the assignment is reversed. Furthermore, the authors argued, if sensory response effects are necessary antecedents of voluntary responses, as claimed by the IMP, the same compatibility phenomena as between stimuli and responses should appear between responses and effects. Thus, to demonstrate the IMP, response-effect compatibilities are to be shown.

In the experiment, participants were requested to press a key either softly or strongly in response to imperative colour stimuli. Doing so, they produced either a quiet or a loud effect tone. The critical variation concerns the assignment of the effect tones to the keystrokes. Strong keystrokes either produced loud and soft keystrokes produced quiet tones (compatible mapping), or vice versa strong keystrokes produced quiet and soft keystrokes produced loud tones (incompatible mapping).

The results show that participants responded significantly faster if their responses triggered tones of compatible intensity than if they triggered incompatible tones. This response-effect compatibility phenomenon has been proven to be a very robust one. The phenomenon occurs in the dimension of space, time, and intensity [18–21]. In all these experiments, the participants were never required to produce these effects but they simply appeared incidentally after the execution of the response. That they nevertheless impact the response latencies proves that representations of these non-intended effects were activated before the responses were selected and initiated.

The use of response alternatives that differ in intensity additionally allowed a qualification of response execution. For example, if participants are required to complete a soft or a strong keystroke the peak force that is reached provides an appropriate measure of response execution, allowing to explore whether response-effect compatibility would affect not only response latencies but also response execution. This was indeed the case. The intensity of the effect-tones uniquely affected the peak forces of soft as well as of strong keystrokes in a contrast like fashion. As Fig. 4 illustrates, loud effect-tones reduced and quiet effect-tones

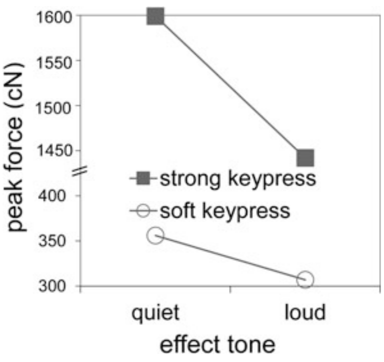

Fig. 4 The peak force for intended strong and soft keystrokes in dependence on the intensity of the effect-tones the keystrokes produced (after Kunde et al. 16)

intensified the peak forces of intended soft keystrokes as well as of intended strong keystrokes.

For an appropriate account of the found contrast, it is to notice that peak forces indicate the intensity of the tactile feedback by which participants start to reduce the force of their hand because they feel the intended force (strong or soft) to be reached. In this view, the data show that less strong tactile feedback is required to feel the intended force completed if a loud effect-tone follows and stronger tactile feedback is needed if a quiet effect-tone follows. Figure 5 illustrates two possible accounts for this contrast. A simple feedback loop for the execution of a prescribed pressure force is depicted: The imperative stimulus determines the set point (the

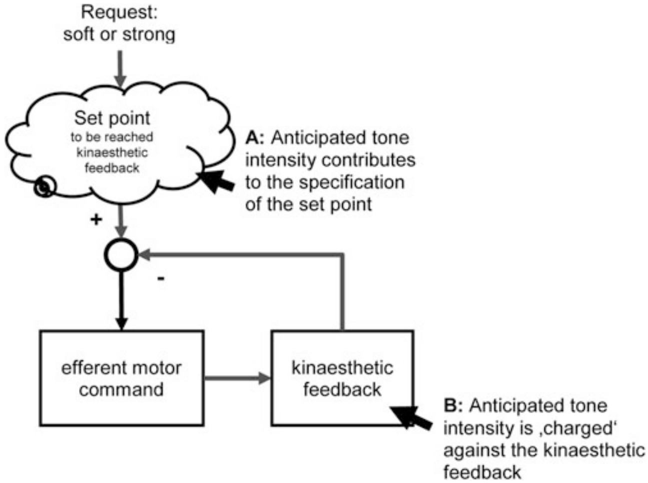

Fig. 5 Illustration of two possible points of action at which anticipated effects might affect behavioural control

proximal reference), i.e. the proprioceptive feeling is anticipated which has to be reached in order to realize either a strong or a soft keystroke. The difference between the set point and the current feeling (the current proximal feedback) determines the appropriate motor commands which are activated until the proprioceptive feedback from the fingertip and from the muscles signal that the set point is reached.

Within this loop the additionally anticipated intensity of the distal effect-tone might on the one hand (A) influence the set point so that the set point is somewhat enhanced if a quiet tone is anticipated, and the set point is somewhat reduced if a loud tone is anticipated. In this way the intended force of the keystroke would be adjusted in order to compensate for the anticipated force of the effect tones. On the other hand (B) it might be that the anticipated intensity of the distal effect-tone is charged to the proximal feedback so that an anticipated loud tone earlier evokes the feeling that the set point is reached and an anticipated quiet tone delays somewhat the appearance of this feeling. Both mechanisms provide an account for the contrast effect and they both may conjointly contribute to it. In any case, the present data provides profound evidence that anticipations even of unintended response effects are not only involved in the selection and initiation of voluntary actions but also take part in the control of their execution.

6 The Interplay of the Reafference and the Ideomotor Principle: Structuring the 'Mental World' by Anticipation

The central matter of psychology are experience and behaviour of humans. The RP deals with a basic part of experience—perception, and the IMP deals with a basic part of behaviour—the control of voluntary behaviour. In both conceptions anticipations play the crucial role: in the RP, anticipations of action effects assure the stability of perception and in the IMP, anticipations of action effects allow the determination of voluntary actions. On the one hand it is assumed that sensory anticipations are triggered by actions and at the other hand it is assumed that anticipations trigger actions. In any case, perception as well as behavioural control seem to rely on coincidences between motor and sensory activations.

Coincidences between motor and sensory activation already play an important role in the control of the most elementary motor unit—the muscle. Figure 6 (left side) illustrates the basic elements of the so called gamma spindle loop: A skeletal muscle with enclosed spindles is depicted. The spindles serve as sensors for the current length of the muscle. They start to fire if the muscle is stretched or if the spindle itself is contracted by Gamma activation. Additionally there is Alpha activation by which the skeletal muscle can be contracted. The critical point is that the spindles have an excitatory connection to the alpha neurons so that a loop control of muscle length is created. Accordingly, there are two principle routes by

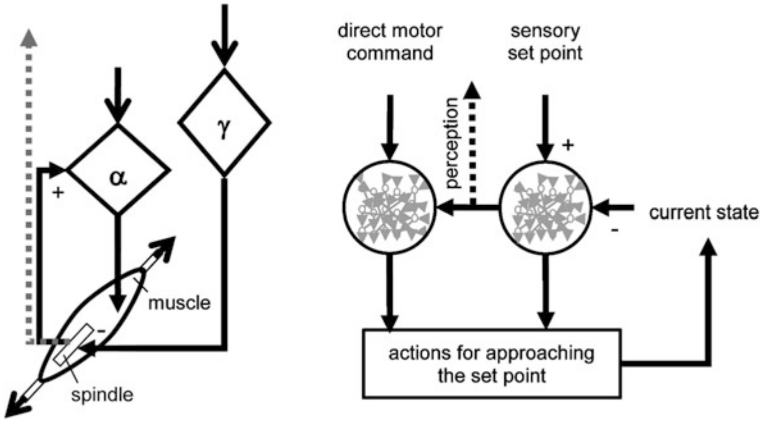

Fig. 6 A simplified illustration of the basic elements of the Gamma-spindle-loop (*left side*) and its principle structure (*right side*)

which a muscle can be and is typically contracted, by direct commands via Alpha neurons and by a control loop in which Gamma activation delivers a set point and the spindles work as controller.

On the right side of Fig. 6 the principle structure of the gamma-spindle loop is depicted in general terms: A set point is generated which can be understood as the anticipation of a desired state or a goal (e.g. the desired length of the muscle). A comparison of the desired to the current state (e.g. accomplished by spindles) delivers the impulse for some action by which the difference between the current and the desired state is reduced (e.g. alpha activation). Simultaneously, the differences are forwarded for perception and they are used in order to tune the activations of an additional direct motor pathway for triggering actions to achieve the set goal.

The point of the matter is the redundant control via two paths: a direct motor pathway and a sensory feedback loop. It might well be that this principle is not only realized for the control of muscles but on all levels of a hierarchical structure for the control of voluntary behaviour [cf. also 22].

Figure 7 illustrates a tentative structure: For the sake of simplicity only four levels are distinguished. On the highest level desired effects (goals) in the environment are specified (e.g. to grasp a cup of coffee). On the next level corresponding effector unspecific set points are generated (e.g. the egocentric location of the cup is fixed to which all limbs have equal access). At this point it is not yet decided e.g. whether to grasp the cup with the right or the left hand. Next, corresponding set points for a certain limb are specified (e.g. the posture of the right arm that brings the right hand to the cup). Finally, the set points for the corresponding muscles are generated (in our example Gamma activations for the muscles of the right arm and hand might be fixed in order to execute a corresponding grasping act). Concurrently, direct motor activations are tuned step for step and level for level in dependence on the continuously reported differences between the forwarded set

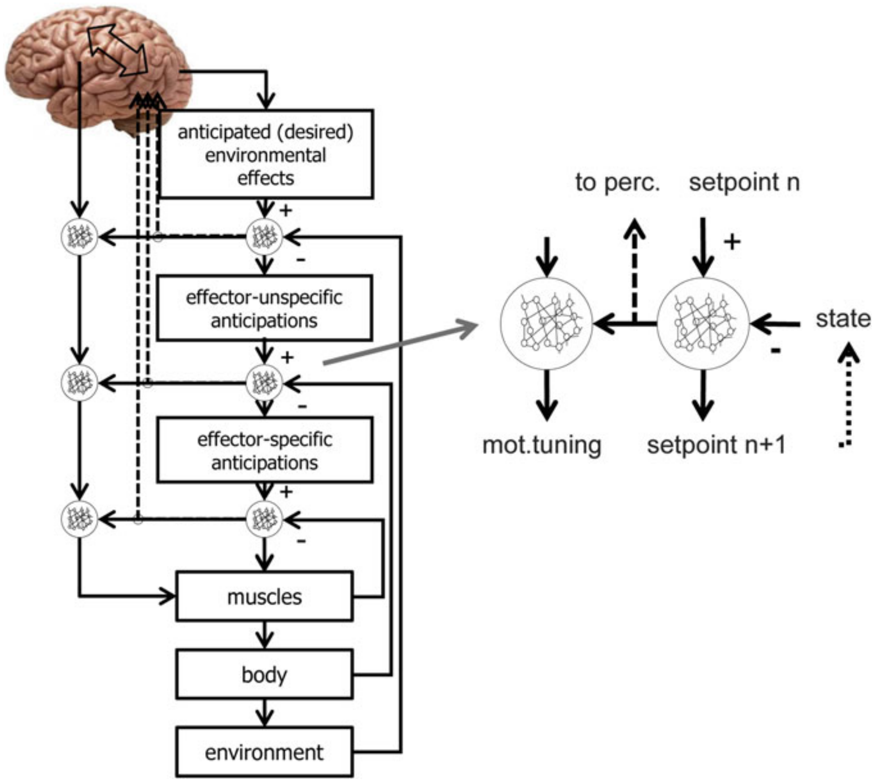

Fig. 7 A tentative cascade of anticipative sensory loops and direct motor commands for the control of voluntary behaviour (*left side*) with an enlarged illustration of one level (*right side*)

points and the confirmed current states. These differences simultaneously provide the data for perception.

If we focus on one of these levels you certainly recognize the general architecture of the gamma spindle loop with the two paths: a sensory control loop and a direct motor path. And if we look on the whole architecture we find the reafference principle, i.e. the anticipation of to be expected reafferences (the set points or desired states) as well as the ideomotor principle, i.e. the determination of motor commands by anticipated sensory input, distributed over different levels.

A concrete act will be finally realized by a continuous cascade of sensory control loops running down from top to bottom und back from bottom to top as well as by consecutively tuned direct motor activations.

The learning dependent formation of such structures refers to several relations at each of the different levels [23, 24]: First, representations of states which are worth to aim at (set points or goal anticipations) are to be distinguished and represented. Second, it has to be learned which differences between anticipated goals and current states are relevant for the determination of set points or goal anticipations on the respective next subordinated level. For example, it has to be learned how to determine the postures of the right arm and hand for reaching a certain point in space. Finally, it has to be learned how to tune the accompanying direct motor commands according to current differences between goals and states. As a result of such continuous adaptations of sensory anticipations and motor commands on different levels of abstraction perception and behaviour might be adopted to each other so that what is anticipated really happens.

These, of course, are tentative speculations which I think however are worth to become further elaborated and examined in order to see how far they reach.

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An Epistemological Compromise Between Actor and Observer

Alastair Hewitt

Abstract The computational aspects of prediction are examined in the context of anticipation. A practical model using reinforcement learning is presented and implications about making predictions from within the system are explored. An argument is put forward that implies the ability to determine the unknown state of a system (be it a hidden region or future evolution) results in an epistemological limit. A simple principle is introduced that defines a complementary relationship between what is knowable and what is mutable. The epistemological aspects of this relationship are explored in the context of how choice affects what can be known and therefore what becomes immutable. Some insight is gained into the relationship between this choice and the irreversibility of the thermodynamic arrow of time.

Keywords Epistemology · Anticipation · Reinforcement learning · Interaction-free measurement

1 Introduction

In the classical view of the world the observer is given a very specialized privilege in that the world is observed from the *outside*. Locations and events are described as if they were placed on a tabletop and examined from above. Even though this approached is superseded in the context of relativity, the replacement still treats the world as an object in the form of the four-dimensional block universe.

This objective approach is challenged in the context of Quantum Mechanics where there is a fundamental issue in maintaining both a realistic and local description of the world [1]. Even here the conventional notions of space and time are maintained and events must be connected with an instantaneous connection governed by a wave function used to describe them as an ensemble.

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This requirement of an instantaneous connection is a side effect of maintaining this external viewpoint where doing something *here* has to simultaneously do something *there*. There is really no *there* since the observer is trapped in the *here* and more importantly, the now.

To better understand the issue some important facts need to be highlighted: Any description of reality must be made from the point of view of an observer, since that is the only point of view available. All observers are embedded within the universe and are unable to escape and attain a viewpoint from the outside. Finally, all observers are emergent within the universe and have never been able to attain an external viewpoint. Based on these facts it seems meaningless to talk about the universe as a *thing* that is independent of an observer, or to consider a model where the world is seen from the outside.

Another important consideration is the notion of space and time relative to the observer. It takes a finite time to both receive information and subsequently affect an event in the distance. An observer will see events as they were in the past and affect events as they will be in the future. Relative to the observer the distant events never exist in the present; there is only information about what existed, and opportunities about what may exist. It is important to stress *what may exist*, since a choice of action to influence the future may not result in a deterministic outcome. It is only when the information returns after the fact does the observer know that an action did effect the future, and only by observing that effect as it now appears in the past.

With limited knowledge about the system being observed the process of observing, acting, and then verifying the action is highly inefficient. An effective observer must rely on *anticipation* in order to close the loop between the observed past and intended future. Here an intention is required along with a model where predictions can be made. The prediction is used to select which action best suits the intention given the information available. Anticipation allows the observer to interact with the system as if the events do exist in the present.

Finally, the relevance of determinism must be considered. Since we have stipulated only the observer's point of view is relevant then this has to be examined in that context. It may seem obvious that practical limitations of what an observer can access in terms of information will lead the observer to experience nondeterministic world. But what if the observer had unlimited resources, insight, and control? Regardless of the capability of the observer there is a fundamental epistemological tradeoff between what the observer can know and change about the system.

2 Computational Model of Prediction

To better understand how an observer can use an internal model of reality a computational model of prediction is introduced. This model lacks the requirement of an anticipatory system discussed by Rosen [2] in that it does not contain a predictive model of itself. This model will not interact with the predicted system and remains independent of the system.

In order to perform a prediction the state of the predicted system must be decomposable and encoded for use by a *prediction strategy*. In general, the prediction strategy is a computational process used to determine additional information about a system when only given partial information about the system. In the context of a dynamic system undergoing time evolution, the encoded input is the present state, and the encoded output is a prediction of the future state. The system itself could be quite complex and varies, so the prediction needs a *concern* to focus what type on prediction will be made and what type of information needs to be encoded.

The prediction strategy could be something very simple, essentially always making the same assumption and outputting the same prediction. The input could be complex weather conditions, but if the concern was, “will the sun rise five days from now”, then this sort of prediction strategy could simply encode the prediction to always be “yes” and be correct. If however the concern was, “will it rain five days from now”, then the input would need to be processed against a sophisticated model in order to produce a usable prediction (Fig. 1).

In the diagram above a time evolution is shown as a sequence of events. The state of the system at time t_n is observed by encoding it as i_n. In this example a prediction strategy denoted as S_x is used to take this input and generate a prediction of the future state at t_{n+1} as the encoded state $j_{x,n+1}$. This process can be represented using the following equation.

$$S_x : i_n \mapsto j_{x,n+1} \tag{1}$$

One important feature of the prediction strategy is the ability to compute and encode the prediction before the predicted state is reached. In the diagram the time when the prediction is made is shown as the time $t_{x,n+1}$. The prediction is said to have *utility* if this time t_{n+1} is less than the time t_{n+1}. This is represented as a *window of opportunity* W_x where the prediction can be used to affect the system.

In order to verify the reliability of the prediction strategy S_n the accuracy of the prediction is verified by comparing the predicted state j_{n+1} to the actual state i_{n+1} when time t_{n+1} arrives. The difference between the predicted and actual state is denoted as the error $\delta_{x,n+1}$ and defined as either 0 if the prediction was correct, or as 1 if the prediction was incorrect as follows.

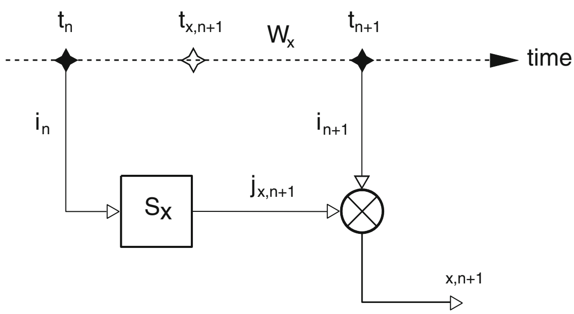


Fig. 1 Prediction strategy

$$\delta_{x,n+1} = [\![i_{n+1} - j_{x,n+1}]\!] \tag{2}$$

Here the specialized function denoted with the square brackets will map a delta to either 0 or 1, where the value 0 represents no error, else the value will be 1.

$$[\![\Delta]\!] : \Delta \mapsto \{0, 1\} \tag{3}$$

This takes into consideration a single prediction and whether it was a successful attempt to predict the future state of the system or not. To better understand the overall reliability of a prediction strategy many predictions must be made and the accumulated error averaged. The reliability of a prediction strategy S_x can be denoted r_x and defined as follows:

$$r_x = 1 - \lim_{t \to \infty} \left(\frac{1}{t} \sum_{n=0}^{t} \delta_{x,n+1} \right) \tag{4}$$

Here reliability ranges from 0 for a highly unreliable strategy to a value approaching 1 for a strategy with almost no errors. It is important to understand what reliability means in terms of how it relates to the system being predicted. If the system behaves in a random way then it is easy to assume a prediction strategy is going to be unreliable and the value of r_x will be close to 0. This is not necessarily the case as can be seen by a simple example: If the system is fair coin toss and the prediction strategy assumes that every result will be a head then the value of r_x is going to be 0.5. However, a value like this that is half way does not imply randomness. The system could be "10 fair coin tosses" and the prediction strategy could be "not all heads". In this case the reliability is going to be close to 0.999. The behavior of the system is essentially random and the strategy is very simple, but the reliability is very high.

To understand the reliability of a prediction strategy and what it reveals about the underlying system the set of all strategies $\mathbb{S}$ must be considered:

$$\mathbb{S} = \{S_1, S_2, S_3, \ldots\} \tag{5}$$

Iterating over each prediction strategy in set $\mathbb{S}$ and testing the predictions will generate the set of all reliabilities $\mathbb{r}$.

$$\mathbb{r} = \{r_1, r_2, r_3, \ldots\} \tag{6}$$

The statistical properties of this set are much more interesting in terms of what it expresses about the predictability of the system. If the system has any kind of deterministic behavior that can be successfully modeled then there will be a prediction strategy with a reliability of 1. This is the strategy that perfectly predicts the future state of the system and never generates an error. Conversely the strategy that computes the opposite of this strategy will have a reliability of 0. The statistical range of this set is therefore 1, and in this specific case, a range of 1 indicates that the system being predicted is deterministic. More generally the predictability $\mathcal{P}$ of the system can simply be defined as the range of reliabilities for the set of all prediction strategies:

$$\mathcal{P} = R(\mathbb{r}) \tag{7}$$

The predictability of a system ranges from 0 for a random and unpredictable system to 1 for the deterministic system described above. In the case of a random system there are no strategies that are more or less reliable than any other. This can be further demonstrated by the fact that the set of all strategies must contain the strategy *no strategy*, which is simply a random choice in terms of the prediction. For a random system, every strategy has the same reliability as *no strategy*.

3 General System Using Reinforcement Learning

A general system is introduced consisting of an agent and its environment. The agent will interact with the environment and since its actions can be taken into consideration as part of a prediction strategy, it would satisfy Rosen's definition of anticipatory system [3]. The agent utilizes reinforcement learning to analyze the environment and build a prediction strategy; the agent only requires some simple initial parameters to guide an interaction with the environment and construct a detailed model. Such systems [4] demonstrate anticipative behavior by examining the model and planning actions based on their expected impact.

The agent's interaction with the environment is through a concern over an observed state. The environment is encoded via a set of indicators that can have one of two values, true or false. This finite set of observables O is expressed as follows:

$$O = \{i_1, i_2, \ldots, i_n\} \tag{8}$$

Where the value of each indicator is either 1 for true, or 0 for false.

$$\forall i \in O, i \in \{0, 1\} \tag{9}$$

An additional set V is constructed to contain the enumeration of all possible states of the observed system, as represented by the combination of values contained in the set O. Since each element of O is a binary value, the cardinality $|V|$ will be 2^n, where n is the cardinality of the set of indicators $|O|$. The finite set V is expressed as follows:

$$V = \{v_0, v_1, \ldots, v_{2^n-1}\} \tag{10}$$

Each element of the set V can be thought of as a *vertex* on an n-dimensional hypercube. The numbering of each vertex is based on the binary number representation of the indicators contained by I. As an example, if the indicators where observed as {0, 1, 1, 0} then the state would be represented by the vertex v_6. More formally the value of x is defined as follows:

$$x = \sum_{y=1}^{n} i_y 2^{y-1} \tag{11}$$

The hypercube analogy has additional relevance because when a transition occurs, only one indicator is considered to change at a time. The environment may contain simultaneous transitions in the indicators, but the indicators are only observed in sequence, and action is taken based on the first transition to be observed. As an example, if the observed state is v_6, or {0, 1, 1, 0}, then only the states v_7, v_4, v_2, v_{14}, or {0, 1, 1, 1}, {0, 1, 0, 0}, {0, 0, 1, 0}, {1, 1, 1, 0}, can be observed next. This is analogous to only being about to travel along the n possible edges between each of the vertices, where n is the dimensionality of the cube.

3.1 Desirability

In order to have a concern about the state of the environment, the agent attaches desirability to each of the possible states it observes. This desirability is determined by assigning a value d_y to each of the indicators in O, where the value of d_y represents the *true desirability* of the condition when the indicator i_y is true. The value of d_y has a range from 0 for the least desirable, to 1 for the most desirable. This is a very simple arrangement, but it does come with some subtleties in terms of what the desirability represents. The agent will attempt to avoid undesirable states and by default arrive at desirable ones; therefore a desirability of 0.5 does not imply the agent does not care to be in the state, but that the agent will avoid this state half of the time.

Formally the indicators' desirability will be represented as a vector **d** as follows:

$$\mathbf{d} = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{bmatrix} \tag{12}$$

where the vector **d** contains an element for every indicator in O.

$$\forall i \in O, \exists d \in \mathbf{d} \tag{13}$$

A function D is used to determine the *actual desirability* of the current state of an indicator i_y with associated true desirability d_y.

$$D(i_y) = i_y \odot d_y \tag{14}$$

This function is represented by the operator $\odot$ and is simply the magnitude of the sum minus one.

$$i_y \odot d_y = |i_y + d_y - 1| \tag{15}$$

For example, this means that with a true desirability d_y of 0.8, the actual desirability will be 0.8 when the indicator i_y is true, and 0.2 when the indicator i_y is false. This function can be expanded to the set of all indicators represented by the vertex v_x and is represented by:

$$D(v_x) = v_x \odot \mathbf{d} \tag{16}$$

In this case the operator forms the product when applied to each pair of i_k in v_x, and d_k in $\mathbf{d}$, as follows:

$$v_x \odot \mathbf{d} = \left| \prod_{k=1}^{n} (i_k + d_k - 1) \right| \tag{17}$$

The value of $D(v_x)$ represents the desirability of the system being in state v_x. The most desirable states are those where the indicators with high true desirability are true, and the indicators with low true desirability are false.

In order to prioritize the choices available given a specific state of the system v_x the edges connecting that state need to be considered. The adjacent vertices connecting the vertex v_x can be represented as $v_{x,y}$, where y ranges from 1 to n. The value of x for v_x when represented as $v_{x,y}$ is calculated using a bit-wise exclusive-or function on the value x with 2 raised to the value of y minus 1 as follows:

$$v_{x,y} = v_{x \otimes 2^{y-1}} \tag{18}$$

Using the example from before to consider the vertex v_6: when y equals 1, the vertex $v_{6,1}$ is equivalent to v_7, the vertex $v_{6,2}$ is equivalent to v_4, the vertex $v_{6,3}$ is equivalent to v_2, and the vertex $v_{6,4}$ is equivalent to v_{14}.

The edges connected to vertex v_x can be represented as the vector $\mathbf{v_x}$ as follows:

$$\mathbf{v}_x = \begin{bmatrix} v_{x,1} \\ v_{x,2} \\ \vdots \\ v_{x,n} \end{bmatrix} \tag{19}$$

Applying the desirability function to each of the elements of this vector results in the desirability vector $\mathbf{d_x}$ defined as follows:

$$\mathbf{d}_x = \begin{bmatrix} v_{x,1} \odot \mathbf{d} \\ v_{x,2} \odot \mathbf{d} \\ \vdots \\ v_{x,n} \odot \mathbf{d} \end{bmatrix} \tag{20}$$

As can be seen, for every vertex v_x there is a corresponding desirability vector $\mathbf{d}_x$. Each of these vectors represents the combined desirability of all transitions from each state in the system.

3.2 Choice and Strategy

The agent is able to interact with the system by selecting from a set of available actions. Choosing to take action a_z will result in the state of the system changing. As described before, the state transition will be from the current state v_x to one of the adjacent states contained in the vector $\mathbf{v}_x$.

$$a_z : v_x \mapsto v_{x,y} \in \mathbf{v}_x \tag{21}$$

The available choices are represented by the $1 \times m$ matrix $\mathbf{C}$ containing m possible actions.

$$\mathbf{C} = \begin{pmatrix} a_1 & a_2 & \ldots & a_m \end{pmatrix} \tag{22}$$

With a current state of v_x, the probability of a transition to the state $v_{x,y}$ given a choice of action a_z is defined as follows:

$$p_{x,y,z} = P\left(v_x \to v_{x,y} | a_z\right) \tag{23}$$

The probability of all possible transitions from state v_x given action a_z is also represented as a vector. This vector $\mathbf{s}_{x,z}$ contains each of the transition probabilities from v_x given action a_z as follows:

$$\mathbf{s}_{x,z} = \begin{bmatrix} p_{x,1,z} \\ p_{x,2,z} \\ \vdots \\ p_{x,n-1,z} \end{bmatrix} \tag{24}$$

The probabilities in this vector provide usable information about what is likely to happen from a state v_x and given an action a_z. Formally, this vector represents the *prediction strategy* available to the agent for choice a_z when in state v_x. The agent does not simply look for the most probable transition within the strategy and assume that will happen given the action. Instead the agent compares this vector to the desirability of the transitions $\mathbf{d}_x$ to determine the *suitability* of the choice. The suitability is essentially the angle between the two vectors, where the smaller the angle the better. The closer these vectors are together then the higher the probability of a desirable transition and the lower the probability of an undesirable transition. This suitability $\theta_{x,z}$ can be determined as follows:

$$\cos \theta_{x,z} = \frac{\mathbf{d}_x \cdot \mathbf{s}_{x,z}}{\|\mathbf{d}_x\| \|\mathbf{s}_{x,z}\|} \tag{25}$$

The matrix $\mathbf{S}_x$ can be constructed to contain all of the vectors $\mathbf{s}_{x,z}$ for the choices in $\mathbf{C}$. This matrix represents the *decision strategy* available to the agent for evaluating the best choice of action given state v_x.

$$\mathbf{S}_x = \begin{bmatrix} p_{x,1,1} & \cdots & p_{x,1,m} \\ \vdots & \ddots & \vdots \\ p_{x,n,1} & \cdots & p_{x,n,m} \end{bmatrix} \tag{26}$$

3.3 *Confidence and Predictability*

In some states there may be a lot of ambiguity in the information represented by the prediction strategy. In these situations there will be similar probabilities in what possible transition will occur given an action and the agent will have low *confidence* in selecting the best action. This is represented as the confidence $c_{x,z}$ in prediction strategy $\mathbf{s}_{x,z}$. The confidence is simply the *Shannon redundancy* [5] defined as follows:

$$c_{x,z} = 1 - \frac{H_{x,z}}{H_{max}} \tag{27}$$

where $H_{x,z}$ is the entropy and H_{max} is the maximum entropy:

$$H_{x,z} = -\sum_{k=1}^{n} p_{x,k,z} \log_2 p_{x,k,z} \tag{28}$$

$$H_{max} = \log_2 n \tag{29}$$

The confidence ranges from 0 when the entropy in the prediction strategy reaches the maximum, to 1 when the entropy is zero. The first situation will be seen when the probability of all state transitions are identical. The second situation will be seen when only one state transition can occur, so the probability is either 1 for this transition, or 0 for all the others.

There is a close relationship between the confidence and the reliability of the prediction strategy discussed in the previous section. It is important to understand that these two things are not the same however. The prediction strategy reliability was calculated by averaging the deltas between the expected and actual state transitions. The system described here relies on reaching equilibrium where the probability of transition is as close as possible to the desirability of those transitions.

The confidence in a prediction strategy is already a measure of the predictability of the system. Predictable systems will lead to strong correlations between the actions and the resulting state transition. Systems that are unpredictable will have weak correlations and the entropy in the observed behavior will be high.

3.4 Example Implementation

To better understand this general system an example is presented along with some considerations for implementing a practical agent. In this example the agent is a simple mobile automaton and the environment is a two-dimensional surface. There are two observables: a green light, which is considered relatively desirable, and a red light, which is considered significantly more undesirable.

$$O = \left\{ i_{green}, i_{red} \right\} \tag{30}$$

The true desirability of seeing the green light is 0.7, and the desirability of seeing the red light is 0.2.

$$\mathbf{d} = \begin{bmatrix} 0.7 \\ 0.2 \end{bmatrix} \tag{31}$$

There are four possible states in the system and the actual desirability of each state and their transition relationship can be shown as follows:

$$\begin{matrix} D(v_0) = 0.24 & \leftrightarrow & D(v_1) = 0.56 \\ \updownarrow & & \updownarrow \\ D(v_2) = 0.06 & \leftrightarrow & D(v_3) = 0.14 \end{matrix} \tag{32}$$

As can be seen, the most desirable state is v_1 where the agent is traveling towards the green light and away from the red. Conversely, the least desirable state is v_2 where the agent is traveling towards the red light and away from the green. For each state the desirability vectors are as follows (Fig. 2):

$$\mathbf{d}_0 = \begin{bmatrix} 0.56 \\ 0.06 \end{bmatrix}, \mathbf{d}_1 = \begin{bmatrix} 0.24 \\ 0.14 \end{bmatrix}, \mathbf{d}_2 = \begin{bmatrix} 0.14 \\ 0.24 \end{bmatrix}, \mathbf{d}_3 = \begin{bmatrix} 0.06 \\ 0.56 \end{bmatrix} \tag{33}$$

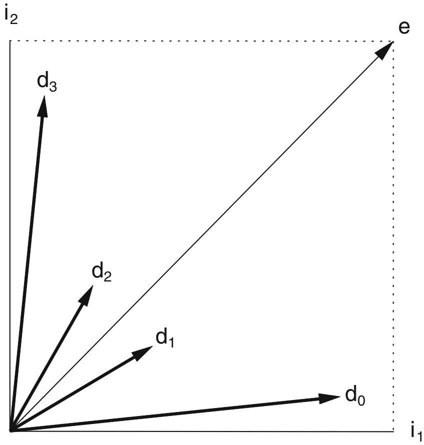


Fig. 2 Desirability vectors

To better understand these vectors they are drawn on a diagram above. The vector **e** represents the *equivocal* desirability where there is no preference in desirability for the next transition and consequently an ambiguous choice. The further the vectors are away from the vector **e** the stronger the choice will be. This can be seen for states v_0 and v_3 where there is one very desirable state transition (v_1) and one very undesirable transition (v_2).

Two choices of actions are made available, either to turn clockwise, or to turn counter-clockwise.

$$\mathbf{C} = \begin{pmatrix} a_{cw} & a_{ccw} \end{pmatrix} \tag{34}$$

So far the practicality of determining the probability of the state transitions given an action has not been discussed. This is where the agent will build up its knowledge of the system via interaction. The agent can select actions from the available choices and then record the resulting state transition. To record these the agent maintains a *tally* of the different state transitions observed for each action. The tally $t_{x,y,z}$ is simply the number of times the transition from v_x to $v_{x,y}$ has been observed given the action a_z:

$$t_{x,y,z} = N\left(v_x \to v_{x,y} | a_z\right) \tag{35}$$

The probability can be calculated from the tally as follows:

$$p_{x,y,z} = \frac{t_{x,y,z}}{\sum_{k=1}^{n} t_{x,k,z}} \tag{36}$$

A *tallied prediction strategy* $\mathbf{t}_{x,y}$ can be constructed from the tallies instead of the probabilities. This vector points in the same direction as the original prediction strategy $\mathbf{s}_{x,y}$ and is therefore equivalent since only the angle between the vectors is relevant. From here a matrix of tallies for choices can be constructed as the *tallied decision strategy* $\mathbf{T}_x$.

$$\mathbf{T}_x = \begin{bmatrix} t_{x,1,1} & \cdots & t_{x,1,m} \\ \vdots & \ddots & \vdots \\ t_{x,n,1} & \cdots & t_{x,n,m} \end{bmatrix} \tag{37}$$

The entire dataset needed by the agent can be represented as the tallied decision strategies for each state. These strategies and their relationship in terms of state transition can be represented as follows:

$$\begin{array}{ccc} \mathbf{T}_0 & \leftrightarrow & \mathbf{T}_1 \\ \updownarrow & & \updownarrow \\ \mathbf{T}_2 & \leftrightarrow & \mathbf{T}_3 \end{array} \tag{38}$$

A final consideration is the initial state of the prediction strategy. To prevent issues with zeros, the tallies are initialized as 1 so that everything matches the direction of the equivocal vector e. Also, since there is initially no information in the prediction strategies, and hence no confidence in the choices, the initial state represents an equal probability of every transition and therefore initializes with the maximum entropy.

Consider a sequence of events starting from state v_3. In this state the agent is traveling towards both of the lights and both indicators are registering true. The agent examines the decision strategy $\mathbf{T}_3$ and since there is no confidence in the information the agent must make a *default* decision. The default decision is the first choice available in the list of actions, so the agent selects the *turn clockwise* action. Assuming the agent turns away from the green light the next transition is to state v_2 and the tally $t_{3,2,cw}$ is updated by 1.

Once in state v_2 the decision strategy $\mathbf{T}_2$ is used and since there is still no confidence the agent makes another default decision to *turn clockwise*. The agent will continue to turn away from the red light and will update the tally $t_{2,0,cw}$ by 1 as it transitions to state v_0. Again, the empty decision strategy $\mathbf{T}_0$ results in a continuation of the clockwise turn through state v_1 and then finally back to the initial state v_3. At this point the agent has collected the following information:

$$\begin{array}{ccc} \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} & \leftrightarrow & \begin{bmatrix} 1 & 1 \\ 2 & 1 \end{bmatrix} \\ \updownarrow & & \updownarrow \\ \begin{bmatrix} 1 & 1 \\ 2 & 1 \end{bmatrix} & \leftrightarrow & \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} \end{array} \tag{39}$$

The information available in $\mathbf{T}_3$ can now be used to evaluate the best choice of action. The suitability $\theta_{3,cw}$ between the prediction strategy $\mathbf{t}_{3,cw}$ with a vector of $\langle 2, 1 \rangle$ and the desirability $\mathbf{d}_3$ with a vector of $\langle 0.06, 0.56 \rangle$ is compared to the suitability $\angle \mathbf{e}\mathbf{t}_{3,ccw}$ between the equivocal vector $\mathbf{e}$ and the prediction strategy $\mathbf{t}_{3,ccw}$.

Since $\theta_{3,cw}$ is significantly greater the agent selects the alternative action *counter-clockwise* and turns back transitioning to state v_1 again. Using the information available in $\mathbf{T}_1$ the suitability $\theta_{1,cw}$ between prediction strategy $\mathbf{t}_{1,cw}$ vector $\langle 1, 2 \rangle$ and the desirability $\mathbf{d}_1$ vector of $\langle 0.24, 0.14 \rangle$ is again seen to be greater than $\angle \mathbf{et}_{1,ccw}$. The agent will continue to turn counter-clockwise until it transitions back to state v_0. This time the decision strategy $\mathbf{T}_0$ contains a lower suitability $\theta_{0,cw}$ between the prediction strategy $\mathbf{t}_{0,cw}$ vector $\langle 2, 1 \rangle$ and the desirability $\mathbf{d}_0$ vector of $\langle 0.56, 0.04 \rangle$ than $\angle \mathbf{et}_{0,ccw}$. The agent will reselect the previous choice *turn clockwise* and turn back towards the green light with a transition to state v_1. After this next sequence the information contained by the agent is the following:

$$\begin{array}{ccc} \begin{bmatrix} 3 & 1 \\ 1 & 1 \end{bmatrix} & \leftrightarrow & \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \\ \updownarrow & & \updownarrow \\ \begin{bmatrix} 1 & 1 \\ 2 & 1 \end{bmatrix} & \leftrightarrow & \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \end{array} \tag{40}$$

From this point on the agent will alternate between the states v_0 and v_1; first turning clockwise when seeing no light and then counter-clockwise when seeing the green light. The agent must make a choice to turn one way or the other, so will not reside in any one state. The entire knowledge needed by the agent was garnered by making a single complete rotation. From this sequence of observations the agent collected all the information needed to maintain itself in the two most desirable states. If the agent is moving then it will eventually pass the green light and make another complete rotation to realign itself again. This cycle will be repeated as the agent passes the green light and settles into an orbit around the green light whilst avoiding the red.

3.5 Selection Strategy

An additional strategy was used in the example and is now formally introduced as the *selection strategy*. This strategy utilizes the decision strategy to evaluate the choices and determine the best choice of action. In the previous example the decision strategy was used in very specific way to make a selection: The angle between the desirability vector and each prediction strategy were compared and the action considered most suitable (with the smallest angle) was selected. This specific selection strategy will be referred to as the *instinctive strategy*.

The instinctive strategy only considers the decision strategy from the current state of the system. This is similar to an instinctive behavior where a decision is made immediately without engaging any additional thought. This type of strategy has the lowest computational overhead and subsequently the lowest latency in terms of selecting an action.

The agent has access to information not only about the current state but also the other states of the system. This gives the agent the ability to *look ahead* and examine the decision strategies adjacent to the current state. This type of selection strategy is referred to as the *anticipative strategy*. Here the agent iterates though each of the actions and calculates the suitability as before, but this time the agent will also visit each of the decision strategies in the adjacent states. Each of the possible choices in the adjacent states is examined and the sum of the current and potential future choices is calculated.

Using the example implementation from before, if the current state were v_3, then the agent would start by calculating the suitability $\theta_{3,cw}$ and $\theta_{3,ccw}$. The agent will then evaluate the adjacent states v_1 and v_2 and calculate the suitability $\theta_{1,cw}$, $\theta_{1,ccw}$, and $\theta_{2,cw}$, $\theta_{2,ccw}$. Instead of the suitability of two choices to consider there would now be eight:

$$a_{cw}\begin{cases}\theta_{3,cw}+\theta_{1,cw}\\ \theta_{3,cw}+\theta_{1,ccw}\\ \theta_{3,cw}+\theta_{2,cw}\\ \theta_{3,cw}+\theta_{2,ccw}\end{cases}\quad a_{ccw}\begin{cases}\theta_{3,ccw}+\theta_{1,cw}\\ \theta_{3,ccw}+\theta_{1,ccw}\\ \theta_{3,ccw}+\theta_{2,cw}\\ \theta_{3,ccw}+\theta_{2,ccw}\end{cases} \tag{41}$$

The anticipative strategy would find the most suitable of the eight choices shown above and select the action associated with that value. This way the agent does not just react to the current state, but looks ahead by one-step to find the best choice based on the current and future state of the system.

The process of looking ahead can be extended beyond a single step. When each of the states adjacent to the current state is evaluated, the adjacent state to each of those can also be evaluated. One consequence of anticipation over multiple transitions is the introduction of circular paths: In the example, starting from state v_3, each of the adjacent states v_1 and v_2 will have an adjacent state of v_3. It would appear there is an opportunity to optimize the number of calculations needed to evaluate the choices since an already evaluated state is revisited. This is not the case however, since the impact of the previous choice must be considered in the strategy. The anticipation can be extended to any depth, but since this problem is *NP-complete* it becomes extremely expensive in terms of computation resources.

The computational cost of calculating the suitability scales according to the following:

$$O(n^a) \tag{42}$$

where n is the cardinality of the observables O and a is the depth of the anticipation. The computational cost of selecting a suitable choice, where m is the cardinality of available actions $\mathbf{C}$, is stated as follows:

$$o\left(m^{a+1}n^a\right) \tag{43}$$

By definition, *anticipation* is characterized by $a > 0$ and the instinctive strategy is simply the special case where $a = 0$. Since only the current state is examined for an instinctive strategy the computational cost of calculating suitability is 1 and the cost of selection is m, where only the immediate set of the choices are considered.

3.6 Anticipation

One thing not yet discussed is Rosen's requirement of an anticipative system: The impact of actions considered by the agent must be incorporated into the predictive model [6]. This is not relevant for the instinctive strategy, since only the current state is considered and actions are essentially reactive. There is a requirement to include the actions of the agent in the prediction strategy when future states are considered in the selection strategy. The anticipative strategy examines the adjacent states in the context of those state transitions having occurred given each action. In this case the agent must make a hypothetical tally against both the action and transition before evaluating the suitability of the action. To fully evaluate all possibilities the agent requires $n{\bullet}m$ copies of the prediction strategy where each copy is updated to reflect the transition that is being evaluated in the next step of the anticipation. In effect, multiple prediction strategies are created to evaluate a future version of the system where a state transition has occurred due to a potential action. The single-step anticipation detailed in (41) can be illustrated by the following, where the first column of matrices shows the copies of each possible $\mathbf{T}_3$ needed to compute the 8 possible paths:

$$
\begin{aligned}
a_{cw} & \begin{cases} v_3 \rightarrow v_1 : \begin{bmatrix} 2 & 1 \\ \mathbf{2} & 2 \end{bmatrix} & \rightarrow \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \\ v_3 \rightarrow v_2 : \begin{bmatrix} \mathbf{3} & 1 \\ 1 & 2 \end{bmatrix} & \rightarrow \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} \end{cases} \\
a_{ccw} & \begin{cases} v_3 \rightarrow v_1 : \begin{bmatrix} 2 & 1 \\ 1 & \mathbf{3} \end{bmatrix} & \rightarrow \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \\ v_3 \rightarrow v_2 : \begin{bmatrix} 2 & \mathbf{2} \\ 1 & 2 \end{bmatrix} & \rightarrow \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} \end{cases}
\end{aligned}
\tag{44}
$$

It is worth noting that the memory requirement to store these hypothetical transitions is equivalent to the computational requirement to compute the anticipation. This implies that anticipation is not only the most expensive type of computational problem, but is also the most expensive in terms of space requirements needed to perform the computation.

The computational power of an agent utilizing anticipation has a far greater impact on the system than may be apparent [7]. Consider a living system that is primarily motivated by survival. A non-anticipatory agent is simply reacting to the environment as if it was just another coupled component of the larger system. An anticipatory agent can step ahead of the environment and plan for more suitable future where survivability is maximized. This simple change in behavior will separate the anticipative agent from the environment; not only is the agent directing itself, but directing the environment to benefit its own survivability.

The control the agent has over the environment also has important implications for assigning the initial desirability for each observable. The agent is no longer just reacting to the state of the system but planning the future state as it appears to the agent. The agent can drive the likelihood of certain states to become more likely if desirable and less likely if undesirable. An important consideration here is the need for some kind of inequality in the preference of each state. If the agent sees an equal desirability in adjacent states then the preferred behavior is for an equal probability in those state transitions. As the probability reaches equality the entropy of the system reaches maximum and the confidence in the prediction strategy becomes zero. Even if states are essentially equivalent, making an arbitrary choice to make one more desirable than the other will force the system to a predictable and hence more controllable state.

4 Epistemological Limitations

In the previous two sections a general concept of prediction and predictability is discussed along with a more practical example of system capable to constructing and using a prediction strategy. One critical aspect of these models that was not discussed is the effect that using the prediction has on the predicted system. This is a simple problem of recursion: In order for the prediction strategy to make a prediction beyond the first step of the evolution in the system, the prediction strategy must be taken into consideration as part of the predicted system.

This is a fundamental problem in any system that attempts to use the output of a prediction strategy. This is not just a limitation in computational resources, or the ability to model the predicted system outside of the prediction strategy. Consider an *oracle*, being the prediction strategy S_o that makes a perfect prediction of the future state of the system. The oracle generates a prediction i_n and this is compared to the state at j_{n+1}. By definition the delta for an oracle is always zero:

$$\forall n : \delta_{o,n} = 0 \tag{45}$$

However, if an agent is introduced that can affect the system and it chooses to use the prediction to change the system then a recursive problem is introduced. The oracle would have to include the actions of the agent, but since the agent is using the output of the oracle as its decision strategy, the oracle must model itself.

It is important to notice that the prediction is inaccurate only if the prediction is acted upon. The future state of the system can be known, but the agent is faced with a choice to use the prediction or not. By acting on the prediction the agent must change the system that was used to generate the prediction. This change will affect the accuracy of the prediction, in a sense making the state of the modified system unknowable. This tradeoff will be expressed by the following *epistemological principle of choice*:

What Is Knowable Cannot Be Changed, What Is Changeable Cannot Be Known

As discussed in the introduction there is a more important consideration for any natural system in that any observation must be made from inside the system. Considering the enormous expense of performing any kind of anticipation, simply the acquisition and utilization of knowledge has a large impact on the system. Starting from a set of information about the current state, the future state can be knowable, but cannot be known without changing the system. The change ultimately represents a choice between keeping the prediction correct, or selecting an alternative state that *must be* unknowable (until a selection is made).

Alternatively, if something remains fundamentally unknowable then it can be changed. This goes beyond simple ignorance on the part of an agent and represents a real gap in the available knowledge about the system. The ability of the agent to change the system was taken for granted. The agent is making decisions and affecting the future state of the system, which is considered to be mutable. The principle implies that if an event in the past was unknowable then the agent has the ability to also affect this. This may not seem realistic for a natural system, but under specific conditions this is possible.

5 Interaction-Free Measurement

The conventional notion of time is that events in the past are know and immutable and those in the future are unknown and mutable. It is this intuition that leads to the notion that once an event has happened it is consigned to the past as the history leading to the present. However, perhaps there are two concepts here that are very closely linked but ultimately separate. It is possible to construct an experiment utilizing interaction-free measurement where an event in the past can be changed. This is only possible under specialized conditions, but is a real effect that demonstrates to some extent the relationship between real knowledge of an event and the ability to change it.

To explore this we will consider a Mach-Zehnder interferometer that utilizes two beam splitters: BS_1 and BS_2. Each of the beam splitters is a half silvered mirror designed to either transmit or reflect a coherent light source. A photo of light has a 50 % probability of being transmitted through the beam splitter or a 50 % probability of being reflected. The photons are first split by BS_1 into travelling via either path A_0 or path A_1 with a 50/50 probability (Fig. 3).

The arms of the interferometer are adjusted to create an interference pattern at BS_2. Constructive interference with path A_0 results in complete transmission through BS_2, and destructive interference with path A_1 results in complete reflection by BS_2. The result is that the detector D_1 will detect photons with a 100 % probability and detector D_0 will detect photons with a 0 % probability.

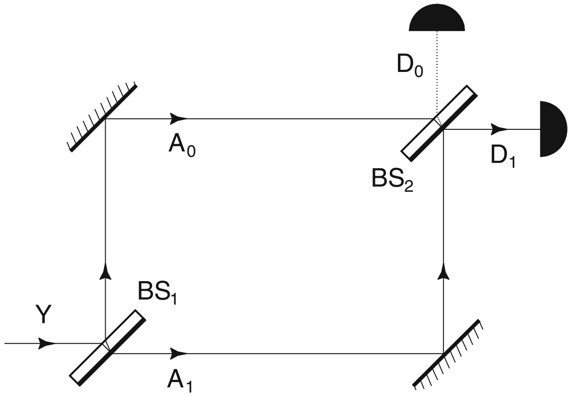


Fig. 3 Mach-Zehnder interferometer

If no observation is made then the photons are considered to pass through the interferometer in a superposition of travelling down both paths A_0 and A_1 simultaneously. If a detector is placed within the arms and the photons are observed then each photon is forced to choose between travelling path A_0 or A_1.

5.1 Elitzur-Vaidman Bomb-Testing Problem

Elitzur and Vaidman [9] proposed an interesting configuration of this interferometer in a thought experiment to test a super-sensitive bomb. The bomb is considered to be so sensitive that a single photon will detonate it, so the bomb detector utilizes the wave function of a photon to detect the bomb without actually interacting with it directly. Placing the bomb in one of the interferometer arms and observing an event where a photon is detected at D_0 will confirm detection without interaction (Fig. 4).

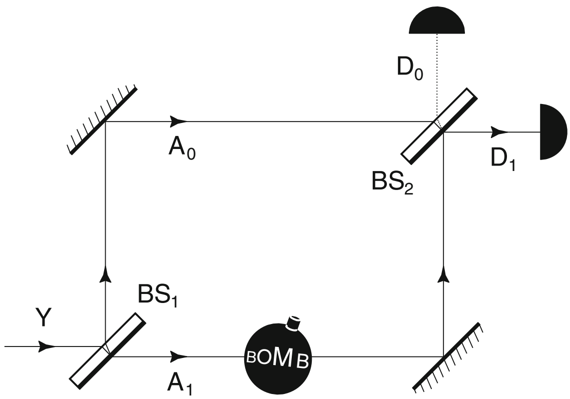


Fig. 4 Elitzur-Vaidman bomb detector

Table 1 Outcome given path and detection

Path	Detection	Outcome
A_0	D_0	Detection
A_0	D_1	Indeterminate
A_1	–	Detonation

In the experiment the photon will travel down path A_1 50 % of the time. In this situation the photon will interact with the bomb and cause a detonation. The other 50 % of the time the photon will travel down path A_0 and miss the bomb altogether. However, even though the photon did not travel down path A_1 its wave function did and the interference pattern previously established is now disturbed.

Once the bomb disturbs the wave function the previously established interference at BS_2 will now allow the photon to be reflected towards detector D_0. The photon may still pass through BS_2 and arrive at D_1 as previously configured, in which case the presence of the bomb is unconfirmed, not that the bomb is not there. In the case were detection is made at D_0 then the presence of the bomb can be confirmed with certainty (Table 1).

The table above shows the outcome given the possible combinations of path taken by the photon and the detections made. The 50 % probability of detonation may seem very unreliable for a bomb detector, but this experiment has been performed by Zeilinger et al. [8] and improvements proposed where the probability of detonation can be reduced to almost zero.

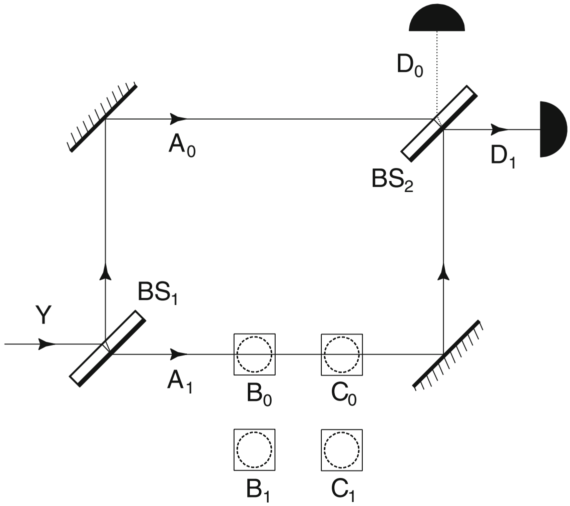
5.2 *Elitzur-Dolev Choice of Histories*

Elitzur and Dolev [10, 11] proposed an even more intriguing version of the bomb detector by allowing the superposition in the photon to measure another superposition. In this scenario multiple atoms are placed in a superposition where the wave function governing their location overlaps path A_1 of the interferometer. As before a photon detection at D_0 indicates that an interaction has occurred, however in this set up the interaction is one wave function interacting with another wave function. The result is a situation where an interaction has occurred between the photon and an atom, but there is still a choice in exactly which atom interacted with the photon after the time when interaction occurred.

To demonstrate this the atoms are prepared in the following superposition: Two spin ½ atoms, B and C, are prepared in an up spin-x state and then split by a non-uniform magnetic field *M* into two z-components, $\langle B_0, B_1 \rangle$ and $\langle C_0, C_1 \rangle$. The z-components B_0 and C_0 are positioned such that they lie in path A_1 of interferometer (Fig. 5).

When a photon traverses the interferometer and interacts with one of the atom there is a chance the photon will arrive at D_0. Therefore detection at D_0 indicates an interaction has definitely occurred between the photon and atom. Interaction with an

Fig. 5 Elitzur-Dolev choice of histories



atom is detected by observing a down spin-x state after a non-uniform magnetic field *-M* is used to recombine the z-components of the atoms. An atom is selected at random and the position measured by observing location B_0 or C_0. If the location reveals an atom then the position information of the other atom is erased by applying the non-uniform magnetic field *-M*. The original up spin-x state is always recovered, so only the observed atom must have been involved in the interaction (Table 2).

The table above shows the outcome given the possible combinations of path taken by the photon, the position in atom B, C, and the detections made. The first three rows show the detection by D_0. Out of these three possibilities two out of three are either B_0 or C_0. As can be seen, when an atom is chosen, two out of three

Table 2 Outcome given path, atom positions, and detection

Path	B position	C position	Detection	Outcome
A_0	B_0	C_0	D_0	Interaction
A_0	B_0	C_1	D_0	Interaction
A_0	B_1	C_0	D_0	Interaction
A_0	B_1	C_1	D_1	Indeterminate
A_1	B_0	C_0	–	Absorbed by B
A_1	B_0	C_1	–	Absorbed by B
A_1	B_1	C_0	–	Absorbed by C
A_1	B_1	C_1	D_1	Indeterminate

times that atom will show an interaction. The classical expectation would indicate that any atom chosen at random would have an equal probability of interaction. However, in this situation there is a 66 % probability that the first atom measured will be the atom that interacted.

Given n atoms, the probability of an atom chosen at random being the one that interacted is given by the following.

$$p = \frac{2^{n-1}}{2^n - 1} \tag{46}$$

As the number n gets large, the probability of choosing the *correct* atom approaches 50 %. Given a large number of atoms there is a 50/50 chance that a randomly selected atom would have interacted with the photon, even though the interaction has already occurred. Most interpretations of quantum mechanics attempt to preserve some nominal concept of motion and causality, but this result is highly counterintuitive. To better understand this result a more subtle relationship is required between what has been determined about the state of this system and what is still yet to be determined.

In the events where D_0 registers detection it is known that one of the atoms has been disturbed. This is known because D_0 can only occur if an atom is intersecting A_1 has disturbed the wave function. More importantly the detection at D_0 is immutable regardless of what other configurations or measurements are made. What remains unknown is which atom has been affected, even though any one of these atoms will intersect A_1 with a probability greater than 50 %.

6 Conclusion

An observer in a natural system must acquire knowledge and perform computation on a prediction strategy within the system itself. This involves changing the system, and in the case of any non-trivial system would make some predictions inaccurate. More precisely, a prediction strategy S_o that attempts to make perfect predictions about a natural system must have a reliability $r(S_o)$ that is less than one. Conversely, a prediction strategy $\overline{S}_o$ will exist that makes the opposite prediction to the strategy S_o and have a reliability $r(\overline{S}_o)$ that is greater than zero. If the prediction strategy S_o is as accurate as possible then the reliability of these two strategies will lie close but not at the edges of the statistical range. This implies that any natural system, when constrained by internal observation, must appear to be nondeterministic from the point of view of that observer. Furthermore, no prediction strategies exist beyond the accuracy of S_o so the behavior of the system beyond S_o is entirely unpredictable and therefore appears random.

The limitation in the predictability of the system presents the agent with an apparent choice. So far choice has been used implicitly in the definition of a principle, but this choice is in fact a consequence of the principle. First consider that for a choice to exist there must be more than one possible evolution of the system and that each of these alternatives must be equivalent. Even if an oracle can observe the single evolution of a deterministic system from outside the system, an internal observer will face randomness in the observed evolution. For an internal observer there is no perfectly reliable prediction strategy available and no way to reliably distinguish between the potential alternatives when making a selection. The agent is presented with what is essentially a free choice since no greater insight can be gained from within the system about the possible outcome of making this selection.

In addition, the act of selection eliminates the apparent choice in the system. The future evolution of the system can become knowable by the successive reduction in choices (degrees of freedom) that are available. Each selection reduces an apparent choice until there are no more choices available. At this point the evolution of the system is now knowable and cannot be changed; the event has passed from the future into the past.

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Part II
Anticipation in Biological and Physiological Systems

Future Perception in Plants

Ariel Novoplansky

Abstract Although a few of the earliest naturalists, such as Theophrastus, made concrete observations regarding the sophisticated ways by which plants sense and respond to their environments, the prevailing attitude toward plants has been based on the Aristotelian paradigm, that at their low rank, slightly above minerals on *Scala Naturae*, plants are mere non-sentient soil-eating blobs. However, accumulating evidence demonstrates that plants are able to not only precisely gauge and respond to their immediate environments but can also perceive, integrate and adaptively respond to myriad internal and external signals and cues that are correlated with their future environments, in ways that maximize their life-time performance.

Keywords Environmental cues · Anticipation · Evolutionary ecology · Future perception · Learning · Memory · Phenotypic plasticity · Plant behavior · Plant development · Plant signaling

1 Introduction

Discussing future perception necessarily requires dealing with the larger conceptual framework of *learning*. Simple learning can be described by its results and long-lasting implications. We look at learning whenever an early perception of a stimulus is stored (memorized) and has adaptive bearings on future responses and functioning. Central nervous systems (CNS's) are obviously capable of executing elaborate forms of learning, many of which are unique to their bearers, but here I present a few aspects of the abilities of CNS-less organisms to perform simple learning in the service of their improved readiness for anticipated future challenges.

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Perhaps the most common mode of learning in nature is demonstrated by the process of organic evolution by natural selection. When populations undergo evolutionary changes, they accumulate and store critical information affected by the actions of evolutionary forces, such as mutations, selection, migration etc., while continuously changing their genetic profiles based on their multifaceted interactions with the environment. Accordingly, each individual organism carries an enormous amount of information relevant to its functioning, survival and reproduction, which is the product of its progenitor's experiences that is stored in its genetic material. Perhaps trivially but certainly crucially, the only reason that Darwinian evolution is relevant for the adaptations of organisms to their immediate environments is *the existence of sufficiently high correlation between the past and the present*, between past conditions that have selected for particular genetically-encoded adaptations and present functional and ecological challenges faced by extant carriers of the same genetic information. However, the passive nature of "evolutionary learning" is not, in and of itself, allowing active acquisition and integration of real-time adaptive information.

Abundant examples show that the carriers of the very same genetic information, such as identical twins, may differentially respond to various internal and external signals and cues to adapt to the ever-changing environmental conditions they are confronted with. Indeed, adaptive responsiveness of organisms to environmental change or stimuli is ubiquitous amongst all known organisms, regardless of the level of their structural and functional complexity. This responsiveness is commonly called *phenotypic plasticity* and it may pertain to a wide spectrum of responses to both internal and external conditions, signals and cues [e.g. 1, 2]. For example, even a short exposure to ultraviolet-containing sunlight would cause significant darkening of the skin, a response proven highly adaptive in light-skinned people. Importantly, much like the level of melanin in our skin, our ability to tan, i.e. to change melanin concentration, is in itself also genetically-encoded and greatly vary across human populations [3]. Accordingly, genes encode for both fixed characters (e.g. all humans have one nose), but also for the quantitative and qualitative determinants of the character's environmental responsiveness, i.e. phenotypic plasticity. Bold examples for this phenomenon are seasonal change in skin tone, life-style determination of body weight and height, education effects on I.Q. etc., many of which are adaptive and all of which are relevant to future functioning of the responding organism and ultimately- its evolutionary success. Importantly, while fixed characters only require genetic information (blueprint), all plastic responses and characters require additional inputs—environmental information that is acquired by the responding organism. Though active acquisition and integration of such information requires the action of additional, at time rather sophisticated and costly perception mechanisms, by no means it has to hinge on mental capacities or elaborated computation capabilities limited to CNS-bearing organisms [4].

Although phenotypic plasticity is expressed at all organizational levels, from the molecular to the organismal, the subject of most ecological and evolutionary studies is *developmental plasticity*, whereby organisms change their size, morphology and architecture in response to internal and external stimuli [5]. Although developmental plasticity plays a major role in the adaptation of both animals and plants [e.g. 6, 7], it has an emphasized adaptive importance in sessile organisms such as plants, in which limited motility prevents sufficiently-rapid avoidance of stressful conditions (e.g. competition, predation) or efficient foraging for ecological opportunities (e.g. finding and utilizing patches of high resource levels, shelter, reproductive partners). It is for such slow-moving organisms that plastic responsiveness pertaining to future conditions is so critically important. As plastic responses—especially those related to the development of tissues and organs and to resource allocation and translocation—require substantial time, useful information must be relevant to the *future environment and conditions* that the organism will eventually functions in [4, 8]. This principle is ubiquitously important for any decision-making system, yet it is especially crucial when organisms are functioning in game settings, i.e. when antagonistically confronted by competitors, pathogens and predators, the responses of which strongly depend on the responses of their counterparts [9, 10].

Here, I shortly describe a few examples for the ways brainless plants are able to not only plastically respond to a variety of environmental signals and cues but to do it in ways that improve their survival, functioning and reproduction in the context of their *anticipated growth conditions*.

2 Modes and Implications of Future Perception in Plants

2.1 Mild Predicts Acute, Minor Correlates with Major

Perhaps the simplest-possible type of future perception is based on autocorrelations commonly demonstrated by episodes of stress or opportunity. More often than not, a mild stress progresses in time or space into a full-blown stress. For example, in temperate regions, occurrences of sub-optimal temperatures at the end of the growth season are tightly autocorrelated with further decreases in temperature and the approaching of the fall and winter, which are not only less suitable for biological activity but can be detrimental for an oblivious plant. Similarly, in Mediterranean and arid regions, an occurrence of a mild drought or salt stress typical to the spring is tightly autocorrelated with forthcoming occurrences of severe and potentially-detrimental droughts and saline conditions in the subsequent summer. Accordingly, where such environmental correlations are sufficiently tight, selection prefers those genotypes that not only respond to the current stress levels, but that in response to mild stresses "over-respond" in preparation for a forthcoming severe stress. In some cases, a short or mild exposure to stress initiates limited or no apparent stress response but triggers an *elevated readiness* (coined priming) to forthcoming stress. For example, following an earlier exposure to sub-acute drought [11] root competition [12] or salinity [13], plants are quicker and stronger to respond to subsequent severe stresses, and following an early mild insect herbivory, some plants produce defensive insect repelling toxins more swiftly and vigorously [14; see 2.4].

2.2 *Pure Signals and Cues: Non-functional Proxies for Functional Utilities*

Pure signals and cues are internal or external entities that bear information related to biologically-relevant processes but that, in and of themselves, do not necessarily serve any relevant biological function [15]. Providing a sufficiently-tight correlation between early quantitative or qualitative discriminants of such pure signals or cues, and forthcoming conditions, their perception can help organisms to better prepare in anticipation for future states. Here I touch on a few examples for the sake of demonstrating the mode of operation of such predictive systems.

Hormone Action and Resource Allocation. Plants demonstrate significant adaptive phenotypic plasticity in most aspects of their functioning, with often dramatic environmentally-induced modifications to their size, shape and relationships between their parts and organs. A common plastic response involves increased allocation to a successful organ, at times at the expense of other, less fortunate organs on the same plant [16]. Increased resource allocation to a branch involves the development of additional vascular strands (pipes) that allows improved supply of water and minerals from the roots and more sugars and other photosynthetic products from that shoot to the roots. Can a brainless plant judge which of its branches are more successful and can it allocate its limited resources to the most promising (i.e. having higher probability of future success) branch? Auxin is a hormone that is responsible for numerous signaling pathways in the plant [17]. When minute fluxes of auxin flow through primordial (i.e. cambium) or partially-differentiated plant tissues (e.g. parenchyma), they induce them to differentiate into vascular strands. When a young shoot is growing, it is producing and emitting increased fluxes of auxin that flow towards the roots while inducing the formation of new vascular strands between the roots and the developing shoot. This, in turn, increases the supply of water and minerals from the root while delivering to the roots increased quantities of sugars. This simple system is based on a positive feedback, whereby success bestows success and failure bestows demise…; where further shoot growth is accompanies by increased production of auxin that induces the differentiation of even more and larger vascular strands towards the growing shoot, which conducts greater fluxes of auxin and sugars to the roots etc., all in the service of the development of the successful shoot and if resources are limited—at the expense of resource allocation to less successful shoots on the same plant [18]. Rather than a resource or a structural element, and much like most other hormones- auxin serves as a mere carrier of information from the shoots to the rest of the plant. Its concentration and flux are *proxies for the potential future success* of the emitting shoot [19]. Interestingly, various plant parasites, such as aphids, the existence of which depends on plant metabolites, have evolved to produce cues that imitate auxin signaling, cheating the plant into directing precious resources toward them, at an obvious functional cost to the plant [e.g. 20].

Light Cues. Amongst the most studied anticipatory systems in plants are those responsible for the perception of light cues correlated with ecologically-important functions. Photoperiodism depicts the plant's responsiveness to the relative lengths of light and dark periods within a day. In response to specific lengths of the dark period (night), plants alter their growth and resource allocation, flowering and reproductive timing, shoot elongation, architecture, rooting patterns etc., *in ways that best match the anticipated forthcoming season* [21]. For example, many temperate deciduous trees integrate both (low) temperatures and (long) dark photoperiodic cues to initiate leaf fall in anticipation of the cold season [22]. In some, leaves turn colors when conditions are still suitable for growth (at the significant cost of lost growth), to facilitate orderly evacuation of precious resources, such as proteins and sugars, into the protected parts of the root and trunk, where they are safely stored for future use in the following spring [23]. Some Mediterranean annual plants require long nights (short days) to germinate in anticipation for the forthcoming rainy growth season [24]. Many plants will only start flowering after perceiving certain photoperiodic cues. While some winter-flowering "short-day" plants, such as *Chrysanthemum, Poinsettia* and Christmas cactus, require nights longer than 12 h to commence flowering, "long-day" plants, such as dill and spinach, only flower if perceiving short nights that indicate the approaching of the spring and summer. Notably, some plants, such as *Campanula medium*, initiate flowering only when a sequence of short days is followed by long days, ensuring blooming in the spring and not in the fall. Similarly, other plants, such as *Bryophylum* and *Cestrum*, secure early fall flowering by requiring a sequence of long photoperiod followed by short-days [21]. The latter examples demonstrate the ability of plants to perceive and integrate multiple environmental cues over long periods and to gauge *changes* rather than mere absolute levels of environmental variables, all in preparation for the anticipated season most suitable for their flowering and reproduction. Here too, the length of the night, is neither a resource nor a functional entity in itself, (the differences in the length of the daily photosynthetic period does not play a role here), but rather a reliable proxy for critical weather variables, the direct gauging of which, due to their statistically-noisy nature, would convey much less reliably predictive information [25].

Anticipating Competition. Competition is one of the most important selective forces in nature. Because most plants have the very same requirements for water, minerals and light, competition for these resources can be intense. Photoreceptors enable plants to monitor their light environment, to gauge and differentiate to what extent they are shaded by other plants or by (usually less threatening) inanimate objects, and most-importantly- to anticipate imminent shading [26]. Sun-loving plants, typical to open habitats, respond to vegetative shade through stem elongation, increasing their probability to escape the shading of their neighbors [27]. This well-known response, often coined the "shade avoidance syndrome", comprises both avoidance and confrontational behaviors; plants that succeed in lifting their canopy above their neighbors both avoid competition and actively shade their neighbors [28]. In contrast, plants typical to shaded understory environments do not compete for light, but rather adapt to tolerate the shade of their much larger (usually canopy trees) neighbors [29]. But how can plants decide when to avoid, confront or tolerate shade? Plants have several light-responsive mechanisms that enable them to detect both light intensity and quality (i.e. spectral composition). Photosynthetic light comprises photons with wavelengths ranging from 400 to 700 nm. Longer-wavelength photons pass through or reflect from the vegetative canopy. Thus, light that passes through or reflects off leaves is depleted in photosynthetic light (400–700 nm) and is *relatively* rich in non-photosynthetic far-red light (>700 nm). Phytochromes are a group of photoreceptors that detect red (photosynthetic) and far-red (non-photosynthetic) light and are particularly important for the perception of day length (see above), and the perception of other plants. Phytochromes exist in two alternative conformations that predominantly absorb photons at 660 (red) or 730 (far-red) nm. When absorbing red photons, phytochromes change their conformation into a form that predominantly absorbs (non-photosynthetic) far-red light, known as Pfr. When Pfr absorbs far-red light, it switches back to a conformation known as Pr that predominantly absorbs (photosynthetic) red light. Thus, phytochromes serve as sensitive sensors, precisely gauging the ratio between red and far red light (red/far-red), which is a very precise proxy for the presence of neighboring plants and for *probable future competition for light* [30, 31]. In contract, the shade of inanimate objects, such as dead plant tissues or rocks, is spectrally neutral, i.e. causing similar reduction in light across all spectral ranges, which does not affect the phytochromes' conformation. Although sun-loving plants do respond to neutral shade, they are much more responsive to low red/far-red ratios that indicate future competition for light, even when their neighbors are still far or small [26, 32]. Plant responses to low red/far-red ratios affect multiple aspects of plant development and behavior, including inhibition or delay of seed germination, increased stem and leaf elongation, leaf movement to a more vertical orientation, decreased number of branches and accelerated flowering [31]. Similarly to photoperiodic cuing (see above), red/far-red ratio in and of itself does not serve any photosynthetic function, but rather acts as a reliable proxy for forthcoming light competition [30]. Some plants with a prostrate growth habit can anticipate neighboring shading and orient their growth direction to avoid it even before the occurrence of any photosynthetic shade. A nice example is presented by young seedlings of the common purslane that grow and branch in ways that minimize both self-shading and anticipated shade from neighboring plants [32]. When young, these plants avoid growing towards directions from which they perceive low red/far-red ratios, even when that means growing toward directions from which they receive less photosynthetic light. This means that for young purslane seedlings, future light competition might be more important than current levels of photosynthetic light, i.e. rather than opportunistically maximize present absorption of photosynthetic light, these plants are able to perceive and integrate directional spectral cues and respond in ways that *maximize their expected total long-term light absorption and growth* [33].

2.3 Trajectory Perception

A potentially informative source of anticipatory information is the spatial and temporal gradient trajectories of resources, signals and cues. Environmental gradients often exhibit predictable and tightly autocorrelated trajectories that can be informative of future conditions. For example, *Calendula arvensis* and *Phlox glandiflora* developed larger canopies and produced more seeds when provided with *increasing* rooting volumes than when growing in *the largest yet constant* rooting volume [34]. A similar phenomenon was exhibited when studying resource allocation to roots. Young pea plants were grown so different roots of the same plant were subjected to variable temporally–dynamic and static homogeneous and heterogeneous nutrient regimes. When given a choice, plants not only developed greater root biomasses in richer patches; they discriminately allocated more resources to roots that developed in patches with *increasing nutrient levels*, even when their other roots developed in richer patches. These findings demonstrate that rather than responding to mere absolute resource availabilities, plants are able to perceive and integrate information regarding dynamic changes in resource levels and utilize it to anticipate growth conditions in ways that maximize their long-term performance [35].

2.4 Eavesdrop on Thy Neighbor

An important source of information regarding forthcoming growth conditions can come from neighbors. Many animals produce warning signals, aimed at their kin, group or flock members regarding imminent dangers, which is usually related to predators. Growing evidence shows that damaged or stressed plants produce and release various volatile chemicals and root exudates that are perceived by their neighbors [36]. Whether these chemicals have evolved to elicit responses in the emitting plant itself or in other individuals remains an interesting open question, but it is clear that plants can eavesdrop on each other and adaptively respond to various cues correlated with imminent damage or stress. Some of the emitted compounds may have evolved primarily to convey information to herbivores and/or the enemies of the herbivores. For example, wild potato can produce an aphid-alarm hormone that repels herbivorous aphids, and many plants respond to herbivory by producing volatile compounds that attract parasitoid or predatory arthropods [37]. In a classic study, Karban et al. [38] compared tobacco plants that naturally grew near sagebrush shrubs that had been mechanically wounded or not. The tobacco plants that grew near the wounded sagebrush produced elevated levels of a few insect repellents and demonstrated a lower level of herbivory compared with control plants that grew near undamaged sagebrush plants. This results indicate that some information (warning cues) had been transmitted from the wounded sagebrush to the undamaged tobacco plants and helped the latter to prepare for an imminent herbivore attack. As defensive responses involve increased allocation of various metabolites and energy to the production of expensive metabolites and defensive organs, such responses may cause significant performance costs and reduced growth if the plant is eventually not attacked. These costs give a selective advantage to plants that in response to warning cues do not generate the maximal level of defense response but, instead, go into a primed state (see above), i.e., increase their readiness to a future attack. Such priming usually involves the accumulation of signaling intermediates and precursors of defensive compounds that enable faster and more vigorous response if and when the plants are attacked in the future. Such priming is also costly but it is much less expensive compared to an all-out defensive state [14].

Recent studies demonstrate that plants are able to eavesdrop on drought stress cues emitted from their neighbors. Plants such as pea, buffalo and Bermuda grasses, among others, were subjected to drought while neighboring unstressed plants could exchange with them different cue combinations. Shortly after drought induction, significant defensive drought responses (e.g. closure of the stomata) were observed in both the stressed plants and their nearest unstressed neighbors but these responses were only apparent in unstressed neighboring plants that shared their rooting space with the stress plants [39]. Further investigation revealed that a short exposure of unstressed plants to root exudates of drought-stressed plants significantly affected their readiness and increased their survival when exposed to a long subsequent periods of drought [Mauda et al*., in prep*.]. The evolutionary rationale for the responsiveness to warning and stress cues is rather straightforward. Plastic responsiveness to anticipatory cues regarding imminent challenges can help plants to avoid potentially-significant costs associated with constitutive, genetically-deterministic adaptations ([14 and references therein). In the cases of herbivory and drought stress, both constitutive and induced adaptations may incure costly allocation to specific attributes [e.g. 40], which might limit plant performance under benign conditions [39]. It is therefore expected that unstressed plants that perceive stress cues also incur long-term costs related to stress priming, which may be manifested under benign conditions. Weighing the potential costs and benefits, the prevalence and strength of plastic responsiveness to communicated warning and stress cues are expected to depend on the reliability of the stress cues and thus to positively correlate with the coefficient of correlation between incidences of anticipatory stress cues and the probability of subsequent occurrences of herbivory or stressful conditions [4, 41]. Regarding drought stress, it can be expected that responsiveness to anticipatory cues is more prevalent in plants that live where early or sub-acute drought or salinity incidences are tightly autocorrelated with subsequent occurrences of severe drought or salinity. Similarly, elevated responsiveness to communicated stress cues is expected wherever tight spatial autocorrelations exist in drought or saline conditions, which is expected to be common near and around seasonal or fluctuating bodies of fresh or brackish water [42].

While the selective value of plastic responsiveness to warning cues is rather intuitive, the adaptive rationale for emitting warning and stress cues is much less obvious. A trivial reason for the emission of honest stress cues might be related to direct and unavoidable damage caused to plant tissues and the consequential leaking of various metabolites that serve as reliable stress cues for the eavesdropping neighbors. Indeed, such an apparent mode of cuing has been demonstrated in a few prey–predator systems, where chemical cues emitted from the excrement of predators or prey wounds were perceived by conspecific prey as warning signals [e.g. 43]. Although this explanation might be feasible for the case of herbivory, it might not account for the communication of drought stress cues. The fact that communicated unstressed plants were as affective as stressed plants in inducing stress responses in other unstressed neighbors suggests that the communication and relay of drought cues are not based on the emission and perception of damage products alone. Alternatively, the emission of drought stress cues might be related to direct or indirect selective advantages conferred to the emitters of stress cues. For example, the emission of warning and stress cues could be beneficial, in spite of costs related to helping potential competitors, in large or highly sectorial plants [e.g. 44], where direct internal communication is not efficient or possible [45], or in large clonal plants, where the spatial distribution of plant parts increases the probability of tighter neighborhood between members of the same clone or family [46, 47].

2.5 Trans-Generational Inheritance

According to the classic model of genetic inheritance, the information transmitted to the offspring is nullified from all somatic states and experiences and is limited to the information encoded in the DNA based pairs [48]. Although this scheme is mostly correct, accumulating evidence demonstrates that parental developmental and environmental experiences can have significant adaptive effects on offspring [49]. Delving into the properties and implications of epigenetic inheritance is beyond the limited scope of the present essay but a discussion of future perception in plants cannot be complete without touching on a few examples.

Due to the vast temporal and spatial variability in growth conditions, natural selection favors mechanisms that allow plants to avoid unfavorable conditions. In many plant species, predominantly those inhabiting extreme and less predictable environments, seed dormancy decreases the risk of extinction during catastrophic growth seasons [24]. By spreading seed germination over multiple seasons, plants can significantly increase the probability that at least some of their offspring will successfully complete their life cycle [50]. In addition, a tighter accounting for *anticipated probabilities of success* is achieved in many plants by utilizing germination induction mechanisms that rely on environmentally-relevant inputs, such as photoperiod (see 2.2), minimal wetting periods of the seeds, which in contrast with sporadic summer rains is tightly autocorrelated with the approaching of the rainy season, nutrient availability, salinity, etc. [51, 52]. Interestingly, recent studies found that in a few desert plants, seed germination was significantly affected by the maternal environment. Specifically, the more seeds mother plants produced, the less probable was the germination of these seeds in the following growth season. The ecological rationale for this phenomenon may reflect selection on and by the mother plants. Seeds that are produced in a favorable season are more likely to belong to a larger and denser cohort of siblings, the concurrent germination of which would create increased levels of sibling competition that, in turn, could drastically decrease the cumulative reproductive success of their mother. Under such conditions, it is easy to see why natural selection would favor plastic, maternal-controlled seed dormancy [53]. The precise mechanism of this maternal effect is yet unknown but it might involve the differential deposition of maternally-produced germination inhibitory substances in the seed tissues, which is well documented in other cases [54], without necessarily involving the offspring's strategy. The following example demonstrates a clear case of adaptive maternal activation of offspring metabolism. In what seems to be a clear, and now classic, case of maternal epigenetic transmission of ecologically-relevant information, Agrawal et al. [55] demonstrated that an exposure of wild radish plants to a mild herbivory not only induced a few defensive responses (see 2.4), but also caused their offspring to be better defended against herbivory, compared to offspring of control untreated mother plants.

3 Conclusions

Compared to most animals, plants are rather limited in their ability to move away from harm's way, and instead have evolved impressive abilities to plastically adjust in response to changes in their environment. However, as developmental changes require time, mere responses to existing conditions can cause costly mismatches between the plant's phenotype and the environmental changes it is attempting to trace [4]. In addition, as plants are almost invariably subjected to antagonistic biological interactions with competitors, predators and pathogens, inevitable ecological and evolutionary arms races develop, whereby the involved parties (plant-plant, plant-predator, plant-pathogen) can gain significant advantages by preempting their opponents and incur significant costs and lower survival if not keeping up with the moves of their counterparts [9, 10]. Accordingly, natural selection strongly favors the utilization of mechanisms that allow the perception and integration of diverse cues and signals that are correlated with anticipated conditions. From the standpoint of the individual plant, or of any other organism for that matter, the origin and purpose of the emission of such predictive information is totally irrelevant. Whether the information is delivered to a single developing organ via a hormone from other organs on the same plat [see 2.2; 19], by an entire plant via spectral signals or volatile chemicals from neighboring plants [see 2.2; e.g. 14, 30], or from various abiotic patterns [see 2.3; 35], the value of any information would only depend on its relevance and reliability. While the great majority of the predictive information is passively transmitted via genetic inheritance (see 1), substantial specific and detailed information is actively perceived and integrated by individual plants, using simple learning and memory utilities. While the mechanisms of these information integrators are mostly unknown, some studies suggest that they are at least somewhat similar to mammalian CNS [56].

It is suggested that better understanding of plant perception and anticipative adaptations to future conditions can be utilized to improve agricultural protocols and technologies. For example, putting to work the knowledge about plant responsiveness to red/far-red spectral cues, Novoplansky et al. [57] were able to develop greenhouse covers that converted some of the blue and green light into additional red light and increased red/far-red ratios. Plants growing under such covers interpreted their highly competitive environment as less competitive and developed significantly more flowers compared with plants that developed under unmodified light, which wastefully allocated larger proportion of their resources to competitive organs at the expense of flowering. With this understanding in mind, future genetic engineering can be aimed at the development of plants that are less sensitive to red/far-red cues (e.g. by partially blocking phytochrome responsiveness; see 2.2), enabling improved resource allocation and increased agricultural yields [57]. Similarly, genetically manipulating the responses of plants to stress cues emitted from other plants could increase plants' tolerance and reduce the economic costs caused by pests or abiotic stresses.

In summary, recent studies suggest that even the most rudimentary organisms are capable of performing a variety of surprisingly sophisticated behaviors. The fact that plants are able to anticipate future conditions nicely demonstrates that complicated environmental interactions, behaviors and even adaptive learning and memory can be attained using relatively simple physiological and morphogenetical controls, without the involvement of mental CNS-based processes or other centrally-governed information processing systems. Deciphering the mechanistic aspects and functional implications of these intriguing abilities is not only an important scientific challenge, it is also presenting a fascinating and sobering intellectual journey questing a deeper understanding of our position on the tree of life.

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Certain and Uncertain Futures in the Brain

Daniel S. Levine

Abstract A variety of brain imaging and single-cell results on anticipation in neural systems is reviewed. The broad categories of neural processes under consideration include (1) anticipation of intended movements, both what movements to perform and when to perform them; (2) anticipation of rewards and punishments; (3) certainty or uncertainty of anticipated outcomes. These literatures are mostly separate from each other and so a general network theory of anticipation and prediction in the brain has not yet emerged. Yet there are now many sophisticated neural network models available that unify perceptual, behavioral, and valuation data, and in the next generation these models can integrate the neural data on anticipation.

Keywords Anticipation · Future · Prediction · Brain · Uncertainty · Prefrontal cortex · Emotion

1 Memory of the Future

The evolution of greater complexity in primate brains has required elaborate brain representations of future events. This includes encoding of future actions that the organism intends to perform, both the actions themselves and the times they are to be performed. It includes encoding of the anticipated consequences of those actions, as well as anticipations of other future stimuli the organism expects to experience. Those consequences and future stimuli could include rewards or punishments, or they could be emotionally neutral. Also, there could either be certainty or uncertainty about what future events will occur, and if there is uncertainty a rough estimate of the probability of occurrence may or may not be available.

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Hence the anticipatory system in the brain has to include interactions between representations of intentions, projected time, expectations, emotions, and probabilities. We do not yet have a systematic neural network theory that links all these elements and the known functions of brain regions. Yet a combination of animal single-cell and human brain imaging studies enables us to develop partial hypotheses about each part of the system. Clearly the human development of language makes available to our species a much more elaborate schema for anticipation than is available to non-human animals. Yet some of the key elements of anticipation seem to be present at least in monkeys and apes, as shown by the development of the prefrontal part of their association cortices and the "expectancy waves" of prefrontal origin that have been measured.

One of the first seminal articles dealing with anticipatory brain representations was written in 1985 by the neuroscientist David Ingvar, who coined for these processes the widely used term *memory of the future* [1]. What Ingvar meant was "the action programs or plans for future behaviour and cognition. As these programs can be retained and recalled, they might be termed 'memories of the future'." (p. 127) Later investigators (e.g., [2–4]) have given such stored memories of planned future actions the more prosaic term *prospective memory*.

Ingvar located these action programs in the prefrontal cortex, based on the work of Joaquin Fuster and several other investigators, much of it summarized by Fuster [5–7]. This work included deficits of prefrontally damaged patients and monkeys on delay tasks that required linkage of events across time. They also included observations of a slow negative EEG wave when a human or monkey has experienced one stimulus and is waiting for a second stimulus; this expectancy wave, called the *contingent negative variation* (*CNV*) was first observed in humans [8] and later in monkeys [9].

Fuster [10] listed three overarching cognitive functions of prefrontal cortex that are important for linking events across time. These functions are "short-term memory, preparatory set, and control of interference" (p. 169). At the time he wrote there had been only a few studies of blood flow in the brain during cognitive tasks, and the fMRI methods commonplace today had just barely been developed, so it was hard to link each task definitively with a particular frontal lobe region. Yet Fuster was able to assign short-term memory largely to the dorsolateral prefrontal cortex (DLPFC; Brodmann areas 9 and 46 of the cortex) and control of interference to the orbital and medial prefrontal cortex (OMPFC; areas 11 and 12), and these assignments have stood the test of time. More recent imaging studies (e.g., [4, 11]) have suggested a role in preparatory set for the furthest forward part of the frontal lobes or *rostral prefrontal cortex* (rPFC; area 10), also known as the *anterior prefrontal cortex* or the *frontal pole*. Fuster [10] saw these three functions as interrelated parts of the overarching function of "mediating cross-temporal contingencies." Since that article was written, there has been considerable work on the specific functions of prefrontal subregions, but less work on integrating all these function into an overall theory of prefrontal involvement in anticipation. In part this reflects that fMRI tends to say more about separate regions than it does about their interactions. In part it also reflects the reward structure of the scientific research community, whereby short-term measurable results yield both grants and publications at a faster rate than do broad theoretical studies. This paper will review some of the literature on all these segments of anticipation and make a few tentative suggestions about their interrelationships.

2 Hierarchies in the Prefrontal Cortex

Fuster [10] proposed that processing of intended motor actions in the cerebral cortex is roughly parallel to the processing of sensory stimuli except reversed in time, with high-order association areas that form the intention to act projecting to motor areas that gradually become more and more specific about what actions to perform. Again, recent studies have largely supported this theoretical proposal (see [12] for a partial review).

A considerable number of recent fMRI studies (e.g., [11, 13–15]) have shown that different parts of the prefrontal cortex encode different levels of abstraction, both of stimuli and of intended behaviors. Roughly the hierarchy goes from less to more abstract as one moves further forward in the lateral portions of the PFC.

Clearly the prefrontal machinery that has evolved in humans, and to a lesser degree in other primates, enables far more abstraction, and thereby anticipation, than is available to other animals. Christoff and Gabrieli [11] note that the rostral (particularly rostrolateral) PFC (RLPFC) is the final terminus of this abstraction, so there are limits to the amount of abstraction that can occur even in humans. Yet we have not discovered to this date what those limits are, and fMRI studies have uncovered neural substrates for a great many of our complex mental capabilities. For example, Christoff and Gabrieli found evidence that the DLPFC deals with working memories of external events while the RLPFC deals with working memories of internal events, such as intentions. Schubotz [16] notes that the rostral PFC (rPFC) connects to other prefrontal areas involved in monitoring actions [17] and in retrieval from both semantic and episodic memory [18]. She concludes that the rPFC is of major importance in prospective memory due to its ability to link together two or more different cognitive processes operating simultaneously (see also [19]).

A further advance was the fMRI study of Momennejad and Haynes [4], which uncovered evidence that the rostral PFC encoding of intentions could be decomposed into the What and When of future actions. These researchers gave their subjects a task which involved classifying a display of a number by color (red or green), parity (even or odd), and value (larger or smaller than 5). The subjects were told to perform the color classification but also told that after a certain time (either 15, 20, or 25 s) they had to switch to another classification task (either parity or value). Momennejad and Haynes used a general linear model to fit activation of different brain areas to the possible time delays (which the subject had to store internally, as they were not given feedback about when that time had passed) and to the possible second tasks. This model showed that different parts of rPFC stored "what" and "when" during the color task, and then the pattern of activations changed during the second task that followed.

Another brain region that has long been associated with working memory is the hippocampus. Buckner [20] reviews evidence that in addition to consolidating new memories of past events, the hippocampus and its connections to prefrontal and other areas of cortex are active when people envision future events. The hippocampus seems to replay event sequences including novel combinations of events, and to facilitate predictions about future events. Moreover, hippocampally damaged amnesics show an impoverished ability to imagine the future.

3 Anticipation and Emotion

Anticipation often includes an expectation of a potential reward or punishment, combined with the degree of certainty that this reward or punishment will ensue. To this date there has been a considerable literature on the anticipation of reward or punishment, but this literature has been largely separate from the literature on anticipation involved in cognitive tasks. This reflects in part the continuing culturally-based tendency to regard the emotional and cognitive realms as separate, or even mutually antagonistic, in spite of overwhelming evidence that emotion and cognition are deeply interlinked in the brain. Specifically, Pessoa [21] notes that the *lateral* prefrontal cortex, sometimes considered "cognitive" by contrast with the "emotional" orbital PFC, is actually an important area for cognitive-emotional interactions, if only because emotional stimuli have a selective advantage in the competition with other stimuli for working memory storage.

The neurotransmitter dopamine is known to have a strong connection with reward, not so much in the actual feelings relating to receiving or expecting a reward but in the energizing of behaviors and actions that lead to reward [22]. A series of seminal single-cell studies on monkeys by Wolfram Schultz and his colleagues (e.g., [23, 24]) showed that dopamine also plays a major role in the *anticipation* of reward. Schultz and his colleagues have found that in the course of a typical conditioning experiment where a previously neutral stimulus is paired with reward, in the early stages dopamine nuclei in the midbrain experience a burst of firing when the reward occurs. After a period of training, however, these same dopamine cells burst in response to the conditioned stimulus and not to the reward itself. Also, in extinction trials when the conditioned stimulus is presented and not followed by reward, these dopamine neurons experience a dip in responding.

The subcortical region that particularly receives reward-related dopamine inputs is the ventral striatum of the basal ganglia, in particular the nucleus accumbens. This region plays a particularly important role in a combined EEG and fMRI study of reward anticipation by Plichta et al. [25]. Plichta and his colleagues found a network of interrelationships between the ventral striatum, thalamus, and supplementary motor area of the cortex in humans anticipating a monetary reward. These interactions included the contingent negative variation (CNV) EEG which could be predicted by a combination of thalamic fMRI response and top-down regulation from the supplementary motor area to the two subcortical areas.

Also, many studies show that the DLPFC (Area 46), sometimes carelessly regarded as a more "cognitive" than "emotional" area, is key to the anticipation of rewards or punishments. Leon and Shadlen [26] gave monkeys a working memory task in which they received a water reward for eye movements toward the location of a previously lit target stimulus, with the color of the fixation point indicating the size of the reward they would receive. A significant number of DLPFC neurons responded more strongly to a larger reward, as long as the target was in the neuron's visual receptive field. Watanabe and Sakagami [27] found that neurons in the lateral prefrontal cortex (which part unspecified) responded to both the cognitive and motivational context of stimuli.

One of the possible motivational roles for DLPFC is due to its influence on dopaminergic nuclei in the midbrain [28]. But more importantly, the DLPFC as a working memory region needs to integrate motivational and emotional information with other forms of information, and in large part performs that function through inputs from the anterior cingulate (ACC; Brodmann area 32), another key area for integrating cognitive and emotional information [29, 30]. Medalla and Barbas [29] also found strong excitatory connections from ACC to the rPFC (area 10) which could play a role in deciding between the demands of multiple tasks.

This integrated system enables emotional information, and information about the anticipated reward or punishment value of different classes of stimuli or actions, to be represented at each of the levels of abstraction indicated by different parts of the lateral PFC. Dias, Robbins, and Roberts [31] previously found that OMPFC and DLPFC both make affective discriminations but DLPFC does so at a higher level of abstraction. The distinction of "affective and attentional shifts" from the title of their article is misleading because their attentional shifts are about which attribute of a stimulus is relevant for learned reward expectation, and therefore are also affectively significant. Based on the work we have cited by Christoff and her colleagues and other work reviewed in [16], RLPFC should be expected to make affectively relevant discriminations at a still higher level of abstraction.

4 Certainty and Uncertainty in the Future

In addition to their positive or negative affective value, expectations about significant future events should also be influenced by the degree of certainty or confidence that the events will in fact occur. Certainty or its absence has a strong influence on emotions. For example, the classic studies of Ellsberg [32] showed that people tend to avoid situations where probabilities are unknown if there are available alternatives with known numerical risks.

There have been many recent behavioral studies of the effects on decision making of inducing emotions which engender feelings of certainty or uncertainty; some of that literature is reviewed in [33]. Tiedens and Linton [34] induced their participants to feel one of the four emotions of contentment, anger, worry, and surprise. They found that participants induced to feel emotions of certainty (contentment or anger) but not those induced to feel emotions of uncertainty (surprise or worry) tended toward a heuristic that made them examine evidence less carefully. Specifically, they were more likely to agree with an argument about education if they believed the argument had been made by a professor than by a student, and were less influenced than other participants by the essay's content. There was no significant difference between the positive and negative emotions at each certainty level.

Yet with some more challenging cognitive tasks, certainty emotions can have the reverse effect of making people more confident in their own cognitive processes and thereby more deliberate. Inbar and Gilovich [35] gave participants some general knowledge questions that have quantitative answers (e.g., the boiling point of water on the top of Mt. Everest) which they were expected to guess by "anchoring" on values they were likely to know already (e.g., the boiling point of water at sea level) and then adjusting upward or downward as appropriate. The amount they adjusted from these anchor values was considered an indication of how deeply they engaged their cognitive processes. If the participants generated their own anchor values, they adjusted more from self-generated anchors if they had seen film clips promoting anger or disgust (certain) than if they had seen clips promoting sadness or fear (uncertain). Inbar and Gilovich's explanation was that "the appraisals of certainty associated with some emotions can lead individuals to feel confident and in control, and thus to engage in more energetic cognitive processing" (p. 567). The same effect did not occur if the anchor was experimenter-generated.

If the task instructions cue cognitive passivity, certainty emotions (positive or negative) can lead participants to feel confident in answers they have already arrived at, engendering heuristic processing. But if the task instructions cue a high level of cognitive activity, the same certainty emotions can lead participants to feel confident in their own mental acuity, engendering careful processing. Another example of certainty emotions leading to more careful processing arose in a study of ratio bias from my laboratory [36]. In the ratio bias task, participants are asked to decide which of two small probabilities is larger; with incongruent pairs, whereby the larger numerator and denominator correspond to the smaller probability (e.g., 9/100 versus 1/10), many choose the larger numbers even with worse odds (e.g., [37]). Liu [36] induced in different groups of participants, through cuing recall of emotion-appropriate life experiences, the four emotions of happiness (positive and certain), hope (positive and uncertain), disgust (negative and certain), and fear (negative and uncertain), and then gave her participants problems involving judging which is the larger of two probabilities expressed as ratios. She found that certainty-inducing emotions, especially happiness, led to both greater confidence and greater accuracy on this numerical judgment task.

There have been a few studies of brain correlates of certain and uncertain emotions: so far they have not been conclusive and have focused predominantly on the negative effects of uncertainty. Sarinopoulos et al. [38] found that fMRI responses in two brain regions sensitive to aversive pictures, namely the amygdala and insula, were larger after visual cues that were uncertain (i.e., on different trials those cues either preceded an aversive or a neutral picture) than after cues that always preceded an aversive picture. The magnitude of the difference in responses of those regions to these two situations correlated negatively with uncertainty-related activity in the ACC, suggesting that the ACC plays some kind of anticipatory or preparatory role in the perception of uncertainty. This observation is consistent with previous theories linking dorsal ACC activation to situations which are high in error likelihood [39] or just uncertainty [40]. Stern, Gonzalez, Welsh, and Taylor [41] gave their participants a task where they were told the distribution of red and blue cards in two different decks, and then upon being presented with a sequence of cards from one of the two decks had to decide which deck they came from and state how confident they were in their answers. These researchers distinguished between objective uncertainty (based on the distribution, and largest when the ratio of red to blue was closest to 1:1) from subjective uncertainty which varied between individuals. They found that subjective uncertainty correlated with activity in the OMPFC, presumably reflecting emotional arousal.

Yet uncertainty has an attractive as well as an aversive aspect. Many researchers have noted that decision making in complex environments involves a trade-off between exploitation and exploration; a gambler, for example,

> balances the desire to select what seems, on the basis of accumulated experience, the richest option, against the desire to choose a less familiar option that might turn out more advantageous (and thereby provide information for improving future decisions) [42, p. 876].

Daw et al. [42] did an fMRI study of humans in a gambling task and defined as exploitative any decision based on what previous experience had indicated would provide the best payoff, calling all other decisions exploratory. The area which was more active during exploratory than exploitative decisions was the rostral prefrontal cortex (rPFC). Given the role we have discussed for the rPFC in high-level abstraction and prospective memory, this brain region could also be a site for integrating information about the potential benefits of options with unknown consequences.

5 General Discussion

The human ability to envision the future in detail is clearly facilitated by the development of our capacity for language, as noted by Ingvar [1]. The neural network modeler Leonid Perlovsky has described mental development throughout one's lifetime as involving parallel streams of cognition and language that have separate and merging dynamics (see, e.g., [43, 44]).

Yet there are considerable data indicating that at least other primates who lack our language capacity still anticipate upcoming events. These data include the anticipatory EEG waves [9] and the dopamine cell responses to expected rewards [23, 24].

Principles are emerging from sophisticated neural network models that promise to unify all these results, in both monkeys and humans [45–47]. Some of the principles are stated in [47] as follows:

> In summary, perceptual/cognitive processes often use excitatory matching and match-based learning to create stable predictive representations of objects and events in the world. Complementary spatial/motor processes often use inhibitory matching and mismatch-based learning to continually update spatial maps and sensory-motor gains. Together these complementary predictive and learning mechanisms create a self-stabilizing perceptual/cognitive front end for activating the more labile spatial/motor processes that control our changing bodies as they act upon objects in the world (p. 226).

Various models of interacting cognition and emotion [45, 46, 48] have been successful at reproducing data on emotional valuation of these sensory and motor processes in neural networks that include analogs of several cortical and subcortical brain regions. Future extensions of some of these networks should be able to incorporate the data on sensory-motor, affective, and probabilistic anticipation described in this chapter.

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Neural Systems Underlying the Prediction of Complex Events

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> *Smiles, walks, dances, weddings, explosions, hiccups, hand-waves, arrivals and departures, births and deaths, thunder and lightning: the variety of the world seems to lie not only in the assortment of its ordinary citizens—animals and physical objects, and perhaps minds, sets, abstract particulars —but also in the sort of things that happen to or are performed by them* [1].
>
> *The fraction of an action is more than a movement* [2].

Abstract Animals depend on predictions about the near future to react and act in a timely, situation-appropriate fashion. Prediction is particularly challenged in the face of events: these entail a stimulus whose temporally directed structure is meaningful in itself. Many simple events, e.g. regular motion, can be predicted by means of dynamic-forward extrapolation. For this class of predictions, the premotor-parietal network is active which we also need to plan our own body movements. However, when it comes to complex events such as action, speech, or music, we additionally need to retrieve semantic and episodic memories in order to feed and restrict the required predictions. These processes are reflected in activity of functionally specialized brain networks, as outlined in the present article for the case of action prediction. Here, knowledge about objects, rooms, and actors is exploited, but also action scripts that account for the actions' probabilistic architecture.

Keywords Action observation · Dynamic-forward extrapolation · Action scripts · Probabilistic prediction · Object knowledge · Rooms · Actor · Episodic memory · Semantic memory · Premotor cortex · Inferior frontal gyrus

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1 Prediction in Cognitive Neuroscience

Prediction, anticipation, expectation, and prospection are terms that describe some kind of mental orientation towards the future. Cognitive neuroscience is addressing how this mental orientations manifests in the brain. In principle, there are two phenomena that cognitive neuroscience is interested here: firstly, the manifestation of an energetic investment, i.e., an increase in activity reflecting that some source of information in memory and/or in the environment are exploited in order to produce an estimate of the upcoming; and secondly, the manifestation of a benefit, i.e., a decrease in activity reflecting that some information provided by the environment does not have to be awaited or fully processed because it already has been estimated or deduced from other sources of information. As will be outlined in this paper, the networks where these two effects can be measured may sometimes overlap, but mostly they are fully dissociated. Many studies in prediction use expectation violation paradigms: showing that the unexpected event corresponds to an increase of brain activity is taken as an indirect evidence for the preparation that has occurred beforehand.

Historically, the notion of a predictive brain has been propelled by Helmholtz' proposal of efference copies cancelling self-induced sensations during saccades [3]. Travelling faster than the efferent signal itself, they were taken to stabilize head-centred representations of object locations. This notion has been incorporated, generalized and further developed in modern concepts on how animals tune and optimize their body movements, particularly motor control theory [4] and predictive coding [5–7]. Cognitive neuroscience is nowadays concerned with prediction in all classical domains, including action, perception, and cognition [8, 9].

Hardly surprising, there is a confusing multitude of factors to specify the very nature of predictive phenomena across different contexts: Predictions are deemed probabilistic or deterministic, they are highly or sparsely specified, can be explicit or implicit, and they occur on very short to very long timescales [10]. Against this backdrop, there has as yet been no success to provide a systematic account of predictive mechanisms, neither behaviourally nor with respect to the brain, although there are recent efforts to do so [8]. The present paper addresses the neural basis of prediction of complex perceptual events and the peculiarity thereof.

2 'Event' in 'Event Prediction'

When we expect, for instance, the bang of a detonation while observing a blasting operation, we expect a sensory state happening at a certain point of time, e.g. after an acoustic warning signal. Although one may say that the detonation bang is an event that occurs, the term 'event perception' or 'event prediction' is used to refer more specifically to the transformation or metamorphosis of some present stimulus that continuously evolves in spacetime. This entails that some parts of the upcoming stimulus are already there in the presence and remain unchanged while the event takes place, such as for instance the ball remains the same when being kicked and undergoing a trajectory.

Taking trajectories as a starting point, event prediction can come in two forms: either as a dynamic-forward extrapolation from current states and changes; or as a probabilistic estimation based on a number of previous samplings. Both kinds of prediction may be combined. For instance, when we observe the ball, its present position and the direction and velocity of its motion are considered when engaging a dynamic-forward kind of prediction; alternatively, when we seek to estimate its landing point without tracking the ball during motion, a probabilistic approach of prediction seems more appropriate. For many events that we face in reality, we get along quite well with a combination of dynamic-forward and probabilistic sampling-based predictions.

However, there are further sources of information that shape our predictions, based on facts and factors that are learned and stored as our associative, episodic, or semantic memories. To stay with our example, even before the ball is kicked, we predict the ball to rise in an arc-shaped fashion and to return to ground because we have learned that balls do so in our world.

While the role of semantic knowledge is limited when we predict ball behaviour, it becomes highly relevant when it comes to human behaviour, particularly language and action. Prediction of these kinds of events can be considered being complex in the sense that they entail several layers of predictions and are most probably fed by several memory systems. At least, prediction of human action draws on the observer's script knowledge, but also often includes retrieval of episodic associations and social rules.

In the following, I will first turn to dynamic-forward kinds of prediction and their typical premotor-parietal network. Thereafter, some studies are reported addressing the factors that drive prediction of human action. They yield a neural basis that goes beyond the premotor-parietal network, reflecting the requirement to further fan out, feed and restrict prediction in the face of semantically loaded events such as action.

3 Dynamic-Forward Prediction

We developed the so-called serial prediction task to investigate explicitly instructed prediction of highly controlled visual or auditory stimulus sequences. It consists of stimulus sequences that are regularly structured—and hence predictable—with regard to one stimulus property, for instance size, colour or location. Participants are asked to attend to this property and to indicate in a dual choice response mode whether the regular structure was maintained until the end of the sequence or not. In the latter case, switching the presentation order of the last stimuli of the sequence violates its regular structure.

Studies show that serial prediction, as contrasted to serial match to sample, target detection, or n-back tasks, draws on the lateral premotor cortex and its corresponding projection sites in the lateral parietal cortex (for overviews, see [11, 12]). These cortical areas are organised in multiple parallel and largely segregated loops and known to subserve sensorimotor transformation, that is tuning voluntary body posture and movement to environmental conditions and vice versa [13]. How could this specific sensorimotor function be reconciled with the same areas' role in serial prediction? One way is to adopt the notion of action as being planned and controlled by the action's anticipated sensory consequences or re-afferences (for a review of this so-called ideomotor theory, see [14]). Generalizing this predictive account from motor control to perception, it has been proposed that premotor-parietal loops serve not only the prediction of self-induced sensory change but also the prediction of externally induced sensory change—in other words, events [15]. Note that the term "event" is meant to refer to the above-proposed definition—change that can be extrapolated from current state and changes—and that the prediction mediated by the lateral premotor-parietal network is meant to be dynamic-forward extrapolation. Thus, the particular quality of premotor-driven prediction is in the spatiotemporal reality (or *situatedness*) of the transforming body or object that constrains its possible behaviours (Fig. 1).

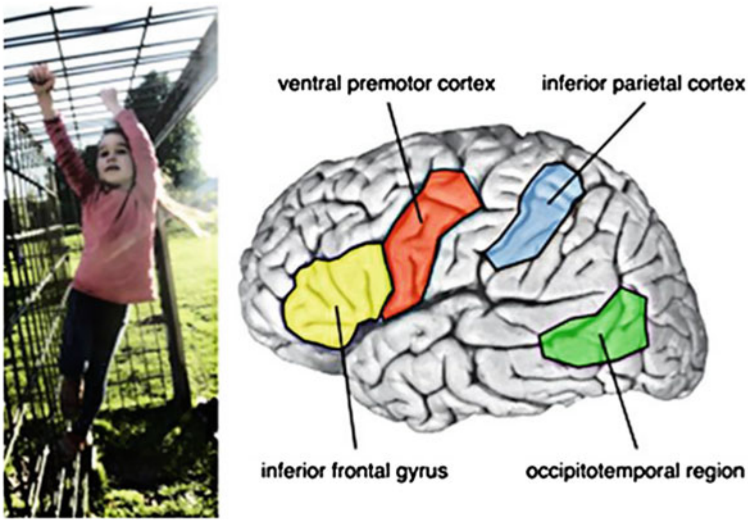

Fig. 1 Human action entails transformation that can be predicted in a dynamic-forward manner, but also transitions whose prediction requires the retrieval of semantic and episodic memories. The former draws on premotor-parietal networks, whereas the latter additionally engages a multitude of prefrontal and occipito-temporal areas, some of which are depicted here

4 Prediction of Observed Action

When we witness an action, a dynamic-forward kind of prediction is up to the transformation that an observed body and/or manipulated objects undergo. Hence, premotor-parietal loops can take on prediction up to this level of complexity. It can be shown that the lateral premotor cortex contributes specifically to the prediction of upcoming action stages as compared to memorizing current action stages [16, 17]. Recently it showed that premotor activity varies as a function of the selection among possibly upcoming object manipulations, whereas parietal and occipitotemporal cortex were reflecting the number of possible manipulations that a given object is associated with [18]. These findings are well in line with theories on the premotor-parietal interaction during action control [19]. They suggest that premotor cortex master a repertoire of transformation operations changing the body and/or object to specified end-states.

However, action is often more complex than a single object-directed manipulation of movement [20] and when action observation is compared to serial prediction, it shows that both share premotor-parietal loops, but action observation draws on additional sites in the brain [21]. Actually, four areas make up the typical 'action observation network' that has been found in most of the numerous studies in this field: in addition to lateral premotor and parietal cortex, it includes the inferior frontal gyrus (BA 44, 45, and/or 47) and the boundary between lateral temporal and occipital lobe shortly called occipitotemporal cortex. However, depending on the particular experimental paradigm and the addressed research question, still more brain areas can be found to be active during action observation. Obviously, human action bears large amounts of informational detail that draw on our memory systems, which in turn can be supposed to generate expectations on the upcoming action and to adapt and restrict these expectations to the actually observed action course. Yet, we are largely ignorant about what information action observers read out from the scene, and whether memories that may aid prediction are retrieved and shaped on the basis of these cues. Recent attempts to address some of these issues will be reported in the following.

4.1 Objects, Rooms and Actors as (Predictive) Cues

It is plausible to assume that taking into account what actions the manipulated object is frequently involved in, and where the action takes place, should improve action prediction. Or should we rather say: action *recognition*? One has to be cautious with claiming that certain neurophysiological effects are reflecting predictive but not retrodictive computations in the brain. As will be detailed below, we found that object-implied actions as well as room-implied actions have an effect on brain activity in action observers. We also know that object and room stimuli are processed much faster than manipulation stimuli, presumably because the latter are temporally extended (event-like) and disambiguate only over time. Therefore, finding that object-implied and room-implied actions modulate brain activity in action observers seems to support the idea that prediction is shaped by stimulus-cued semantic memories. However, these studies cannot settle whether the reported effects are really due to predictive or rather due to retrodictive processes—they merely show which cues are spontaneously considered in action scenes, not more. Still, this is an important step on our way to understanding the factors that may be relevant for human action prediction.

Neuroimaging data imply that even before manipulation of an object is shown, the mere presentation of this object triggers associated actions in memory, which in turn can impact action recognition [18]. Similarly, also the room wherein an action takes place is associated with a set of actions that are typically (frequently) observed therein, and data show that we spontaneously retrieve this information during action observation. For instance, when actions are shown in incompatible rooms as compared to either compatible or neutral contexts, activity increases in the inferior frontal gyrus [22]. When using pixelation to mask the manipulated object while preserving manipulation information for the observer, the same effect is observed, thereby ensuring that the effect is due to a conflict between the incompatible room and the presented manipulation, not between room and object. Under the same object-masking conditions, it shows that action-incompatible rooms slow down action recognition, whereas compatible rooms enhance correct recognition rates [23]. Finally, we found that already children at the age of four exploit contextual information during action recognition [24]. Here, it interestingly shows that compatible room settings are particularly beneficial for action recognition when experience with the presented action is sparse.

Together, these findings indicate that both object as well as room information are used during action observation to shape action recognition. As objects are associated with certain actions, and rooms are as well, one may speculate about a cascade of perceptual and retrieval processes that use object and room information to shape memory retrieval of associated and hence expectable actions. Competition, interactions and dependencies between these sources of information remain to be empirically investigated in detail. First studies reveal a fundamental cross talk between context, object and manipulation during action observation [25].

Beyond room and object information, action entails an actor or actress. We found that even when the actor or actress is task-irrelevant for the subjects, and attention to the actor or actress is hampered by a limited time window when focusing on identification of the presented action video, the identity of the actor or actress can have considerable effects on the neural processes of the observer. For instance, the observer's brain clearly registers whether the action takes place from the first or from the third person perspective (the latter being indicative of the presence of another one); whether the face of the actor or actress is visible or not; and whether the actor or actress is the same or a different as compared to the preceding action video [26]. Moreover, previous encounters with the same actor or actress trigger the attempt to integrate all actions of this actor or actress under one overarching goal, even if implausible [27]. Thus, re-encountering an actor or actress after a sub-minute delay, provokes a reference of his or her current action to those we saw him or her performing before.

Above reported findings indicate that objects, rooms and actors serve as cues that trigger expectation for certain actions. This is true in two respects. On the one hand, rooms and objects themselves imply which actions are typically associated with them. On the other hand, re-encountering an object, actor or actress triggers the expectation that the previously associated goal is now continued. The latter finding points to the activation of a script memory. These scripts enable embedding the current perception into a larger temporal and semantic frame that can be used to both build predictions and restrict interpretations.

4.2 Script Knowledge

In a series of recent studies, we addressed the role of the inferior frontal gyrus in action observation. We here resort to the concept that the inferior frontal gyrus aids semantic and episodic retrieval by shaping stimulus-derived associative memories and selecting among retrieved associations [28]. Our working hypothesis is that this region's role in action observation is to retrieve action scripts the currently observed act fits into, thereby building the basis for predictions on upcoming action steps.

A script is meant to refer to a temporally structured sequence of acts ruled by the achievement of an overarching goal [29]. Formally, script memory is a sub-category of semantic memory, i.e. generalized knowledge about objects, facts and events, including their particular properties and systematic relationships to other objects, facts and events. Still, scripts are peculiar as they mostly consist of prototypical or generalized episodes and are intrinsically event-like. The term 'structured event complexes' coined by Grafman may account for this particular profile of knowledge format [30].

We found evidence favouring that during action observation, the brain spontaneously generates predictions on upcoming action steps by retrieving script knowledge, and that these processes are specifically reflected by an increase of activity in the inferior frontal gyrus. We argue that this search occurs spontaneously, as subjects were neither instructed to prepare for upcoming actions nor did this preparation improve the performance of their task to recognize actions in an unspeeded, retrograde manner. Activity in left inferior frontal gyrus transiently increases when the goal changes from one action video to the next [31]. This effect is specific for goal switching, i.e. it does not show up for object switches. The same area parametrically decreased during the unfolding of episodes with a coherent overarching goal [32]. Correspondingly, activity in this area increased during the unfolding of episodes that were incoherent with regard to their goals, but only when they were coherent with regard to the actor [27]. This finding indicates that the actor may serve as a trigger to search for an overarching goal. In yet another study, activity of bilateral inferior frontal gyri co-varied positively with the quantified level of goal coherence of two consecutive actions [33]. Interestingly, this latter effect depended on whether the two actions shared a common object, indicating, as in [31] and similarly as for the shared actor, that this object served as a trigger to search for an overarching goal.

Together, these findings suggest that objects, rooms and actors effectively trigger the memory of actions that we associate with them. These can be either retrieved from long-term semantic (particularly script) memory, or from previously encountered actions to which the current action seems to be linked by virtue of these cues.

4.3 Using Stochastic Structures in Action Sequences

Human (or animal) prediction is stochastic, not deterministic; i.e., we engage in probabilistic estimations against the backdrop of our short- and long-term knowledge. Based on a history of probabilistically distributed events, we acquire knowledge about their general (or absolute) probability, but also knowledge about their conditioned (or relative) probabilities given certain contexts and/or preceding events. For instance, the overall probability of thunder is quite low, whereas it is very high after lightening. A straightforward assumption therefore is that when we engage in prediction of events, we should exploit statistical knowledge about the world, as this is the best that we have. Following the currently much-noticed predictive coding account, perception can be generally understood as Bayesian inference process [34]. While this conception has been spelled out for stimuli whose basic properties remain largely invariant across the range of seconds such as objects, prediction seems even more required when we face events. That is because, events consist not only of a contingent sequence of perceptual states, but their informational core, i.e., their *meaning*, originates from the particular temporal and probabilistic structure between these states.

To an observer, actions provide an ongoing stream of sensory stimulation. Still, observers are quite sensitive to the segments of actions and their probabilistic relationships [35, 36]. We found that these segments or fractions of actions are not simply movements of the observed actor or the manipulated objects. Thus, when observers segment videos showing tai-chi sequences or actions, only the latter engage a complex network of prefrontal, parietal and parahippocampal areas when the stream passes a segment boundary [20]. Thus, actions are not simply perceived as modulations of the actor's movement kinematics (which is true for both tai chi and action videos, as indicated by increase in motion-sensitive area MT), but amount to meaningful action steps that trigger complex re-orientation processes propelled by retrieval from long-term memory of action scripts.

What now about the probability structures among consecutive action steps? As defined in the beginning, a script is here meant to be a temporally structured sequence of acts ruled by the achievement of an overarching goal. Depending on the particular situation and many other factors, one and the same script can consist of different sequences of acts, all effective to achieve one and the same goal.

For instance, when you visit a restaurant, the first step when entering the restaurant can either be searching for a free table, or rather waiting to be seated by the restaurant's staff. Knowledge about the particular restaurant's policies, or certain external cues such as the presence of a desk near the restaurant's entrance, help us to select the appropriate action step. Actions are made of such probabilistic 'decision trees', and observers seem to apply this knowledge to the actions performed by others.

In experimental settings one seeks to control the quantifiable probabilistic structure of the actions the participant is presented with. In our studies, we therefore train subjects by iterative presentations of action sequences that feature fixed transition probabilities between consecutive action steps. After training, subjects enter the fMRI experiment where they encounter the same sequences again. Here we can investigate what structures co-vary with either the predictedness (level of surprise) of a given action and its predictability (level of entropy). Both predictedness and predictability quantify corresponding brain responses, indicating that the brain engages in probabilistically tuned prediction, even when not required by the current task [37]. Recent unpublished data indicate that humans consider even the 2nd level of statistical structure in action sequences, i.e. the action preceding the preceding action, especially when the predictive information provided by the preceding action is low. Note that none of these studies required subjects to report or register probabilistic structures in actions, suggesting that measured effects reflect spontaneous and ecologically valid processes of prediction.

The violation of prediction based on conditioned or unconditioned event probability is considered being an indirect evidence for default preparatory mechanisms in perception. There is a unique surprise related to the first encounter with an unexpected course of a given action, and this surprise is typically followed by a slower learning process that needs several iterations of the new action course during which the involved cortical areas adapt to the novel script. For instance, when subjects were implicitly trained by action videos, and these actions were later repeatedly presented in a slightly modified version, we found a parametric attenuation in the action observation network mentioned above. This network hence showed to be sensitive to violations of predicted action courses and slowly adapted to the new script [38]. Interestingly, areas of the frontomedian wall (BA 10 and adjacent anterior cingulate cortex) also reflected the amount of bias between the two alternatives of a given action script. That is, when the number of video presentation times led to a bias such that one of the two alternatives had a higher predictive capacity than the other, activity increased in these areas. Based on the literature, we suggested that these biased states entailed a suppression of the weaker script version (see [38] for a detailed discussion).

Further studies corroborated the finding that areas of the frontomedian wall increase in activity when prediction has to be adapted. For instance, activity in dorsal frontomedian BA 8 was associated with the unexpectedness of observed actions, be they action errors or not [39]). Activity in the same cortical field was found to increase for actor movements that violated the observer's cued expectation [40]. In addition to frontomedian cortex, also caudate nucleus and the hippocampal formation (both particularly connected to the prefrontal cortex) are tuned to the violation of prediction and subsequent learning processes [40, 41]. Based on these findings, we have argued that caudate nucleus, which is established as a carrier of reward-related prediction errors, may contribute more generally in signaling for prediction errors, not only when reward-related.

5 Concluding Remarks

The current paper aimed at giving a short introduction into prediction of complex events and our attempts to elucidate its presumed neural basis. Prediction as dynamic-forward extrapolation from current states and changes builds a basic but limited capacity to estimate how bodies and objects will change with regard to certain properties such as their location, speed, colour, pitch and so on. In contrast, the prediction of action additionally requires the exploration and exploitation of a rich body of semantic and episodic knowledge associated with the action in its particular context, including at least objects, rooms, actors, and the action scripts embedding them.

We think that our findings provide a new view on the action-observing brain—a brain that engages in a huge number of informational details even when not required to do so. It is an open question why the brain invests so much energy to tap and integrate all these informational sources (Notably, most of these processes occur without the participant's explicit awareness or drive). It seems as if the brain does not care a lot for the cost-benefit ratio when investing resources in prediction. One obvious explanation is that current predictive profit is maximized. A slightly different explanation could be that this enormous effort is made in order to improve our knowledge (or 'internal models') about the world and thereby to become better predictors in future. According to this notion, there is always a certain surplus of information considered, simply in order to learn and train for new situations.

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Time and Consciousness

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Abstract Some theories in physics and beyond argue that the emergence of an arrow of time is strongly related to conscious experience. Few approaches—known under the term quantum models of the mind- even claim that *consciousness creates time*. In the following we will provide theoretical arguments and empirical evidence showing that the arrow of time disappears when an individual's information processing mode changes from conscious to unconscious states of mind. This implies that unconscious processing allow for a better than chance anticipation of random future events. The theoretical and practical implications of these models are discussed.

Keywords Time · Consciousness · Retro-causation · Precognition · Quantum mind

1 Introduction

The central idea we would like to put forward here is based on a millennia old argument made by philosophers, theologians, physicists, and psychologists stating that the concepts of time and consciousness are strongly interwoven and cannot be understood without mutually referring to each other (for an overview see, [1]). Some authors in philosophy, physics, or psychology even propose a causal relationship between them and suggest that *consciousness establishes an arrow of time* or in other words that *consciousness creates time* (see for example, [2]). Advances in theoretical physics and especially in quantum mechanics provide solid grounds for this hypothesis and we will outline these theories in more detail in the first part of this paper. In the second part, we will review empirical evidence showing that conscious states of mind have an arrow of time that uniformly points from the past

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to the future whereas unconscious states of mind seem to act time undirected and thus unconscious processing is able to anticipate classically unpredictable future events.

The terms “consciousness” and “time” need to be defined as we will use those in the following theoretical considerations. According to Searle [3], consciousness consists of subjectively experienced qualitative states and processes of awareness. The qualitative aspect is the core feature of conscious experience making it distinct from other mental activities. Chalmers [4, 5] calls this subjective knowledge of how it feels to be in that state “Qualia”. Consciousness evolves through discrete events occurring one after the other being separated in time [6]. Conscious information processing is characterized by categorical thinking, that is based on binary classifications that decide whether something belongs to that category or not (Boolean logic; [7]). Unconscious states on the other hand occur without awareness and phenomenal experience and process information in an acategorical manner with overlapping and imprecise categorical borders.

With regard to time, Römer [2] referring to McTaggart [8] distinguishes between an A-time and a B-time. A-time is an internal time carrying the quality of “nowness” that experientially moves into the future turning the nows into the past. B-time, in turn, is the objective time of physics characterized by the ordering of two physical events into before and after, although the directedness of this strict order can be absent if time-symmetric laws are involved. A-time could be described as psychological time based on subjective experience and B-time as an objective time measured by clocks or similar cyclic repeating devices. In our paper here we refer to B-time when using the term “time”.

2 Consciousness Creates Time: Theoretical Considerations

Most theories in physics treat the passage of time as pure illusion and natural laws are formulated without any reference to and independently of time. This is documented by the fact that many physical laws are time-symmetric and equally work for forward and backward time propagation (see [9]). However, there are a few exceptions which naturally introduce time-asymmetry into the description of our world. Interestingly these special cases within the family of physical laws are somehow related to conscious experience.

One example is the second law of thermodynamics introduced by Boltzmann (see [10]). It states that entropy steadily increases from the past to the future and in this way is related to the arrow of time. Penrose [11] argues that entropy is the most basic principle from which time evolves. According to him “…our experience of the passage of time is dependent upon an increasing entropy….so whatever time-direction we believe to be the ‘future’ must be that in which entropy increases… had the entropy been decreasing … then our conscious feelings of temporal flow would project in the reverse direction…. Thus, so the argument goes, our psychological experiences of the passage of time would always be such that the Second Law holds true, irrespective of the physical direction of the progression of entropy (p. 52)". It is not the flow of time that forces entropy to increase, rather an increase of entropy is consciously perceived as passage of time. Time in this framework is nothing else than a consciously perceived order of events that follows the road of increasing entropy. The arrow of time in this framework is thus a consequence of conscious perceptions of changes in entropy.

Recently, Smolin [12, 13] went even further and argued that the passage of time is based on objective grounds and constitutes an innate principle of the universe from which all physical laws evolve. This approach is now known as *temporal naturalism* [13]. According to his view, time is understood as a succession of moments that defines the future as elements that presently are not real and there are no facts of the matter about it, whereas the past is characterized by events that have been real and could in principle be described by facts. In other words the past is consciously knowable and the future is not (yet) consciously accessible. The author also emphasizes a strong relationship between the passage of time and the emergence of conscious experiences about the world. "Qualia", that is conscious moments of experience, can only be incorporated in theories that are grounded on the passage of time whereas conscious moments cannot exist in a timeless description of the world. As Smolin [13] says "qualia can only be real properties of a world where "now" has an intrinsic meaning so that statements about now are true non-relationally and without contingency. These are the case only in a temporal natural world (p. 32)." According to this approach, the undeniable existence of consciousness in the universe forces time and an arrow of time to exist as well (see also [14]).

Another group of theories relating the passage of time to conscious experiences is based on quantum mechanics [2, 15–24]. In these theories the transition from the quantum to the classical state is usually caused by a collapse of the wave function. This transition marks the origin of a conscious moment and a series of collapse-dependent conscious moments introduces the passage of time. These theories relate quantum states to unconscious processing and the sudden reduction of the state vector to a conscious 'now'. Although there is some disagreement amongst these models with regard to the proposed physical reality underlying the wave-function [25] and with regard to the exact nature of the collapse postulate, they all agree in quantum-based timeless existence during unconscious states of mind and that the flow of time evolves in strong relation to conscious processing states that are based on classical physics.

We try to explain the relation between quantum physics and consciousness in more detail by referring to the Orch OR model as one prototypical theory of quantum mind processing ([18] for a recent description see [24]). Although applicable to any physical system the authors focus on quantum mechanical descriptions of basic brain processes located in the micro-tubulins of nerve-cells and how 'qualia' can evolve from those structures. According to this theory, before a conscious experience is made, unconscious processes exist in a state of superposition. Superposition involves the simultaneous and timeless existence of qualitatively different pre-conscious thoughts. They are captured within a quantum framework as slightly differing space-time geometries [22]. Each space-time relates to one unconscious thought that has a specific potential of becoming conscious according to a probability function assigned to the superposed states. Before the collapse, they exist in a space of potentialities [26] and are pre-real in the sense that they can be experienced only on a vague, unconscious, non-verbal level. These processes provide pre-factual knowledge represented in an implicit style most likely experienced as weak affective impressions. They are timeless, that is past, present, and future are undistinguishable and future impressions can causally influence past ones. The collapse that marks a conscious moment of 'now' is caused by quantum gravitation based on spacetime-separations. These separations resemble a curvature being located between superposed states. The frequency rate of the collapse can vary from a few milliseconds but might normally occur at much slower pace "…, say, one half a second or so, i.e. ~500 ms,…" [24, p. 16]. Thus, within a time window of a few hundred milliseconds timeless states of minds co-exist, which implies that within this time period past, present, and future are interchangeable. After the collapse the ordinary classical flow of time is observed.

A similar quantum mechanical approach of consciousness that however abandons the collapse process is the Extended Everett Concept (EEC; [19, 20]). It is based on Many-Worlds interpretation of the evolution of the Schrödinger Equation (see [27]; see also [19, 28]) which assumes that during the state of superposition all quantum states involved in a system branch up into separate worlds each of them representing one potential quantum state. The collapse postulate is replaced by a change in perspective during the measurement process. During superposition all quantum states are treated as a whole leading to wave-like outcome of the quantum system. This is metaphorically described by Tegmark [29] as the bird perspective. After the measurement the observer takes on a frog perspective [29], that is one single branch of the superposition is randomly selected (particle-like outcome). Importantly, the other braches still exist but are during that perspective temporarily inaccessible and separated from each other. In EEC, Mensky [19, 20] identifies this separation of alternatives with consciousness. Limited consciousness provides access to all experiences made in the alternative worlds simultaneously. Since these alternatives co-exist timelessly such a state of mind also provides access to future experiences. Future events can thus be experienced in a pre-conscious state of mind and influence behavioral choices accordingly. Individuals who rely on unconscious impulses during decision making could have a richer amount of information than those who just base their decisions on conscious thinking. Mensky [20] calls this phenomenon "super-intuition". The innovative idea in EEC is that changes within mental states are able to explain transitions from timeless quantum alternatives to time-dependent experiences of the classical world. Similar as in the theories described above, the existence of consciousness is strongly related to the emergence of an arrow of time (see also [2]).

3 Consciousness Creates Time: Empirical Evidence

According to the quantum models of the mind mentioned above, conscious states of mind are strongly related to the arrow of time and unconscious states are operating timeless. On the one hand, this implies that conscious processing can only be affected by past experiences including anticipations of future events that are based on past experiences and thus are nothing else than extrapolations of memories (see other authors in this volume). Causal effects in this processing mode therefore always emerge from the past. On the other hand, unconscious information processing should exist in a state of timelessness and therefore the usual direction of causality could be reversed in some occasions. In other words, unconscious processing could also be affected by and benefit from unpredictable future events. Such phenomena are known as *retro-causal* effects.

In the following paragraphs we will describe a number of psychological experiments and meta-analyses that report retro-causal effects of future events on human reactions in the past. Also a number of replication failures will be reported. We briefly describe those studies in the following section and we will show that—taken the whole picture including successful und unsuccessful replication attempts—retro-causality is restricted to unconscious processing modes. Next we present studies from our own research group [30] that directly tested the effect of unconscious processing during the avoidance of random negative future events.

In a recently published series of nine experiments using five different paradigms, Bem [31] demonstrated that classically unpredictable future stimulus presentations had an effect on participants' responses preceding these presentations. For example in Experiment 2 participants had to indicate their preference for one of two neutral pictures (an original and its mirror image) by pressing a key on the keyboard. After the key-press a randomly chosen negative or a positive masked picture was presented subliminally three times. The hypothesis was that if the individual unconsciously 'knows' or feels the future consequence of his or her preference judgment, he or she should be more likely to choose that neutral picture from the pair that leads to the presentation of a masked positive picture. This should lead to a better than chance (50 %) avoidance of a subsequent negative masked picture presentation. The results were in line with the predicted avoidance of negativity effect: On average, less negative subliminal pictures were presented than expected by chance. Similar retroactive influences of future events were found for precognitive selection (forced choice) of erotic stimuli (Exp. 1), time-reversed evaluative priming (Exp. 3 and 4), retroactive habituation (Exp. 5 and 6), retroactive induction of boredom (only marginally significant, Exp. 7), and retroactive facilitation of recall (Exp. 8 and 9). In the latter two experiments, future practice of some items had a positive effect on recall performance for these items in a preceding memory task. One of the memory studies yielded the highest effect size ($d = 0.42$, Exp. 9) and was considered to be the easiest of the nine experiments to be replicated.

As explicitly suggested by Bem [31] several independent research teams tried to replicate the retroactive memory practice effects [32–34]. These replication attempts took into account most of the critical arguments raised in response to Bem's work focusing on various statistical issues [35, 36]: They predetermined sample sizes and avoided optional stopping and multiple analyses. In addition, they used the same data analytical strategies, usually simple t-tests, and the same procedure and methods as in Bem's original publication. With few exceptions, almost all of the early replication attempts failed. Galak et al. [33] did a meta-analysis including also unpublished replication attempts (Milyavsky unpublished data; Snodgrass unpublished data; Subbotsky unpublished data; Tressoldi et al. unpublished data) that revealed no evidence for retroactive influences in the facilitation of recall paradigm. Thus, it seemed that the effects reported by Bem were not robust and the existence of precognition effects was called into question. At this point, serious doubts arose whether similar replication failures can be expected for the other studies reported by Bem [31].

However, a meta-analysis of all forced choice precognition experiments by Honorton and Ferrari [37], that included 309 experiments which were quite similar to the design of Bem's Experiment 1, reported a small but significant precognition effect (but see [38]). Furthermore, Mossbridge et al. [39] did a meta-analysis that included 26 studies on the effect of predictive physiological anticipation of unpredictable stimuli. They found an overall significant retroactive influence of emotionally arousing stimuli on various kinds of physiological reactions. This might be considered as a conceptual replication of Experiment 2 in Bem's article in which a similar anticipatory emotional preparedness effect, i.e. avoidance, was found. Rouder and Morey ([40]; see also, Tressoldi et al. submitted) did a meta-analytic Baysian analysis on several types of Bem's experiment. They found some evidence that individuals can avoid negatively valenced pictures, but no supportive evidence for the other paradigms used by Bem.

Given the actual empirical data, it seems that retroactive facilitation of recall might not be a robust effect, whereas the empirical validity of retroactively influenced forced choices and emotional stimulations remained still open at this time. The latter effect was obtained with subliminal presentation modes and was based on affective reactions aroused by the pictures. This indicates that unconscious processing might primarily be driving these effects. Someone might speculate that differences in effect size found between those paradigms might also reflect differences in the degree of how much unconscious processing is involved during response acquisition and stimulus presentation. Also, Bem [31] noted in the discussion section of his manuscript that an unconscious processing mode might increase the reliability of retro-causal effects in the lab. This is in line with the theoretical models described above which restrict retro-causal influences to unconscious states of mind.

As a consequence, Maier et al. [30] took the propositions made by quantum models of the human mind seriously. They developed a research design that ensured an unconscious processing mode throughout each stage of the participants' actions. They applied the unconscious avoidance task, similarly to that originally used by Bem ([31], Exp. 2) with a few minor but important modifications. First, they ensured that the participants' anticipatory responses were made without the involvement of a conscious selection processes. That is, they solved the contradiction of forcing an individual to decide about alternatives without knowing about the decision. Secondly, the future outcome, that was supposed to retro-actively bias these unconscious decisions, was introduced outside awareness by using a subliminal presentation technique. In all studies, participants had to press two keys on a keyboard as simultaneously as possible before the subliminal (i.e., below threshold) picture presentation appeared. Each key was randomly associated to a positive (neutral) or negative future outcome. As one of two keys was always triggered first, either a left or a right key-press was registered and thus resulted in a positive (neutral) or negative masked picture presentation. The participants were not aware of this relationship and did not realize that pressing those keys basically constitutes a decision for one of the two future alternative states. The main idea was that the unconscious mind subtly influences the finger movements in a way that the key-press result was biased in favor of the participant's biological motives (avoidance of future harm). This procedure allows two minimize the likelihood that awareness was involved during perception and decision. In Study 1, each key-press was randomly assigned to either a positive or negative masked picture presentation in the future. Results revealed that participants unconsciously avoided negative pictures and selected more often the positive ones. This study did not allow an interpretation of whether this effect was due to an avoidance of negative future states or an approach of positive alternatives. As research on the impact of approach versus avoidance on behaviors indicates, bad events seem to have more impact than good ones [41]. It seems therefore to be likely that the effect of Study 1 was primarily driven by avoidance. To test this retro-active avoidance effect in isolation, in Study 2 negative and neutral (instead of positive) pictures were used. Again, participants were able to better than chance unconsciously avoid negative future outcomes. In Study 3, a much bigger sample was targeted by doing the same study online. The analysis revealed a significant deviation from 50 %, showing that participants unconsciously avoid negative future outcomes. In another web-based study, a replacement instead of a non-replacement procedure (as in the previous studies) was used for the trial randomization. The results only revealed a statistical trend for an avoidance effect. In another study, that was done after Study 1, the unawareness of the masked pictures was probably jeopardized by mentioning that this study is about positive, negative, or neutral pictures in the instruction (instead of mentioning the term "colored stimuli"). As a consequence, no significant effect was obtained within this study. A further study that explored the effects of individual differences in cortisol level on the avoidance effect failed to reveal a significant avoidance main effect, too. However, in Study 4, Maier et al. [30] run a high powerful study with a more sophisticated randomization, that is a combined use of a predefined randomized list of trials (PRNG) and a hardware based true random generator (RNG, i.e., a quantum based number generator) that passed both DIEHARD and NIST tests of randomness. Participants therefore could not "algorithmically know" the consequence of their response before or during the key-press and thus, any avoidance effects could only be explained by retro-causal effects from the future (see [31]). Results revealed a significant deviation from 50 %, showing that participants were able to unconsciously avoid a negative future outcome.

Taken together, retro-causal effects defined as backward-time causation can be predicted from theories that unify the emergence of consciousness with the arrow of time. Specifically, quantum approaches such as the Orch OR model (e.g., [24]), the EEC theory (e.g., [19, 20]), and the weak quantum model (e.g., [2, 15–17]) predict such time anomalies when unconscious processing dominates behavioral responses in the anticipation of future events. Although the empirical evidence for retro-causal effects is mixed and skeptical critics dominate the field and question the results, one stable pattern can be identified: Affective responses based on unconscious behavioral choices that are triggered by subliminally presented stimuli in the future seem to be sensitive for retro-causal effects. This is true for Bem's [31] Study 2 with supporting Bayesian statistical evidence provided by Rouder and Morey [40] as well as Maier et al.'s [30] Study 1–4, who also provide meta-analytical evidence when null findings are included. Similarly, anticipatory effects of physiological parameters are meta-analytically reported by Mossbridge et al. [39]. Hence, it seems that preliminary empirical evidence exists for retro-causality during unconscious processing states.

At this point, we need to take one step back. Even if someone takes the quantum model of the human mind serious and even if someone is convinced by the admittedly weak empirical evidence for retro-causality during unconscious processing, still there are some quite good theoretical arguments that speak against the existence of retro-causal effects. One is related to the time travel paradox that is involved in retro-causal information transmission and another one is related to the impossibility of supra-luminal signal transfer postulated by special relativity. In the following sections we will describe the problems raised by these issues with regard to retro-causality and try to provide approaches that might offer at least preliminary solutions for them.

4 Retro-Causality, Time Travel, and the Grandfather Paradox

Retro-causal effects found during unconscious processing states imply that –at least on the level of information- time travel is possible. This raises the question: what about the paradoxes involved in time travel? Shouldn't time travel be forbidden, as Hawking [42] argues, through a chronology protection agency since we would otherwise run into unsolvable contradictions? This dilemma is nicely described by the well-known grand-father paradox. Transferring the grand-father paradox to the retro-causal effects described in the psychological studies above would imply that sending information back in time could affect the birth of one of the sender's ancestors. For instance, if the signal chances her grand-father's dating behavior, the sender's mother and the sender herself will not be born and therefore could not send back the signal in time. So, isn't this a strong argument against the possibility of sending information back in time since it would change a known and probably objectively recorded history? The answer is, "No", for one reason: The effect of a future event on the past operates on unconscious grounds. Thus, any effects obtained remain outside a conscious registration and therefore do not alter a consciously accessible recorded history. Thus, the evidence for time travel is only indirect and remains below the horizon of conscious facts and therefore prevents the emergence of a paradox. Changing the grandfather's knowledge about his dating behavior either by the individual himself or an outstanding historian will never occur since only unknown facts might be altered. So the argument goes: Time-travelers might exist but neither they themselves nor any past agent will ever consciously register their presence.

5 Retro-Causality and Supra-Luminal Signal Transfer

At first sight, the notion of information moving also backward in time (which implies that a signal travels faster than the velocity of light) stands in sharp contrast to Einstein's [43] special relativity theory according to which nothing can move quicker than the speed of light. However, this statement needs to be clarified a bit (see also [30]): No *classical* information—defined as a bit of 0 or 1—can move faster than light, but as Gauthier and his colleagues [44] (see [45]) could demonstrate, distorted information, which was made unreadable to some extent, moved faster than the speed of light and thus arrived at a detector before it was sent. The detector needed additional time to decode the bit leading to the results that the classical bit could not be consciously detected quicker than the speed of light. So, for classical information, special relativity holds but for degraded information the classical concept of causality can be violated. If a classical bit is equal to a conscious moment of knowing, any degraded information would be processed unconsciously since it is not fully consciously accessible. This means that the more unconsciously—i.e. not classically—a signal is processed, the more likely it can exert the velocity of light and therefore can travel backward in time (see also [30]).

6 Retro-Causality and Its Implications for the Physical Reality We Are Living in

At the end, we would like to speculate about the features of the physical reality we are living in given that retro-causality is a true phenomenon. In our view at least two possible consequences for the physical reality surrounding us can be identified:

6.1 The Existence Potential Realities or Parallel Worlds

As mentioned above (see also [30]), according to the quantum models of the mind (e.g., [2, 19, 20, 24]) future alternative experiences simultaneously exist side by side and are able to influence the past even if only one of the alternatives classically arises in the future. The future before it becomes classically real can be considered to be a space of potentialities and each potential future event is able to affect the actor's behavior in the present. With regard to the experiments exploring precognitive avoidance ([30], Exp. 2–4; [31], Exp. 2), one could assume that during each trial two potential realities evolved: One containing a negative and the other a neutral (or positive) future outcome. The unconscious mind seemed to timelessly experience both alternatives simultaneously in a state of superposition [20–22]. For example, in a given trial, the unconscious mind simultaneously 'knew' that a left key-press resulted in a negative masked picture presentation and the right key-press in a neutral one. The experiences made in both alternatives states of mind took place in potential realities which are different from classical, but nevertheless can have an effect on an individual's behavioral choice. The causal effectiveness of such a potential reality is demonstrated by the fact that negative masked pictures were unconsciously avoided and therefore, from a classical perspective, not presented, but nevertheless caused an avoidance reaction. In other words, something that is from a classical perspective non-existent had an effect on a previous response and thus must have existed in some non-classical, i.e. potential, form. In sum, potential states can have effects that can indirectly be measured and must therefore exist in a form that is only compatible with the idea of parallel worlds or parallel realities [26]. It seems that our consciously perceived world is swimming on an ocean of potential realities affecting us during any time of our existence (see [30]).

6.2 The Randomness Postulate in Quantum Mechanics

Another important feature of the Orch OR model is that state vector reductions can occur non-randomly [21, 22]. Information embedded in fundamental space-time geometry is able to bias the probability that one of the superimposed states becomes classically real (see also [26]). Penrose identifies this information as Platonic values such as mathematical truth, ethical and aesthetic values along with precursors of physical laws, constants, forces, and intentions [46]. The non-randomness postulate not only provides the basis of free will ([47]; see also [26, 48, 49]), but also allows biological motives, such as harm avoidance, to unconsciously influence the outcome of the collapse [26]. In Bem's ([31], Exp. 2) and Maier et al. ([30], Exp. 2–4) studies, the authors found that a biological motive, harm-avoidance, biased the occurrence of purely randomly chosen alternatives (especially in Bem's Study 2 and Maier et al. Study 4 as true random generators were used). Such a finding is therefore in line with Penrose's idea of non-random objective reductions that is influenced by information embedded in fundamental space-time geometry (see also [26, 47–49]). Similar effects of mental influences on superposition states in a double slit experimental design are reported by Radin et al. [50]. The randomness postulate that plays a central role in leading theories about quantum mechanics seems thus to be violated under such specific experimental conditions. This offers the possibility for Free Will to be introduced into our world (see also [47]).

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Human, All Too Human: Euclidean and Multifractal Analysis in an Experimental Diagrammatic Model of Thinking

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Abstract A nominal, theoretical definition of executive functions and a diagrammatic model of thinking, related to the research and writings of J. Piaget, J. S. Peirce, P. K. Anokhin and N. A. Bernstein, is presented. The model is an attempt to capture the underlying anticipatory inferential dynamics of human thinking. Furthermore the model is substantiated in a microgenetic experimental paradigm that contains a problem-solving task presented to children, adolescents and machine algorithms. Representative examples of Euclidean and multifractal analysis and its results are illustrated. Our findings suggest that the dynamics of inferential processes in humans are like finger-prints, i.e., they display an idiosyncratic character. It is hypothesised that due to the discriminant character of these processes, the paradigm could have a potential clinical use allowing the quantitative description, classification, diagnosis, monitoring and screening of mental conditions that impair executive functions. It is concluded that this model and the related experimental paradigm could help us increase our knowledge of the anticipatory aspects of human cognition.

Keywords Anticipation · Inferences · Executive functions · Multifractal

"By means of a game similar to the *game* of chess -it is perhaps possible to bring about symbolic thought constructions. The former sport of logical disputation was very similar a *board game*." Novalis (1772–1801). *Notes for a Romantic Encyclopaedia, Das Allgemeine Brouillon, pag 173 : 1005.*

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1 Introduction

This paper deals with studies initiated more than 20 years ago [50] and that are still in progress today. It exposes a summary of the theoretic scaffolding used to build an experimental paradigm that allows for a naturalistic study of human anticipation, i.e., “future-oriented action, decision, or behaviour based on a (implicit or explicit) prediction” [78].

The argumentative style chosen to deliver the exposition, rests heavily on the use of original quotes taken from the authors involved, giving the readers the chance to perform their own exegesis.

The importance of what is exposed here should be pondered by its practical outcomes, as Paul A. Weiss suggested; “the validity of a scientific concept is no longer decided by whether it appeals to “common sense”, but by whether it “works”” [97].

The purpose of the first section of this paper is to advocate a new definition of “Executive functions” (EF) based on its lost original sources namely: the Soviet theory of functional systems (FS) of Anokhin and Bernstein.

The second section has three subsections, in the first one, some of the key notions of the theoretical convergence between Anokhin, Bernstein, Peirce and Piaget are highlighted. In the second subsection an inferential engine is depicted using the mature inferences theories of Peirce and Piaget. In the third subsection, an inferential cyclic structure is identified at the core of cognitive FS and it is postulated as the “engine or the executive” of EF.

The third section presents a diagrammatic model that displays the dynamics of the inferential engine, allowing its representation and further statistical modelling using Euclidean and non-Euclidean measures. The model is substantiated in a problem-solving task presented to human and non-human solvers. Moreover some representative results from our previous studies are illustrated and future applications advanced.

2 Executive Functions

The doctrines of the control and regulatory role of the brain in cognition and behaviour were already known in ancient Greek medicine and philosophy since the sixth Century B.C.E. and reached their climax with Galenus in the second Century A.D. [24]. Nevertheless, the mechanisms by which the brain controls and regulates cognition and behaviour were just beginning to be understood in the 19th Century in parallel with the knowledge of the functions performed by the brain’s frontal lobes.

The concept of EF has played a pivotal position in the elucidation of how the brain relates to cognition and behaviour; nevertheless its definition has become one of the most difficult conundrums for neuroscientists and clinicians [13, 27, 34].

Despite the controversy in defining the concept of EF, more than 30 different definitions have been given to date [34]; the currently accepted view considers a wide set of more or less independent neurocognitive processes and abilities i.e.,

- Thinking, reasoning and problem-solving.
- Anticipating, planning and decision-making.
- The ability to sustain attention and resistance to interference.
- Utilisation of feed-forward, feedback and multitasking.
- Cognitive flexibility and the ability to deal with novelty [19, 99, 100].

There has been a great deal of misunderstanding surrounding the concept of EF since its inception. Most scholars trace back its origin to Alexander Luria, but they mysteriously got lost there, like in the story of the search for the source of the river Nile.

The case is that when Luria [60, 64] was re-examining the meaning of the concept of "function" in relation to mental activity, few scholars noted that his references pointed to two Soviet researchers: Pyotr Kuzmich Anokhin and Nikolai Aleksandrovich Bernstein.

To our knowledge, besides Luria; only Ch. Fernyhough, O. A. Semenova and A. Kustubayeva, in a triad of insightful reviews, have remarked the relation between functional system theory and executive functions. These last authors did not however dig deep enough into Anokhin and Bernstein's works, to extract more fruitful consequences of this relationship [31, 49, 88]. According to Luria:

> … a function is in fact a functional system (a concept introduced by Anokhin) directed toward the performance of a particular biological task and consisting of a group of interconnected acts that produce the corresponding biological effect [64].

Moreover, Luria rightly states that this meaning of "function", although in a simplified manner, was already used by Hughlings Jackson; when analysing the anatomical and physiological localisation of movements in the brain:

> For the nervous centres do not represent muscles, but very complex movements, in each of which many muscles serve [41].

As early as 1928, Luria had already been using a rudimentary version of the concept of FS when he was adapting his motor method to study the affective reactions [59], as well as in his 1930 co-authored paper with Vygotsky [96].

Contemporary motor control scholars have kept alive only Bernstein's version of the functional systems theory under the name of "synergies", forgetting Anokhin's contributions [25, 44, 55, 56]. In contrast, both Anokhin and Bernstein's ideas have thrived among ergonomics scholars [14, 18].

It is necessary to accentuate that the original concept of EF is not pointing to an independent system, that controls and regulates cognition and behaviour. In fact EF is an intrinsic aspect of cognition and behaviour that develops and exists only during a cognitive activity or behaviour and does not exist by itself. As Bernstein and Anokhin put it:

> we want to emphasize that control and controllability never and nowhere come into being in isolation, as phenomena that exist just for their own sake. Control is needed whenever a task is set, a goal is determined that has to be reached [30].
> Every functional system possesses regulatory properties which are inherent only in its integrated state and not in its individual components [9].

Luria, following Anokhin and Bernstein, depicted cognitive processes as complex functional systems:

> that they are not "localized" in narrow, circumscribed areas of the brain, but take place through the participation of groups of concertedly working brain structures, each of which makes its own particular contribution to the organization of this functional system [62].

Furthermore Luria distinguishes three principal "functional units" in the brain, whose participation is necessary for any type of mental activity, i.e.:

1. A unit for regulating tone or waking
2. A unit for obtaining and storing information arriving from the outside world
3. A unit for programming, regulating and verifying mental activity.

The third unit is involved in what at present is called "executive functions", Luria clearly states that:

> It would be a mistake to imagine that each of these units can carry out a certain form of activity completely independent … Many years have passed since psychologist regarded mental functions as isolated "faculties" [62].

Regarding the notion of faculties, Luria recalls his friend and co-worker:

> The famous Soviet psychologist L. S. Vygotskii made the decisive contribution to the development of scientific psychology when he stated that psychological processes are not elementary and inborn "faculties," but are, rather, formed during life in the process of reflection of the world of reality, that they have a complex structure, utilizing different methods for achieving their goal, which change from one stage of development to the next. He considered that the most important feature characterizing higher psychological functions is their mediated character, the fact that they rest on the use of external aids (tools for movements and actions, language for perception, memory, and thought) [65].

Noteworthy, every aspect that has been mentioned in the latest reviewed literature as being fundamental for EF, (see Sect. 2, third paragraph), can be seen as subordinate concepts (species) of an extensional definition [70, 92]. Furthermore these subordinate concepts can be mapped directly onto the main "operation stages" of functional systems [13, 27, 35, 46, 57], see (Fig. 1, and Sect. 2.1). These former considerations allow for the advancement of the nominal, theoretical definition [37, 38] of executive functioning proposed here.

This definition of EF is re-linked to the original sources of the concept, paraphrasing Anokhin: executive functions are any of: *"those specific mechanisms of the functional system which provide for the universal physiological architecture of the behavioral act"* [8].

Additionally, this definition could be conveniently summarised and operationalized using the inferences theory proposed by Peirce and Piaget [87, 83], see (Sect. 3).

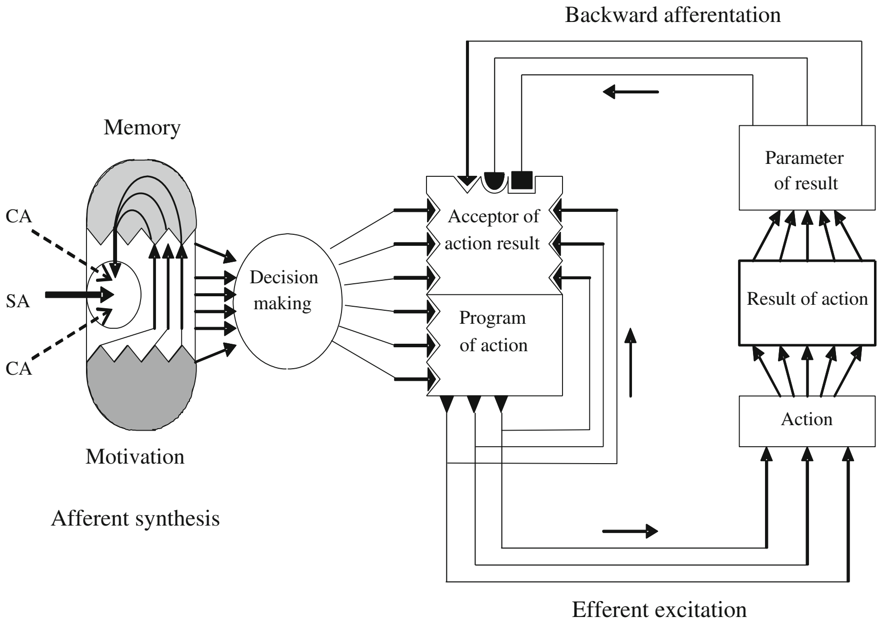

Fig. 1 General architecture of a functional system according to Anokhin [2]. In the diagram: SA is starting afferentation, CA is contextual afferentation. And the operation stages of the functional system are: preparation for decision making (afferent synthesis), decision making (selection of an action), prognosis of the action result (generation of acceptor of action result), generation of the action program (efferent synthesis), performance of an action, attainment of the result, backward afferentation (feedback) to the central nervous system about parameters of the result and comparison between the result of action and the prognosis

To illustrate this definition, in the next subsection, a diagram is presented and a brief review of those "specific mechanisms" as they were portrayed by Anokhin.

2.1 *The Architecture of the Behavioral Act*

According to the theory developed by Anokhin in 1932–5, a functional system is always a dynamic central periphery formation of a cyclic character, that not only includes the central nervous system, but the whole body and the results of the actions exerted by the subject upon the environment. All functional systems, independent of their level of organisation, have the same functional architectonics, where the result is the leading factor to achieve a stable organisation.

> The composition of the functional system is not limited to the central nervous structures which fulfil the most delicate integrating role in its organization and impart the appropriate biological property to it. It must, however, be remembered that this integrating role is necessarily manifested in the central- peripheral relations by which the working periphery

> determines and implements the properties or the functional systems, which adapt the organism to the given dynamic situation by their end effect [9].

Moreover, Luria, paraphrasing Anokhin and Bernstein's concepts, writes in a 1973 review:

> Every behavioral function is really a functional system, which preserves a stable goal but uses different links of operative behavior to come to a desired result. It is obvious that, in all these cases, there is not only a certain "feed-back" needed for control of the effect of behavior, but also a certain "feed-forward," which establishes plans and programs and which is of decisive importance for elaboration of complex forms of behavior [61].

In the following subsections a diagram and a summary explanation of the architecture of a FS is provided according to its sequence of stages of operation, i.e.:

4. Preparation for decision making (afferent synthesis),
5. Decision making (selection of an action),
6. Prognosis of the action result (generation of acceptor of action result),
7. Generation of the action program (efferent synthesis),
8. Performance of an action,
9. Attainment of the result,
10. Backward afferentation (feedback) to the central nervous system about parameters of the result,
11. Comparison between the result of action and the prognosis [9].

Afferent Synthesis. Afferent synthesis is an essential and universal stage in the enactment of any cognition, behavioural act or conditioned reflex. Afferent synthesis is the first stage in the operation of a FS that orders and integrates information simultaneously from the following sub-stages: (a) motivational excitation, (b) situational afferentation, (c) triggering afferentation and (d) memory mechanisms.

(a) *Motivational excitation*: this sub-stage represents the organism's needs to be satisfied by the behavioural act. The motivations can be created by nutritional, hormonal, cognitive processes (problem solving) or social needs. The dominant motivation helps to filter and actively select the relevant information by means of attentional processes, like orienting-investigative reactions, to set up the goals and actions to achieve the appropriate adaptive effects.
(b) *Situational afferentation*: this sub-stage is composed by the total sum of stationary and serial afferences coming from the environmental setting, in which the behavioural act is framed; leading to a pre-triggering integration of actual and latent excitations.
(c) *Triggering or starting afferentation*: is the sub-stage composed by the actual manifestation of all the latent excitations in an active, and discrete moment which maximises the success of the adaptation.
(d) *Utilisation of memory mechanisms*: in this sub-stage, which is essential for afferent synthesis, all the previous sub-stages and the stored, relevant past experiences are linked together as a whole.

The correct functioning of all these sub-stages is assured by the constant active process of attentional mechanisms, like orienting-investigative reactions, that updates the incomplete or insufficient information coming from the different sub-stages.

Afferent synthesis is the main stage responsible for the establishment of goal directed behaviours. In a comment about the "creative" nature of this stage, Anokhin, following Pavlov's ideas stated that:

> As can be seen from the enumeration of four components of the initial stage of development of behavioural acts, it is a truly all-embracing one. It is precisely at this stage, as in no other stage of development of the behavioural act, that Pavlov's prevision of the decisive (the 'so-called creative') role of the afferent function of the cortex of the great cerebral hemispheres applies [6].

Decision Making. The stage of decision making is crucial in the consolidation of all the qualitative information of afferent synthesis and is always preceded by it. In this stage the organism "chooses" to enact one particular type of behaviour among an infinite repertoire of possibilities, in order to achieve its goal. Anokhin remarks that this stage is a kind of "logical process" that has been "designated as ideation, or as a state of the eureka type" [9]. This account is astonishingly similar to the description given by Peirce of the experience of abductive inference:

> The abductive suggestion comes to us like a flash. It is an act of insight, although of extremely fallible insight. It is true that the different elements of the hypothesis were in our minds before; but it is the idea of putting together what we had never before dreamed of putting together which flashes the new suggestion before our contemplation [75].

The decision making stage is not only present in behavioural acts, but also in autonomic functions, like respiration or blood pressure control mechanisms.

> Thus, the physiological meaning of decision making in the patterning of a behavioral act lies in three highly important effects:
>
> 1. Decision making is the result of afferent synthesis accomplished by the organism on the basis of the dominant motivation.
> 2. Decision making eliminates superfluous afferentation, thereby promoting the formation of an integral of efferent impulses having adaptive value for the organism in a specific situation.
> 3. Decision making is a critical moment after which all combinations of impulses assume an executive, efferent character [9].

Generation of the Action Program and the Acceptor of Action Result. Immediately after efferent synthesis and the decision that sets the goal, two simultaneous events take place:

(a) The creation of an action program (derived from the decision making stage) containing the procedural scheme of efferent excitations to be implemented by the peripheral effector organs intended to produce a result.
(b) The creation of a mechanism, called "acceptor of action results", that contains the efferent parameters of the anticipated results of the action to be performed. The efferent parameters are anticipated from predictions based on the logical consequences expected from the actions to be performed.

Performance of Action and Attainment of Results. These two stages correspond to the execution and to the actual performance of the action, as patterned in the action program and also to the actual results obtained.

Backward Afferentation (Feedback). This stage is composed by the stream of afferent impulses, that carries the actual parameter of results, travelling in an opposite direction to the action impulses, to reach the acceptor of action results, closing the behavioural loop.

Comparison Between the Result of Action and the Prognosis. This stage completes the behavioural cycle. In this stage, the actual parameter of results just obtained are compared with the predicted parameters of the acceptor of action results. Depending on the results of this comparison, if the desired results are not obtained a new cycle is initiated, passing this information to create a new afferent synthesis. On the contrary if the desired results are achieved, the cycle ends.

To summarise: the mature concept of EF is rooted in Anokhin's [7, 8] and Bernstein's [16, 98] theory of "functional systems", and Vygotsky methodological approach [95, 101]. This was later used by Luria to analyse the disturbances of higher cortical functions provoked by local brain lesions [17, 61, 63, 64], particularly Luria's work on frontal lobe or dysexecutive syndrome, that was key in differentiating the EF from other aspects of cognition [49].

3 Anokhin, Bernstein, Peirce and Piaget: Some Highlights of a Convergence

The current convergence of complementary theoretical views regarding the nature of cognitive processes, conveys an evolutionary and developmental perspective, that localises thinking processes within organism-environment (including social) co-ordinations, i.e., as embodied and functionally embedded (by means of its sensory-motor cycles) in the world.

Peirce's "Inferences theory" [47, 87], "Soviet functional systems" [5, 8, 15] and "Activity theory" [91]; Piaget's "Genetic Epistemology" [81–83] "Ecological psychology" [28, 42, 90] and the "Non-linear Dynamical Systems" theory [43], makes it now possible to advance dynamical models and to explore new experimental paradigms in cognition.

Some of the basic tenets of the embodied mind thesis have a long history in Western culture. These ideas can be found in early Greek medicine of the fifth Century BC. Hippocrates' text "On the Sacred Disease" [40] and Aristotle's book "De anima" (On the soul) [11] brings out a compelling account of that. Moreover, Lo Presti [58] has recently remarked that the ancient Greeks' accounts of cognition are similar to the contemporary views provided by the so-called 'embodied mind' theories.

Later in the 17th century, Baruch Spinoza explains, in the second part (Concerning the nature and origin of the mind) of his "Ethica, ordine geometrico demonstrata", in the proposition XVI, that humans can only have cognition throughout the modification of the human body due to the influence of the environment and vice versa by the modification of the environment due to the influence of the human body. Moreover in the note to the proposition VII, Spinoza declares the dynamic nature of thinking, pointing out that an idea can not be thought of by itself as a single act, i.e. an idea can only be perceived through another thought, which is again perceived through another thought and so on forming an endless chain [89]. A comprehensive account of modern embodied mind theories can be found in the book the "Embodied Mind" by Varela et al. [94].

Likewise Peirce, who was the first one to put forward an integrated and plausible theory, (anticipating cybernetics concepts by more than 40 years) that considered cognitive activities, like thinking as a dynamic, self-controlled semiotic process, affirms that; every thought is a sign that can only be interpreted by another subsequent thought-sign in a cognitive stream [74].

Moreover Peirce established the intrinsic reciprocity between the semiotic elements (Icons, Indexes and Symbols) and the inferences (Abduction, Induction and Deduction) carried-out in a process of enquiry:

> Now, I said, Abduction, or the suggestion of an explanatory theory, is inference through an Icon, and is thus connected with Firstness; Induction, or trying how things will act, is inference through an Index, and is thus connected with Secondness; Deduction, or recognition of the relations of general ideas, is inference through a Symbol, and is thus connected with Thirdness [77].

Apel [10] and recently Magnani [67] have commented on this fundamental relationship as well.

Peirce's idea that every cognition rests on inferences was taken from Kant, who advanced that: "there is no cognition until the manifold of sense has been reduced to the unity" [29]. Peirce's inferences theory could be separated in two periods, firstly the syllogistic period followed by methodological period, that is related to enquire processes.

Peirce's later theory distinguishes three basic kinds of inferences that are interdependent and work in an interconnected fashion: abduction, which is a twofold process of generating hypotheses and selecting some for working on them; deduction that draws out testable predictions from the hypothesis, while induction evaluates those predictions coming from deduction by comparing them with the actual results [87].

Notwithstanding Peirce, in his paper "A theory of probable inference" went beyond the logical aspects of cognition, observing the analogy between the structure of the syllogism and the elements and mechanics of the animal's reflex arch. Habermas has shown convincingly that for Peirce, the "logical forms pertain categorically to the fundamental life processes in whose context they assume functions" [36]:

> In point of fact, a syllogism in Barbara virtually takes place when we irritate the foot of a decapitated frog. The connection between the afferent and efferent nerve, whatever it may be, constitutes a nervous habit, a rule of action, which is the physiological analogue of the

> major premise. The disturbance of the ganglionic equilibrium, owing to the irritation, is the physiological form of that which, psychologically considered, is a sensation; and, logically considered, is the occurrence of a case. The explosion through the efferent nerve is the physiological form of that which psychologically is a volition, and logically the inference of a result [76].

Peirce juxtaposes vis-à-vis the three kinds of inferences according to the cyclic sequence of stimulus in the mechanic of the reflex arch:

> Deduction proceeds from Rule and Case to Result; it is the formula of Volition. Induction proceeds from Case and Result to Rule; it is the formula of the formation of a habit or general conception–a process which, psychologically as well as logically, depends on the repetition of instances or sensations. Hypothesis proceeds from Rule and Result to Case; it is the formula of the acquirement of secondary sensation–a process by which a confused concatenation of predicates is brought into order under a synthetizing predicate [76].

From a physiological point of view, Ivan Pavlov noticed that the main adaptive feature of conditioned reflexes is its signalling character that gives rise to an anticipatory activity [73]. Krushinskii has commented, in extenso, about Pavlov's views regarding these matters; and some special kind of "associations" that express the cause-and-effect relationship between stimuli at a particular moment, namely "extrapolation reflexes". According to Pavlov, this type of association, that bears the causal relation of world events, "must be regarded as the beginning of the formation of knowledge, the forging of a permanent connection between objects" [48].

This insight, particularly regarding the signalling and anticipatory aspects of these kind of processes, is the core principle of Functional System Theory, developed later by Anokhin [4] as an improvement of Pavlov's ideas. The notions developed by Anokhin provides a physiological and psychological substantiation to Peirce's inferences theory [3, 8].

In a remarkable text, Anokhin departing from his FST; arrives at similar conceptions of the mechanisms involved in the creation of "meaning", and of all kinds of searching behaviour (including enquire processes) to those proposed by Peirce and Piaget:

> The conceptions expounded by us are of special interest in relation to the physiological analysis of specifically psychological conceptions. The conception of "meaning" in education and in perception of the outside world, for example, is obviously a variant of coincidence between the stored conditioned excitation and return afferentations, which are "meaningful" in relation to this stored excitation. All education proceeds with return afferentations playing an obligatory correcting role, and indeed it is only on this basis that education is possible. Every correction of mistakes is invariably the result of non-coincidence between the excitations of the acceptor of effect and return afferentations from the incorrect action. Without this mechanism, both the detection of the error and its correction are impossible. It can hardly be disputed that practically any acquisition of habits (speech, labour, athletic etc.) proceeds in the same way as was indicated in the schema for continuous compensatory adaptation. All forms of searching for objects are based on the features of the apparatus of the acceptor of effect. It would be impossible to "find" anything if the object sought did not not agree in all its qualities with the qualities of the excitations in the stored acceptor of effect" [4].

Anokhin, Bernstein, Peirce and Piaget, all share a common naturalistic idea, that is: that the centre of life is a self-regulating process and that there is a continuity and an isomorphism of the self-regulatory mechanism in all the goal directed activities of living organisms. This self-control organisation is present in all the hierarchical levels; ranging from the very basic vital functions to the highest manifestation of cognition, like in thinking and reasoning. Dewey, commenting about Peirce's account of enquire process highlights the importance of this matter.

> The term "naturalistic" has many meanings. As it is here employed it means, on one side, that there is no breach of continuity between operations of inquiry and biological operations and physical operations. "Continuity," on the other side, means that rational operations grow out of organic activities, without being identical with that from which they emerge. There is an adjustment of means to consequences in the activities of living creatures, even though not directed by deliberate purpose [26].

The common source of the self-regulating notions of Peirce and Piaget can be found in J.M. Baldwin's genetic theory of knowledge, (an author that inexplicably remains in oblivion) particularly his idea of psychonomics' regulatory mechanisms [12].

Piaget's theory of equilibration of cognitive structures stand in a close concordance to that of Peirce, Bernstein and Anokhin. In this framework the capacity to draw inferences is in the core of human cognition, performing a central role in the creation of knowledge and the equilibration of cognitive structures [33, 69, 82]. According to Piaget these self-regulating mechanisms consist of a combinatory system of anticipations and retractions "found at all levels from the regulations of the genome to those of behaviour" [80].

> a certain number of other functions or functional properties are common bot to the various forms of knowledge and to organic life, in particular all those which used to be covered by the inclusive and imprecisely analyzed notion of finality until recent days, when cyberneticians have succeeded in supplying teleonomic (not teleological) models or mechanical equivalents of finality. Among these are the properties of functional utility, of adaptation, of controlled variation, and, above all, of anticipation. Anticipation is in fact, along with retroactions, one of the most generally found characteristic of the cognitive functions. Anticipation intervenes as soon as perception dawns, and in conditioning and habit schemata, too. Instinct is a vast systems of surprising kinds of anticipation, which seem to be unconscious, while the inferences of thought promote anticipation of a conscious kind, instruments that are constantly in use [79].

It is worthwhile to remark that the concordance between Piaget, Bernstein and Anokhin is tight; all of them could be regarded as precursors of cybernetics. They started with a similar critique to the Cartesian view of the reflex arch and from there they arrived to an integrative concept of "function". It is not a surprising to find that Piaget's central notions of: "action schemata", "assimilation", "accommodation" and "regulation" and Anokhin and Bernstein's concept of functional systems are just like the two faces of Janus Bifrons.

> In the past, psychologist as well as many physiologist used the term "association" rather than assimilation. Pavlov's dog associates the sound of a bell with getting food and subsequently begins to salivate when hearing the bell, just as though the food were there. But association is only one stage, singled out artificially from the whole process of assimilation.

> The proof of this is that the conditioned reflex is not stable on its own and needs periodic confirmations: if you continue only to sound the bell without ever following it up with food, the dog will cease to salivate at the signal. This signal, therefore, has no significance outside a total schema, embracing the initial need for food and its eventual satisfaction. "Association" is nothing but a piece of arbitrary selection, a single process picked from the center of a much wider process (most people today realize how much more complex the conditioned reflex is than was at first thought: in neurological terms to the extent that it depends on reticular formation and not only on the cortex; and in functional terms by causing the intervention of feedbacks, etc.).

From the quote above it can be observed that when Piaget is referring to the "*total schema, embracing the initial need for food and its eventual satisfaction*" he is clearly outlining what Anokhin and Bernstein have depicted in detail as functional systems.

In the last writings of Piaget et al. [83] and Peirce [75, 85], inferences are portrayed as being beyond mere connections between predicates, as in traditional syllogistic; these authors present inferences in the form of coordinators that create meaningful implications inside and among different cognitive elements (actions, functions, operations) at different hierarchical levels. By these means, inferences regulate and drive the organism-environment system in a continuity from the very basic sensorimotor levels, like in unconscious innate reflex actions; to the highest goal-directed conscious cognitive activities like in logic-mathematical thinking.

The coincidence of both authors regarding the role and mechanics of inferential activity are in total agreement. Piaget in his book "Toward A Logic of Meanings", talking about "meaning implications", stated that:

> Meaning implications are threefold in another way. Such action implications may take the following forms:
>
> (a) Proactive implications: They draw conclusions from the propositions involved; that is, they assert that if A -> B, the Bs are new consequences derived from A.
> (b) Retroactive implications: Instead of dealing with consequences, they relate to preliminary conditions and they express the fact that if A-> .B. then A is a preliminary condition for B.
> (c) Justifying implications: This form of implications relates forms (a) and (b) through necessary connections reaching the "reasons." In other words, implications have a threefold orientation -Amplification bears on consequences; conditioning bears on preliminary conditions; and deepening brings out the reasons" [83].

To emphasize his agreement with Peirce, Piaget, in a footnote in the same book; explains that the distinction between proactive and retroactive implications was already made by Peirce who called them "predictive" and "retrodictive" implications. Or as Peirce used to call them deduction and abduction.

To summarise: Peirce [87] followed by Piaget [39, 83], depicted inferences as organism-environment, goal-directed, cyclic and self-controlled processes (in a continuum that spans from unconscious activities to conscious ones); that regulate the actions performed by the agent and the reactions from the environment (action results) by:

- Guessing the status and reactions from the environment (Abduction /Hypothesis formation).
- Anticipating by predicting, based on the former guess or hypothetical configuration, the status and reactions from the environment (Deduction).
- Evaluating the result of the actions performed by the agent by comparing the former prediction with the actual parameter (Induction).

3.1 The Inferential Engine

The regulator aspect of inferences is not very noticeable at the sensorimotor levels but since a goal-directed behaviour is performed even the unplanned, spontaneous actions of the organism become part of an inferential cycle because these actions once performed produce a "result" that could be evaluated and corrected depending on their success or failure to reach a goal.

Following Peirce and Piaget, it can be postulated that a minimum cognitive organism-environment system, gives rise to an inferential process, taking the form of a functional unit i.e., an active entity composed by three interconnected moments namely: abduction, deduction and inductions that renders a goal-directed and self organised functional cycle.

The motor of this inferential cycle works like an organic Wankel engine, propelled by a three-sided rotary piston whose strokes are: abduction, deduction and induction. The movement of this engine is triggered by a cognitive need (problem) and departs from an initial state of rudimentary knowledge. The first stroke is an abduction that moves the cycle in the direction of creating or selecting (in further steps once the engine is running) a hypothesis. The second stroke is a deduction, that takes the hypothesis developing its formal consequences and generating a (testable) prediction that is carried out in the world, producing a "result". The third stroke is an induction that evaluates the "result" of the practical trial i.e., the accuracy of the prediction, pushing the cycle into a new state of knowledge that will become the new input for the next cycle (see Fig. 2).

Once this engine is running it takes its own dynamical regime i.e., a singular spatio-temporal pattern, that is goal-directed, self-regulated and self-organised by its own results; working at its own pace according to its individual needs and levels of satisfactions, generating a dynamical figure in coherence and continuity with the state of the whole organism.

It is paramount in this account that the organism is coupled to the environment becoming a constitutive element in the cognitive cycle.

As a remarkable coincidence, an isomorphic functional architecture was experimentally unveiled by Anokhin and Bernstein in several physiologic processes and goal-directed behaviours, showing the ubiquitous character of these processes in living organisms TFS [3, 15].

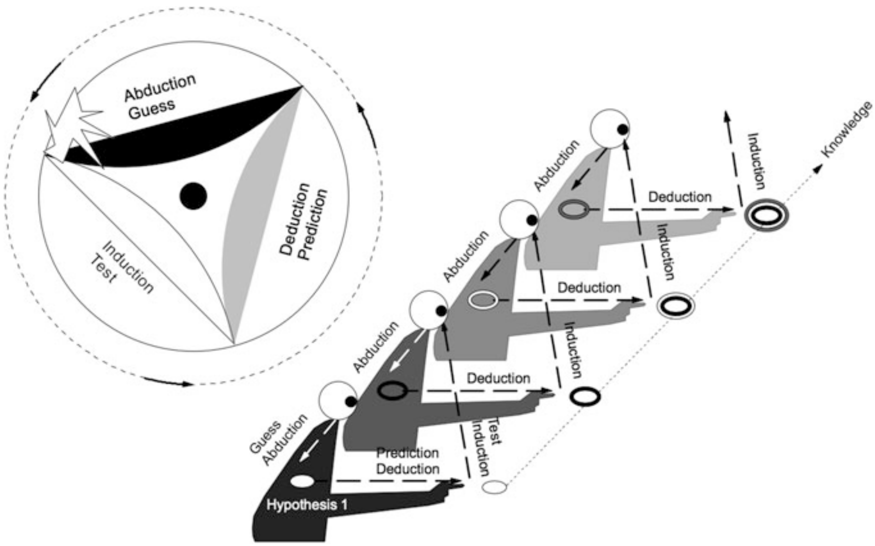

Fig. 2 The inferential engine depicted like an organic Wankel rotary engine (*Upper left*). And the inferences cycles showing the sequence of abduction, deduction and induction during a cognitive task (*Bottom right*)

To acknowledge the striking parallelism between Anokhin, Peirce and Piaget, it can be shown that the inferential engine, depicted above, could be directly mapped onto the TFS in the following way:

Inferences	Stages of operation of functional system	
Abduction	{*Afferent synthesis* *Decision making*}	Guessing
Deduction	{*Action acceptor* *Efferent synthesis*}	Anticipating
Induction	{*Backward afferentation* *Comparison results*}	Evaluating

The sequence of the stages of operation of a FS, contained in brackets, are functionally equivalent to the three kinds of inferences as were described by Peirce and Piaget. Based on this mapping and in the proposed definition of EF, it can be postulated that inferences are in the core of EF, playing the elusive role of the "executive"; forming an integrative, distributed and hierarchical control with the cognitive functions at the top.

As a corollary: it can be said that one way to assess EF is by assessing its inferential engine. In the next section it is shown how this task could be accomplished.

4 A Diagrammatic Turn: The Display and Modelling of Cognitive Anticipation

In his last paper, Bernstein, expressed the need of devising representative tools or procedures with regards to the analysis and representation of anticipatory models:

> At present, the basic problem of primary importance for physiology of activity and even, perhaps, for all biocybernetics is the mathematical problem of displays (models, projections, images, and so forth).
> The outlined theory of biological displays faces many other problems in addition to the general, perhaps principal problem of the analysis of models of the future and representing these models or codes [68].

The editors of Bernstein's last paper remark the same kind of ideas, stating that "science has to think in terms of "images" or (maps) in order to understand the role of the brain", advocating for a naturalistic theory of display. It is challenging that the insights of Bernstein are still waiting to be developed.

Anokhin, when commenting about the key value of the "result" of the action in a functional system, provided us with some penetrating cues stating that:

> It is possible to represent the activity of the system and all its possible changes in terms of its results, this situation highlights the decisive role of the results in the behaviour of the system[1] [2].

Keeping in mind Anokhin and Bernstein's insights, it is our intention to show a way in which the representation, display and analysis of cognitive anticipatory behaviour could be accomplished. To do this, a set of principles outlined by Fugard and Stenning will be followed for the modelling of thinking and reasoning processes. These authors stated that the models must:

1. encode representational elements involved in reasoning and processes for their transformation, that is, some notion of algorithm;
2. include parameters which can be varied in order to characterise individual differences, for example, qualitatively different ways of thinking about problems or tendencies to reason one way rather than the other; and
3. the model must be grounded in data of people reasoning [32].

In two previous experimental research [50, 52] and using a microgenetic approach, it was possible to devise a diagrammatic model [20] and a related problem-solving task to study the dynamic of the inferential reasoning (deduction-induction-abduction).

The working model consisted of a problem task embedded in a 2D diagram that could be used: (a) by the participant as a scaffold to solve the problem and (b) by the researcher to expose the microgenesis of the thinking dynamics entangled in its solution [21, 66].

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[1]Our translation from the Spanish text.

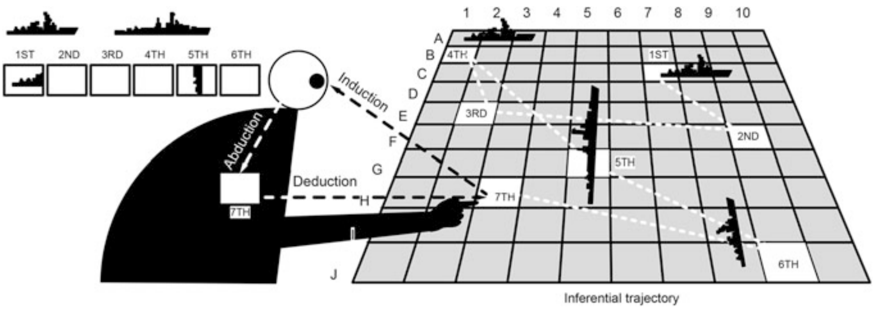

Fig. 3 Abduction-deduction-induction model depicted on a battleship game board

The problem task is analogous to one that was used by Piaget to study the children's dialectical thinking [81]. In our case the implemented task is an adaptation of a well known board game called "Battleship" [52, 53] (See Fig. 3).

Battleship is a popular worldwide guessing game for two players. The original objective of the game is to find and sink all of the other player's hidden ships before they sink all of your ships. This requires the players to devise their own battleship positions while guessing that of the other player's.

Our version of the game has been designed to be played by only one player at a time. In our case, the objective of the game is to find and sink four ships of different lengths (hidden in a board divided by a 10 × 10 grid) using the least possible shots, regardless of the time taken.

The game is a standardized computer version of Battleships that has been developed for our research. The full task includes eight individual games, each one defined by a standard template with the position of the ships [53]. Each participant is seated (beside the interviewer), in front of a computer screen running the game (See Fig. 4).

The child is requested to verbalize the coordinates (letter-number) of their shots and simultaneously click the mouse pointer in the corresponding position on the screen. During the task completion the child receives visual feedback (in the

Fig. 4 Experimental setup

computer screen) about the number of shots already performed, time passed, and their ongoing performance (amount of sunk ships). The total testing duration is approximately 20–40 min.

To fulfill the first modelling requirement outlined by Fugard and Stenning [32], an algorithm was built to render a standardised image-diagram that represents the inferential dynamics. The basic procedure is based on the sequential plotting of the series of (x,y) shot-coordinates and the time between each shot for every game played by the subject [50], (for some examples see Fig. 5).

In the next subsection, it is shown how the second and third modelling requirement suggested by Fugard and Stenning was achieved.

4.1 A Trilogy of Examples: The Individual, the Group and the Sex

The examples presented here have been taken from our past studies, that were aimed to mathematically describe and classify different styles of thinking (inferential phenotypes) from children and adolescents. In order to achieve this, representative diagrams were created and their geometric measures (Euclidean and multifractal) were used as predictor variables (see Sect. 4). Regarding the classification methods performed, we followed the practise currently used in supervised machine learning modelling [22, 23]. For practical modelling purposes, R language and the R software environment were used [54]. The geometric measures, i.e., spectrum of Renyi dimensions and lacunarity spectrum were obtained using the package IQM Scientific Image and Signal Analysis in Java [1].

The first example was taken from a group of 10 school children aged between 10 and 12 years of age, as well as from three artificial algorithms, (N = 13). The purpose of this particular example is to illustrate the descriptive strength of the geometric measures and to show how they can be used to model their individual inferential dynamics and further classification.

The results of each game played by the children or algorithms were represented diagrammatically as shown in Fig. 5.

In this figure, the first 10 rows of diagrams represent the inferential dynamics of 10 children. Row 11 corresponds to the performance of an algorithm with a probabilistic optimised searching and hitting routine, plus a feedback correcting mechanism. Row 12 is composed by the performance of an omniscient algorithm, that knows the exact position of the ships in the board, but fires its shots randomly. Finally, row 13, represents the games of an algorithm that fires all its shots randomly without any kind of feedback.

The first interesting observation noted, was that the visual patterns of certain children, displayed a similarity which is conspicuously different to those produced by another child. Ultimately these patterns express the individual differences of the

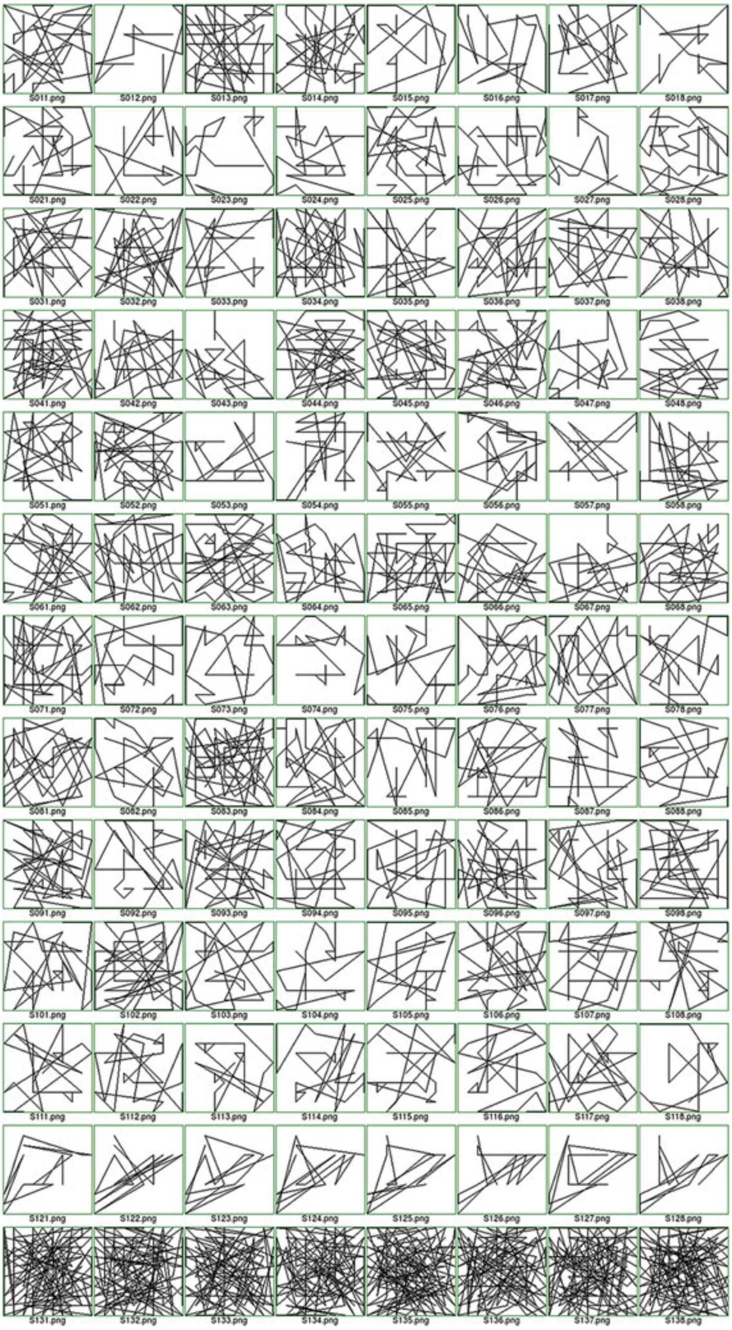

Fig. 5 Sample of images/diagrams representing the inferential dynamics for a group of ten school children (S01*–S10*, *upper ten rows*) and three algorithms (S11*–S13*, *bottom three rows*), N = 13. Each *columns* display one game of a series of eight

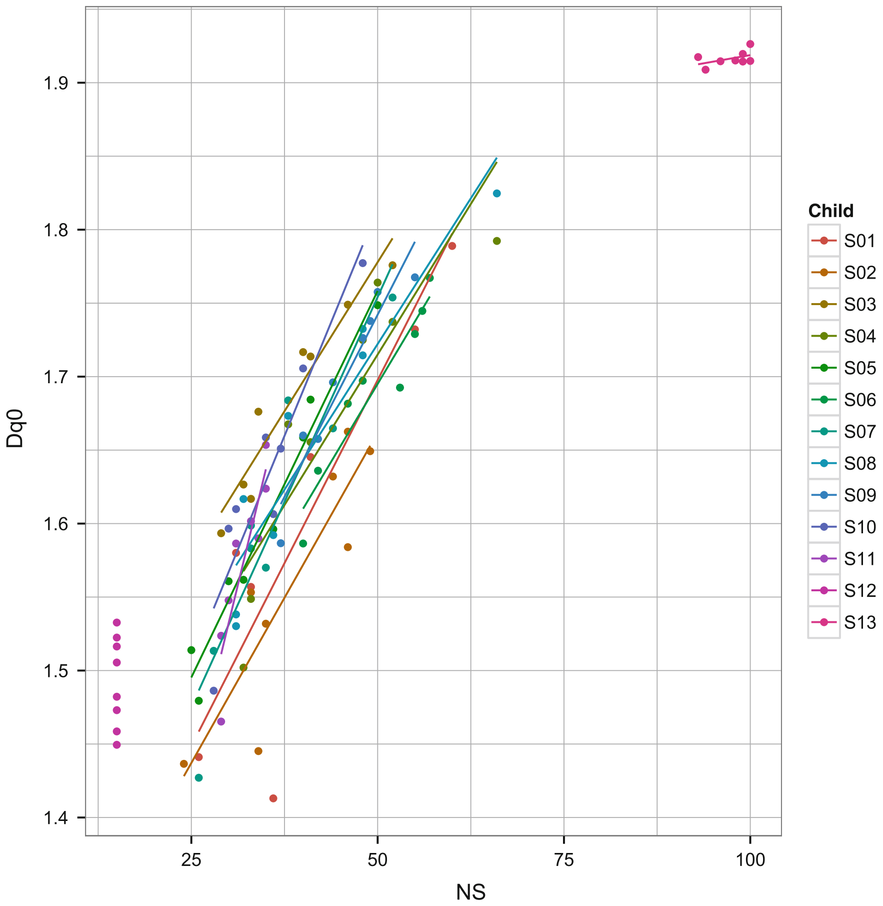

Fig. 6 Graph describing the relationship between the capacity dimension [Dq0] versus the number of shots [NS] performed by the children (S01–S10) and the algorithms (S011–S013). The *coloured lines* represent the fitted regression line for each child and the algorithms

inferential dynamics from each child. This former observation could be supported by using some geometrical measures to describe the performance of the children.

When assessing the relationship between the geometrical complexity of the figures (for example, using the capacity dimension [Dq0] and the number of shots [NS] performed by each child), the statistical models that describe these relationships are very idiosyncratic and remain stable, despite of the improvement in performance due to a learning effect, (see Fig. 6).

To illustrate the discriminant power of the geometrical measures, a linear discriminant analysis (LDA) was performed using the following geometrical predictors: Renyi Spectrum [Dq0–Dq10], Cumulative Length, Number of Shots and the Lacunarity Spectrum [1–10], making a total of 23 measures, see Fig. 7.

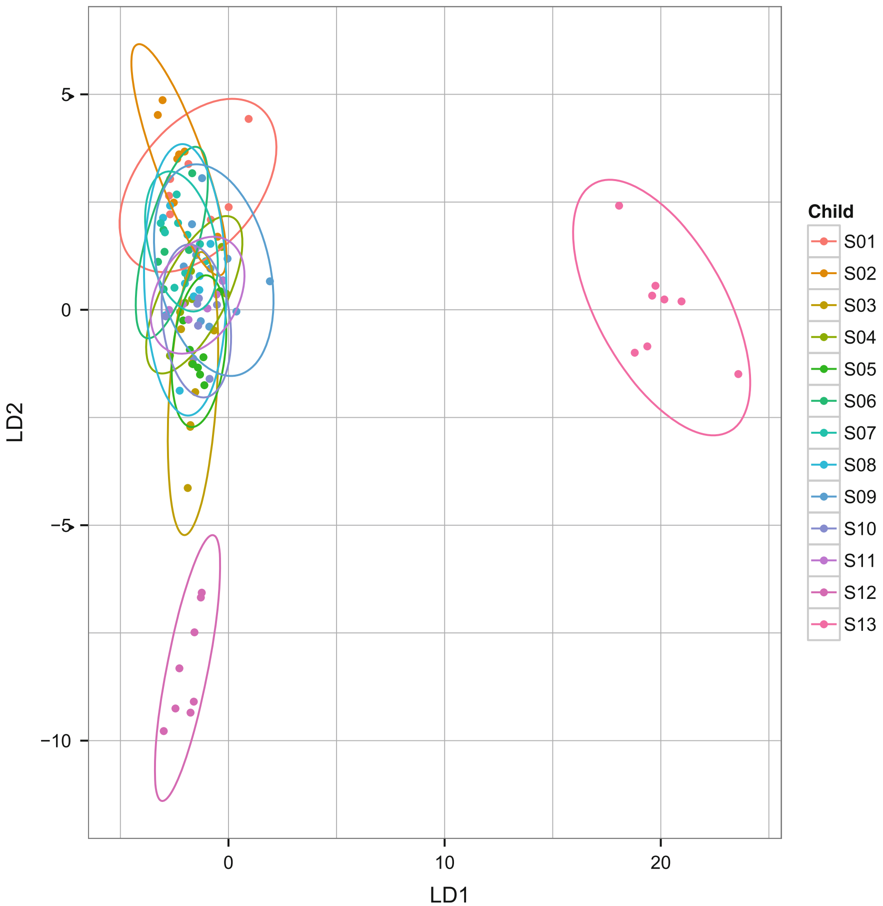

Fig. 7 Combined-groups plot for the canonical discriminant functions from the children (S01–S10) and the algorithms (S011–S013). The 73.0 % of original grouped cases were correctly classified using the geometrical predictors: Renyi Spectrum [Dq0–Dq10], cumulative length, number of shots and the lacunarity spectrum [1–10]

The results of the LDA showed that the set of geometrical measures chosen performed well, characterising and separating the children and the algorithms. The 73.0 % of original grouped cases, i.e., the individual games, were correctly classified. Notwithstanding at the level of individuals, a perfect classification of the children and the algorithms was obtained.

In general, when the inferences performance of each children is described by the diagrams, they display a *sui generis* graphical pattern, that becomes a kind of fingerprint of their inferential dynamic.

The second example was taken from an experimental situation, devised to test the ability of the geometrical measures, to perform group classifications in a diagnostic of accuracy paradigm. Human and artificial data was used. Two artificial data sets were created using data coming from ten children. The artificial anticipatory behaviour was simulated by two algorithms that modify the performance of these children, following two strategies: the first set of data, that we called robots, which was created by an algorithm that randomly shuffles all the shots, i.e., the "scanning" and the "hitting shots". The second set of data, called "cyborgs" was created by an algorithm that randomised only the "scanning" shots, leaving the human "hitting shots" unchanged. The final data set (N = 30) is composed by the groups of ten children, ten "robots" and ten "cyborgs".

A scatterplot of the capacity dimension [Dq0] versus the number of shots [NS] for the three groups is shown in Fig. 8, moreover a regression line is fitted to each group to visually highlight the differences among them.

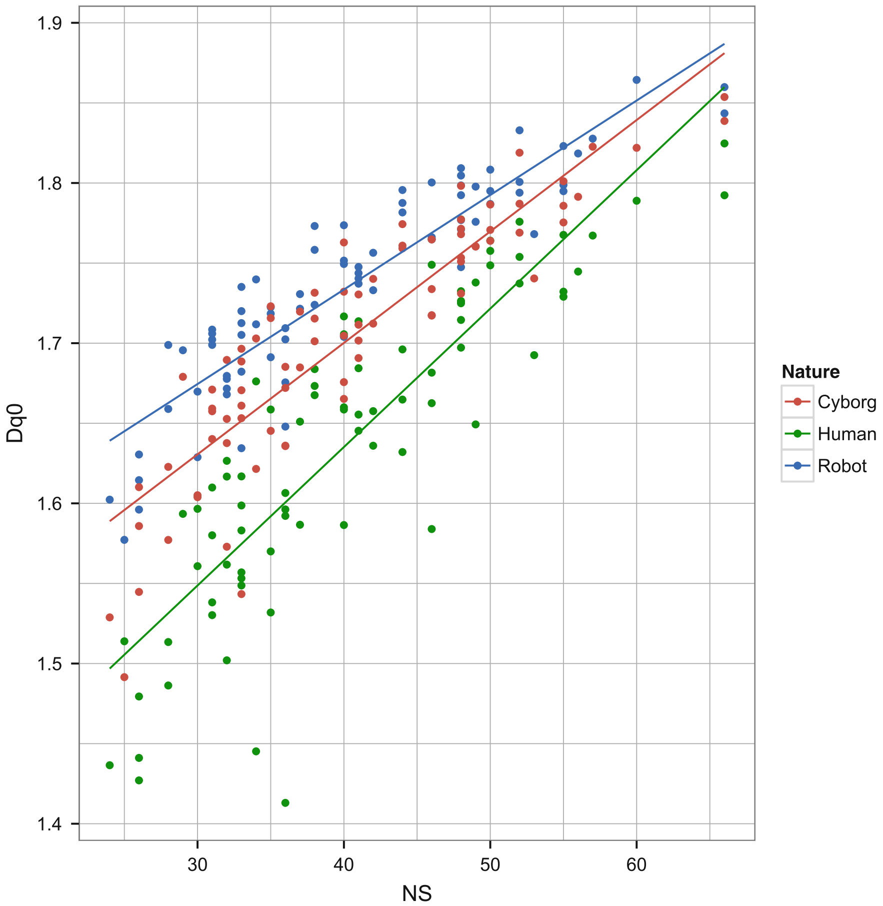

Fig. 8 Graph describing the relationship between the capacity dimension [Dq0] versus the number of shots [NS] performed by the three groups: cyborgs, humans and robots. The *coloured lines* represent the fitted regression for each group

To further assess the classification power of a set of geometrical measures, a logistic regression analysis was performed to separate human from non-human data (Cyborgs and Robots). The result of this analysis is shown using the receiver operating characteristic (ROC) curve in the Fig. 9, in which the fitted model, shows a good classification performance with an empirical AUC statistics = 0.94.

The third example was taken from a sample of ten adolescents to illustrate the discriminant power of a set of geometrical measures which allow the classification of the individuals by sex. To perform the classification, a GLMM model with multivariate normal random effects, using Penalized Quasi-Likelihood (glmmPQL) was fitted to a "training" data set of multifractal, lacunarity and MSSI measures [84].

To test the accuracy of the fitted model, a "testing" data set was used to obtain new cases to be compared with the predicted classes. The predictive performance of the model was evaluated using the (ROC) curve that can be seen in the Fig. 10. As

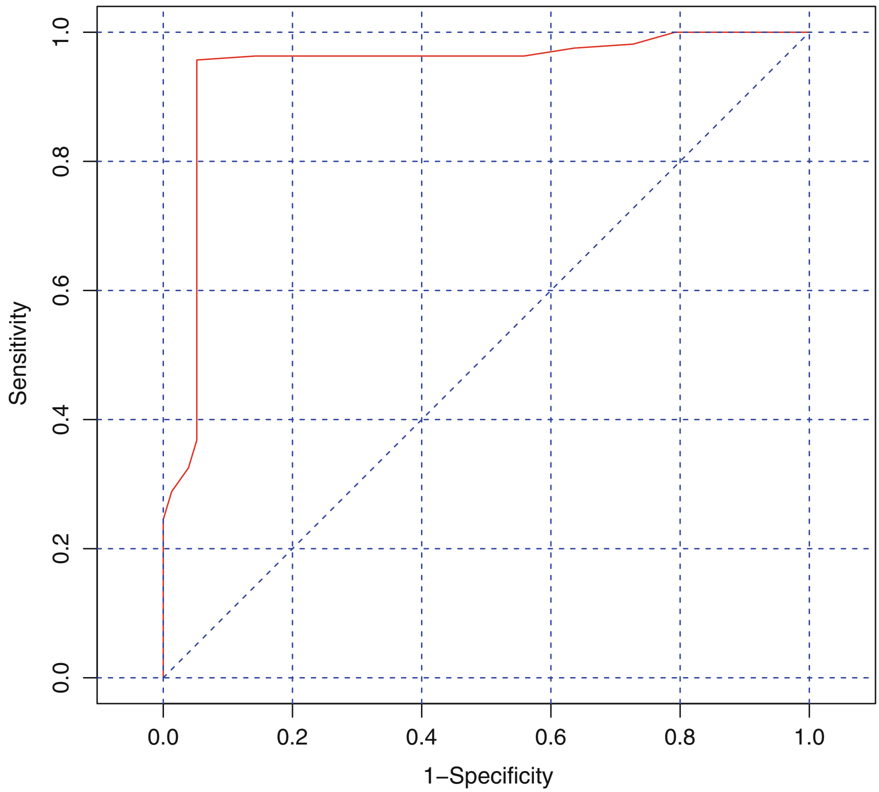

Fig. 9 The empirical receiver operating characteristic (ROC) curve for the target condition nature (human, non-human [cyborgs and robots]), for the data fitted with a GLMM model with multivariate normal random effects, using penalized quasi-likelihood (glmmPQL) and for a set of multifractal and lacunarity measures. The empirical (AUC) statistics is 0.9401243

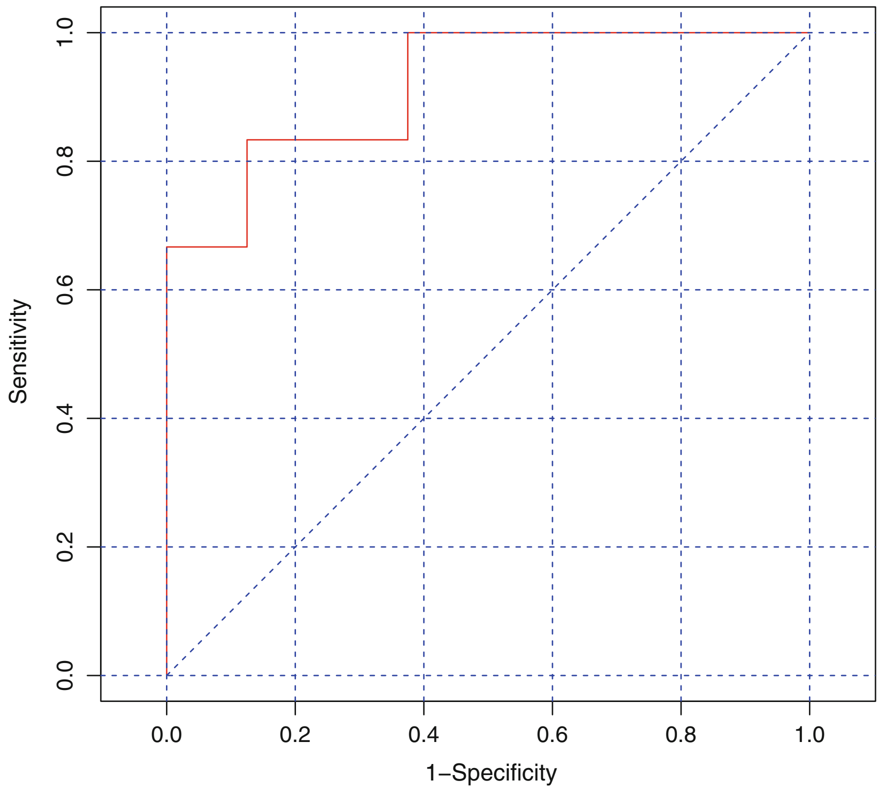

Fig. 10 The empirical receiver operating characteristic (ROC) curve for the target condition sex (male, female), fitted to the testing data with a GLMM model with multivariate normal random effects, using penalized quasi-likelihood (glmmPQL) and for a set of multifractal, lacunarity and MSSI measures. The empirical (AUC) statistics is 0.9166667

it is illustrated in the (ROC) curve, the fitted model, shows a good classification performance in predicting the class of the cases from the "testing" data set. The empirical (AUC) statistics = 0.91.

4.2 Final Observations, Prospects and Conclusion

The given operational definition of EF and the present method allows for the experimental study of human and non-human cognitive anticipation enacted by inferential processes. So far the results obtained appear auspicious; it has been possible to expose different "inferential phenotypes" by representing and analysing them geometrically.

An interesting finding is that the relationship between the geometric measures and the number of shots performed remains constant for each individual, (during the experimental period trialed) despite the learning effect across the tasks, becoming a sort of functional fingerprint of their thought dynamic, showing an identity through change. Additionally, these measures, due to their discriminative power, permit the classification of different inferential phenotypes.

Another interesting observation is that in general, the coefficient of determination R2 from the models that relate the different geometrical measures with the number of shots, seem to be higher for humans solvers than for non-human solvers (artificial algorithms or humans with artificially modified data). In the future this feature may give us a measure of the “humanness” of the fitted models. Paraphrasing Nietzsche’s aphorism, it could be said that the human cognition has something that is “human, all too human”. Moreover it can be hypothesised that in this particular experimental situation, the values of the coefficient of determination R2, could be used as a kind of metric and non-algorithmic Turing test [93].

From a medical point of view, the statistical strength and the reliability of the relationships found between the target variables and the geometric measures used as predictors, suggests that these kinds of measures, i.e.: Rényi’s spectrum, lacunarity and others [45], associated to the experimental paradigm could have a potential clinical use. This paradigm may allow for the quantitative description, classification, diagnosis, monitoring and screening of mental conditions that impairs EF. In this clinical scenario, the geometric measures could be used as quantitative imaging bio-markers [71, 86] to develop tests to facilitate the differential diagnosis in neuropsychology.

In a recent, unpublished preparatory pilot study, that followed these insights and using a combined strategy similar to what was exposed in the second and third example, we performed simulations with ADHD artificial surrogate data. The preliminary results provided a strong empirical support for this line of enquiry; showing the discriminant power of these measures to distinguish between children without the target condition and artificial simulated ADHD children. The ROC analysis performed displayed promising values of specificity, sensitivity and estimates between 0.91 and 0.94 for the area under the (ROC) curve (AUC) for the traditional statistical (multilevel logistic regression) models and machine learning classifiers [72] (Neural Networks, Support Vector Machine and Random Forest) [51].

Also as part of our former research, the same paradigm was used in a cognitive developmental setting. It was concluded that this approach could complement other methods used to evaluate and compare the evolution of cognitive phenotypes at different ages [53].

To conclude, it can be said that the given definition of EF, substantiated in this particular experimental paradigm (and the related models based on certain geometrical measures) could help us to increase our knowledge of the anticipatory aspects of human cognition.

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Part III
Anticipation in Neural Networks

The Closed-Loop Coding-Decoding and Analysis by Synthesis as Basics Anticipatory Principle Functional Organization in the Living Systems

Dobilas Kirvelis

Abstract Theoretical studies of living systems (LS) from the *automatic control* (AC) and *perceptual control systems* (PCS) positions, the *closed-loop coding-decoding* (CL-CD) and *analysis by synthesis* (A-by-S) concepts, as the basic principle of the *anticipatory systems* (AS), reveal anticipation in functional organization of LS. The behavior of animals, especially human organisms, and of society show that model-based anticipation may be constructed cyclically, statistically as Perceptron, by the Kalman filters principles or on phenomenal memory models. It is correlated with the specific neural-structures: reptilian (as Perceptron), limbic paleo-cortex (as Kalman filter), and neo-cortex acting as neuro-quasiholographic, neuro-chaos, and factor analysis in the A-by-S decision-making system. The non-trivial Foerster-Kauffman "machine," as the CL-CD, and *homunculus* of vision as anticipatory perceptive A-by-S systems in the brain are proposed. Social human forecasting as the anticipation for best-organized system management is discussed.

Keywords Anticipation · Analysis by synthesis · Control · Closed-loop · Kalman filter · Coding-decoding · Limbic system · Living system · Cortex · Phenomenal memory

1 Introduction

Every living organism and their *living systems* (LS), from simple prokaryotic cells to the whole human being, as well as human society, according to Miller [1], are cybernetic control systems. These directly depend on the efficiency of their bio-information technologies of the controlling subsystem [1, 2]. The theoretical studies of the LS functional organization suggest that LS are *anticipatory control*

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systems (ACS). Consequently, the LS and their biological evolution may be a good basis for understanding the essence of the *anticipatory systems* (AS) functional organization and AS diversity.

Living systems are *perceptual control systems* (PCS), thus its behavior tends to be functionally purposeful and goal-directed, with extrapolations, predictions, forecasting, and anticipation [2, 3]. Therefore the simple or/and model-based anticipations determine each PCS and LS as well.

The bio-cyber approach maintains that the LS are *automatic self-control systems* because their behaviors are not possible without memory and prediction. Automatic control theory maintains that there are three self-control classes of the cyber-systems functional organization with appropriate variations [4]:

- Feedback control without memory (FB) and with memory (FBM);
- Feed-forward control without memory (FF) and with memory (FFM);
- Composite—feedback-feed-forward without memory (FB-FF) and with memory (FBM-FFM) in different combinations (FB-FFM) and (FBM-FF).

The automatic control system (CS) without special memory (as FB cyclic control) for prediction may be designated as *simple anticipatory systems*. Other CS use a special anticipatory device, such as Perceptron-like or/and extrapolation and forecasting (Wiener, Zadech-Ragazzini, Gabor, Kalman) filters [4]. In addition, LS are self-production systems. According to Gamow and Yčas [5], the simple living cell is as active in plants as in industrial organizations, as well as in autopoiesic self-creation, self-production systems [6].

In 1978, Robert Rosen drew attention to the importance of anticipation for understanding life, the living, and social systems. He introduced the anticipatory system concept [7, 8]. Dubois [9] continued the thought through a series of conferences (1997–2011). Parallel to Rosen, Nadin [10, 11] explored anticipatory systems existing in a number of domains of the living, elaborating his original hypotheses in books and articles. But anticipatory control systems organization as such is not yet understood and needs further experimental and theoretical work.

It is clear, that the essence of anticipation (forecasting, future-casting, extrapolation) lies in the special features of memory mechanisms and information technology organization. The analysis of warm-blooded organisms and especially human behavior show that model-based anticipation may be constructed on the principles of phenomenal memory that is determined by the specific neural-structures (neocortex) acting as neuro-chaos and factor analysis decision-making. A future theoretical model of the anticipatory system may be in the Closed-Loop Coding-Decoding (CL-CD) control system or Analysis by Synthesis (A-by-S) in the brain's neocortex [12–17].

The organism, as with every control system, consists of two special CL-CD informational procedures, closely connected by techno-tools (coders and decoders) converging in qualitatively different subsystems—*controlling* and *controlled subsystems* [13, 14, 17]. Here controlling the subsystem by signals from decoders to the controlled subsystem determines its behavior and that of all organized systems. This informational input generated on he basis of extrapolation, prediction, forecasting, and future-casting as anticipation, i.e., the controlling subsystem, generates decision making before the executive organs begin to act in response to incoming commands.

CL-CD technological convergence, together with the evolving structures of the anticipatory memory, forms the theoretical basis not only the existence of all living systems, but also of techno-creativity. The most obvious examples of anticipatory systems (AS) are bio-organisms, i.e., living systems, understood in Miller's theory as cybernetic control systems ranging from the single cell to whole organisms, populations, countries, and societies [1]. In addition, LS are self-production systems. According to Gamow and Yčas's [5], the simple living cell is active on the molecular level, up to and including the level of industrial organizations, as well in autopoiesic self-creation, self-production systems [6].

Generally, the living world is a continuous bio-engineering anticipatory creature. The behavior of the living and their evolution, from simple convergent predator/prey-like systemic interaction leading finally to the cybernetics of organisms, as well as to scientific-technological development of society through creative techno-convergence developments, is testimony of anticipatory systems. The improved structure of information control (management) and the emergence of more effective memory are reflective of the anticipatoric properties of living systems [14, 18].

One of the main steps in the formation of anticipatory approaches is the emergence of CL-CD as a concept for matter-energy and information technologies convergence. In essence this extends Rosen's Modeling-Relations, systems approach [7, 8]. Earlier (1903–1911), Johannsen [19–21] formulated a similar "genotype-phenotype" concept for biological systems (cells). The "Baldwin Effect" (1896) deserves special attention. It reveals learning in avifauna, mammals, and humans in accord with the anticipatory approach of Lamarckian evolution—which today is interpreted as a manifestation of informatics anticipatory procedure [22].

In addition, the living anticipatory system has a specific evolving, yet incomprehensible, phenomenal memory, which continuously and unceasingly gathers information. This phenomenon is additive, and by special algorithms and technology the organism make decisions on active operations. Some AS features of the possibilities may explain the BIOS: the creation organization concept [23, 24].

Extraordinary attention is required to the social and science-technology strategy of the anticipatory programmatic approach (forecasting, future-casting) in the USA and in Europe in predicting and addressing humanity's future prosperity for the last decade. For example: "Converging Technologies for Improving Human Performance: Nanotechnology, Biotechnology, Information Technology and Cognitive (NBIC); "Convergence of Knowledge, Technology, and Society: beyond Convergence of Nano-Bio-Info-Cognitive Technologies CKTS-NBIC2" (2013–2020) [25]; EP STOA "Making Perfect Life, European Governance Challenges in 21st Century Bio-engineering" (2012), [26].

Rosen's anticipation scheme belongs to the second class of the "self"-automatic control class as the feed-forward control system with memory (FFM). Most of the different levels of living systems depend on the Composite FBM-FFM class. The evolution of living systems, in particular in the evolution of the vertebrate neural subsystem, demonstrates the composite FBM-FFM anticipation level. Important here are the emergence and evolution of the anticipatory living systems interpretations starting as closed-loop coding-decoding control (CL-CDC) procedures and ending with the origin of analysis by synthesis (A-by-S) mechanisms as perceptive, decision-making methods, and their significance.

All of the living systems bio-engineered anticipatory control evolution can be explained in the closed-loop coding-decoding control (CL-CDC) and analysis by synthesis (A-by-S) concepts [15, 17].

2 Closed-Loop Coding-Decoding Concept

The paradigmatic essence of the functional organization scheme is presented in Fig. 1.

Figure 2 represents the engineered scheme of the CL-CD implementation as automatic control or anticipatory control system (ACS) functional organization.

The closed-loop coding-decoding (CL-CD) principle converged in two different technologies—matter-energy transformations and informational control processing—that give rise to new hard-soft technology in a cyclical and organized manner. The CL-CD requires that the real matter-energy system be reflected in the compact form of symbols on the memory, and re-reflected from symbolically expressed memory to real matter-energy structure. This is known as controlled action, or production. With the special organization of memory and learning, such systems become anticipatory systems.

Coding (encoding) should be understood as a reflection of a real system (in nature or in technological process) in an abstract virtual form on memory structures (DNA, hormones, neural networks, programs, books, programs, etc.) in such a way that decoding from the abstract form (objectives, goals, programs) to the real (material)—and purposive actions in real systems—would be possible (see Fig. 1).

This action model, or a coded representation, for control is the essence of information. Decoding is the realization of such a project or the control of bio-technological procedures according to information. In the process of decoding, the activated coded states of the memory structures, or the projects for synthesis of reality, are reflected in the dynamic states of the real world, real body structures, etc. The real world is changed according to the action model.

The full CL-CD system consists of converged, partially autonomic, but technologically organized systems. There are genetic, hormonal, neural, psychological, social, robotic, and other organized systems in the world. Dualistic material↔informational mapping manifests itself in the following technological convergences: signal↔information; phenotype↔genotype; body↔soul; brain↔thought; hardware↔software; biosphere↔noosphere; social group↔management; state↔government, among others.

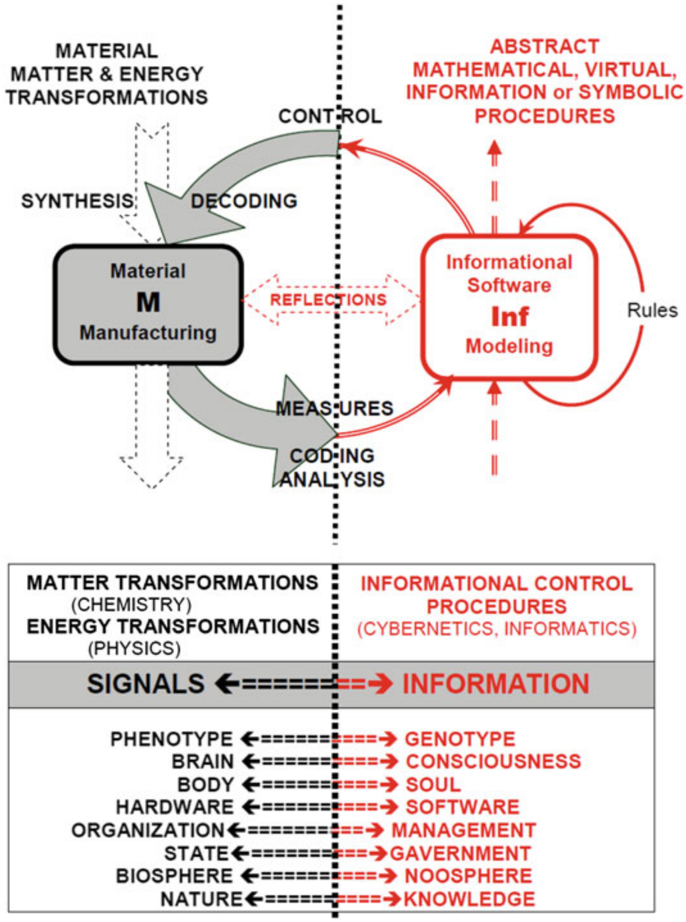


Fig. 1 The paradigmatic scheme of the convergence matter-energy and information technologies or organizationally closed, matter-energy and information open by closed-loop coding-decoding (CL-CD) principle organized self-reference and techno-creativity (Extended concept of the Rosen's Modelling Relation)

The systems converged according these principles are organizationally closed and informationally open. Organizational closeness gives rise to the functional compatibility of coding-decoding and functional sense (semantics) of coded reflections. Informational openness means the ability to join additional information about the environment to the pool of existing world models (the pool of gnostic and action models).

This action model, or a coded representation for control, is the essence of information. Decoding is the realization of such a project or the control of bio-technological procedures based on information. In the process of decoding, the activated coded states of the memory structures, or the projects for synthesis of

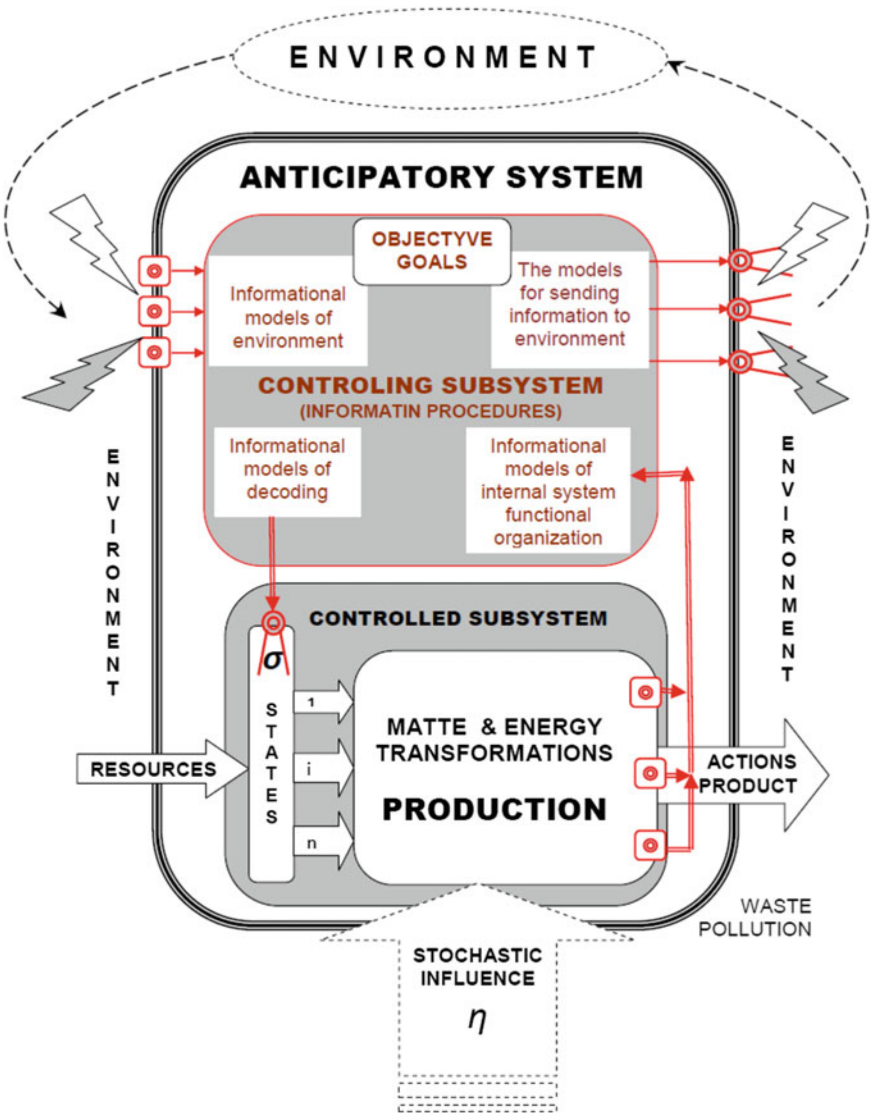


Fig. 2 Engineered scheme of the closed-loop coding-decoding (CL-CD) functional organization as the anticipatory control system (ACS)

reality, are reflected in the dynamic states of the real world, real structures of body, etc. The real world is changed according to the action model.

The concept of CL-CDC presented allows for expanding and generalizing the understanding of the living as anticipatory systems. From the technological viewpoint, each organism needs the ability to control and coordinate the purposive transformations of matter, energy, and information using various technological tools. These transformations have to be controlled by the informational structures of controlling subsystems (controllers).

Automatic control theory consists of three self-control classes of the cyber-systems functional organization, with appropriate variations: feedback control no memory (FB) and with memory (FBM); feed-forward control no memory (FF) and with memory (FFM); composite—feedback-feed-forward without memory (FB-FF) and with memory (FBM-FFM) in different combinations (FB-FFM); and (FBM-FF).

Some of the automatic control system (CS) without the special memory device for prediction, and forecasting (as FB cyclic control) may be designated as the systems of the simple anticipatory. The cyclic control is necessary for every anticipatory control system. Model-based anticipatory control systems require special memory structures. Consequently, ACS systems are FBM-FFB organized structures. The engineered structure of the CL-CD functional organization as the anticipatory control system (ACS) must be able to get information about environment by the coders (sensors) and to form models of the environment, construct models for sending information (signals) to he environment, construct informational models of the internal system (by internal coders) for functional action and decision-making, and create informational decoding models for control of resources, This is what controls the ACS switch σ (see Fig. 2). All this is implemented in a many of CL-CD loops in various technologies. A general scheme shows two main CL-CD loops, inside the ACS, which control the inner system, and the second, which manage the system's behavior in the environment.

The variety of the ACS functional organization is best seen in reviewing the evolution of the LS.

3 The Evolution of the Living Anticipatory Systems

The first controlling information technologies, which emerged on Earth by way of biological evolution and continues to operate in each cell, are genetic, i.e., bio-informational control by genes and proteins (Figs. 3, 4). In metaphytes, intracellular genetic control is enhanced by hormonal means. On the level of metazoa, nervous networks are added. On the biosocial level, control was extended through inter-individual communication agents (pheromones and acoustic signals). On the level of human society, the important and increasing role in control is played by information transmitted in oral and written languages, where graphic symbols are used for different modeling representations in the latter. Along with the development of human society, human reason kept creating and introducing new technologies, from the application of primitive tools and fire all the way up to informational technologies.

In regard to technology, special interest should be paid to understanding the generation of the anticipatory information. The copying (copy) of information is an informational procedure, but it creates no new information. Generation of

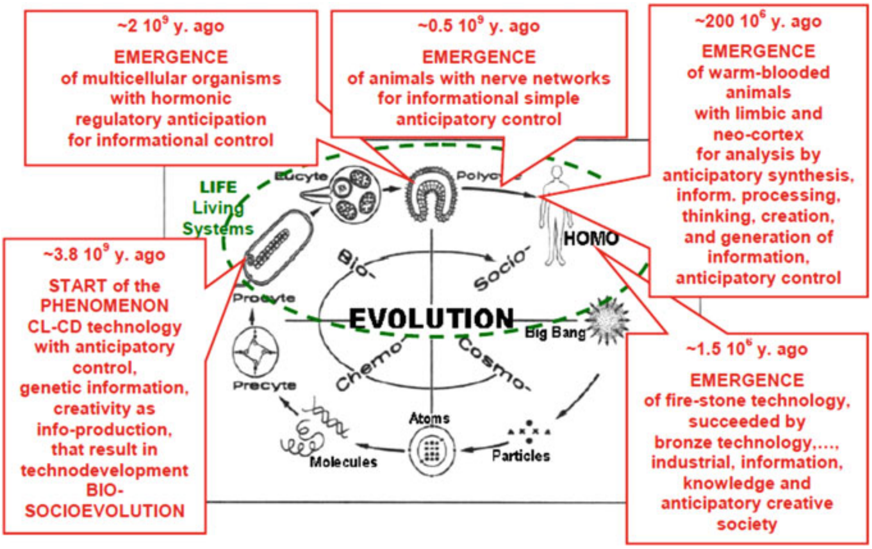


Fig. 3 The generalized scheme of the evolution of the living systems (LS) as an engineered symbiotic development of information technologies for anticipatory control (based on Shwembler's scheme of general evolution)

information is important for creation of new technological projects. Only two bio-informational technologies in living nature produce new information (new gnostic and actional anticipatory models): (1) genetic natural biotechnology, which implements stochastic testing in living populations with the subsequent natural selection (genetic algorithms); and (2) mental natural biotechnology, which implements a motivated search, creation of virtual imitation projects aimed at the achieving a certain purpose, with the subsequent checks, rejection, or acceptance for action.

Therefore, the substance of information theory and informatics as branches of science is to be found in the methods of quantitative estimation of information, its functional value and importance for anticipatory control and management. Undoubtedly, information and bio-information have common roots. They differ only on a level of world organization where they work: bio-information in biological systems and information in social and technological systems. So, informatics should be a general science for both bio-informational and informational control-managing procedures on any organized level of an organized system.

The generalized scheme of the evolution of living systems as engineered symbiotic development of information technologies is represented in Fig. 4. The origin of life marked the start of the phenomena of technology, technological control, and genotype-phenotype systems on the basis of genetic information. It determined bio-evolution (including the appearance of new species) on the population level as stochastic production of information on the principles of genetic algorithms. The

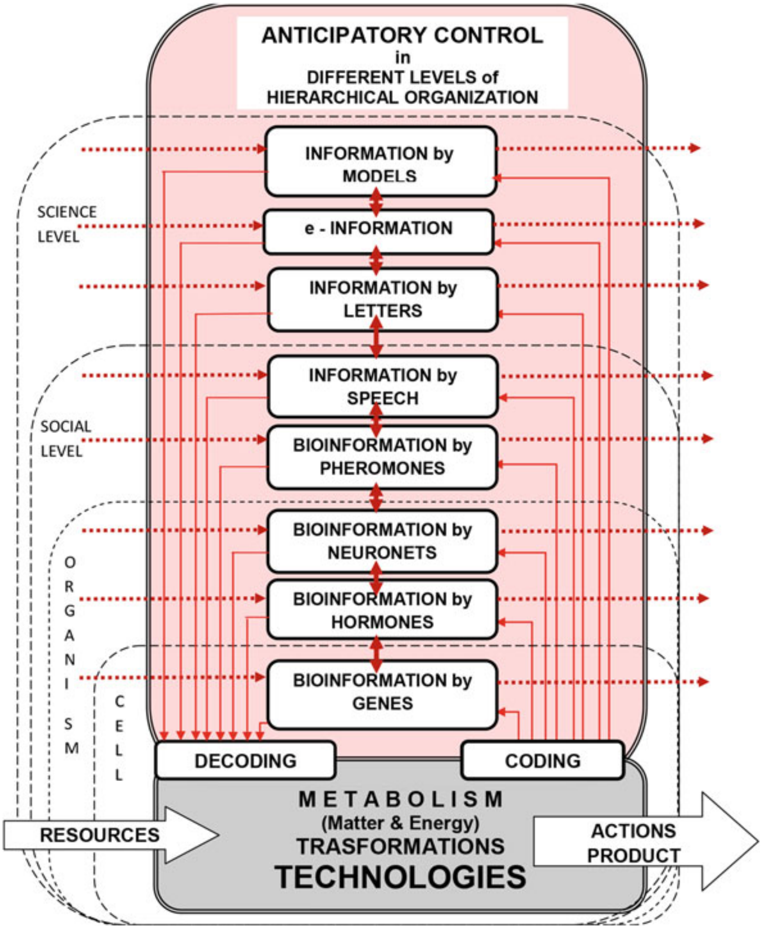


Fig. 4 Different levels of closed-loop coding-decoding (CL-CD) in the different evolutional levels or bio-informational and informational knowledge anticipatory processing in the living (biological, humanitarian and social) systems

origin of life is the emergence of a new sort of organized systems. Its functioning is determined by informational control based on the principles of closed-loop coding-decoding (CL-CD). This results in the development of organisms through special connections of neural networks. Warm-blooded animals (mammals and birds) developed a neocortex in the brain as a new neuro-informational technology that yields the thinking process.

Mental natural biotechnology is executed in special zones of the brain (neocortex) of mammals and birds. The designation for such mental manufacture-generation of information is “creative work.”

Since Aristotle, the bio-theorists dealing with this problem fall into two groups: dualistic-vitalistic and realistic-materialist. Although it seemed that cybernetics solved this dilemma by introducing information and control concepts, to date, different interpretations of biosocial evolution thrive. It would be expected that the explanation of the emergence of life and the evolution of living systems from the perspective of organized holistic systems theory will consolidate these different theoretical approaches. The organized systems theory explains the existence of the living systems as the complex dynamic metabolism of matter and energy. However, sustainable existence and the evolution of living systems is determined by virtual information procedures, in addition to material metabolism. Therefore, the evolution of living systems should be viewed through the evolution of information technologies (Fig. 4).

Evolutionary analysis of the functional organization of nerve systems and of behavior yield five informational control levels: reflexic L.; multi-reflexic coordination L.; regulative L.; perceptronic analyzing L.; Analysis-by-Synthesis L.). These represent specific procedures of closed-loop coding-decoding. It could be that weak anticipatory prediction is realized upon simple reflection and multi-reflexic coordination structures, incursive anticipatory feedback control—in regulatory and simple analyzer structures—and strong anticipation—in neocortex structures that work by Analysis-by-Synthesis. Strong anticipation is perhaps used only in the brains of mammals and birds that are able to create models of future activities, which entails an ability to think. Higher mammals, especially apes and humans, have sensory screens that enhance mental imaging in the Area Striata zone.

4 Genesis CL-CD Cycling, Self-reference, Self-production and Recursion as Evolution of the Predator-Prey-like System

Any ACS, especially model-based anticipation systems, must have cyclic dynamics, generate a variety of versions, compare version information with the existing information, and change the version or leave it in the decision-making process. This can be a simple continuous dynamic feedback system that meets the auto-vibrations underlying coherent requirements or discrete systems recurrence of certain procedures.

4.1 Anticipatory Cycling as Lotka-Volterra Predator-Prey-like System

The first manifestation steps of the anticipatory properties can be seen in the construction of the dynamic of Predator-Prey-like systems, which reflect oscillatory reactions. Linear mathematical models of such dynamic systems are formulated and considered by Poincaré; nonlinear models by Lotka-Volterra. It is possible to see a simple anticipation in them: prediction (or forecasting) of the following step (Fig. 5) [14].

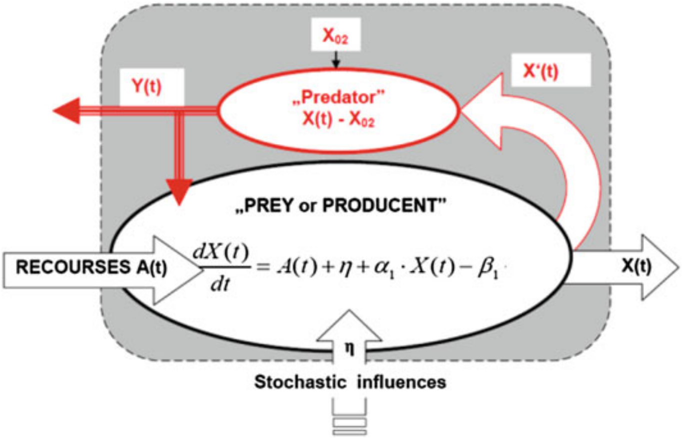


Fig. 5 Lotka-Volterra Predator-Prey-like interaction as regulator or simple anticipatory control system

The mathematical Lotka-Volterra model consists of two "Prey" and "Predator" equations:

$$\begin{cases} \frac{dX(t)}{dt} = A + \eta + \alpha_1.X(t) - \beta_1.Y(t).X(t), \\ \frac{dY(t)}{dt} = +\beta_2.[X(t) - X_{02}].Y(t) - \alpha_2.Y(t). \end{cases}$$

This model shows that the claims of certain auto-vibrations requirements become a special phase portrait to a steady-state $\mathbf{X_{02}}$ situation in which the regulation of the process takes place (Fig. 6). The phase portrait shows that a dynamic system periodically predicts the next step to the new state by a special algorithm of variation (Fig. 6, right). That may be interpreted as simple next-step anticipation.

The engineered biological Lotka-Volterra model is a classic automatic controller, which through negative feedback as informational communication, transmitting about ~ 1 bit of information, helps maintain a stable, purposeful system state (Fig. 7). This static regulator is the simple anticipatory CL-CD control system that predicts the next step by fuzzy More-Equal-Less (M-E-L) logic (+, 0, -) [14, 27].

4.2 Recursive Processes as Simple Anticipatory CL-CD Control

Particularly simply the auto-oscillation, the changes of system states and the characteristics of the properties explain recursive modeling that procedures are expressed in recursive equations. It clearly demonstrates the simple recursive equation $\mathbf{X_{i+1} = X_i - X_{i-1}}$; [23, 24] (Fig. 8.).

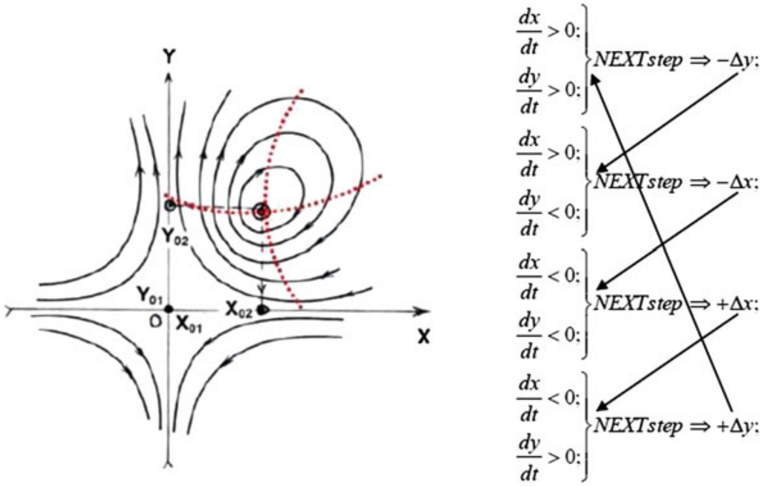


Fig. 6 The phasic portrait of Lotka-Volterra predator-prey system and algorithm of cyclic dynamics as simple next-step anticipation

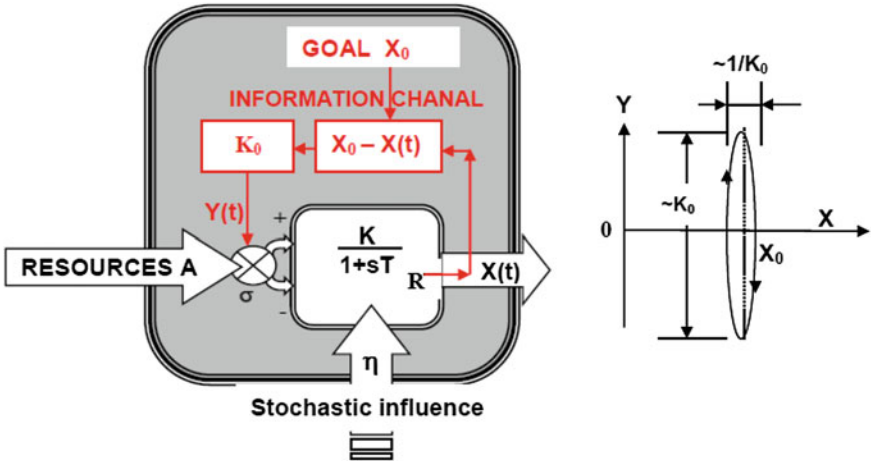


Fig. 7 Static regulator as the simple anticipatory CL-CD system with fuzzy more-equal-less (M-E-L) logic (+, 0, -) controller and phasic portrait of regulation

These simple recursive examples allow for understanding the possibility to synthesize the technology (electronic, molecular biology, neuron nets, etc.) of much more complex networked systems, which may be formed or shaped structures as memory models for anticipatory control. In this regard, it is worth paying special attention to the multidimensional vector, recursive procedures and structures of its specific formation. They can help to understand the possibility of the formation of memory models as quasi-neural fuzzy M-E-L logic sets (Fig. 9) [27].

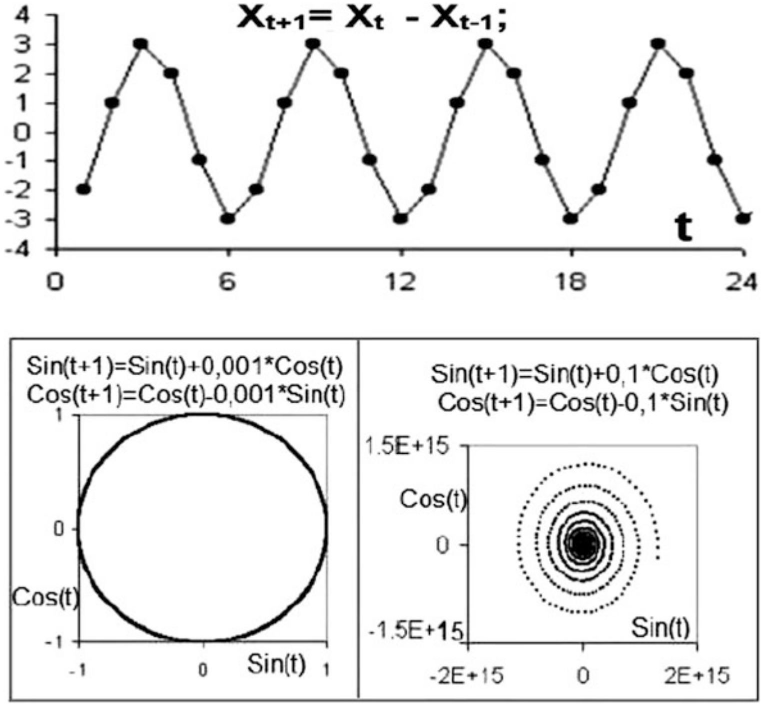
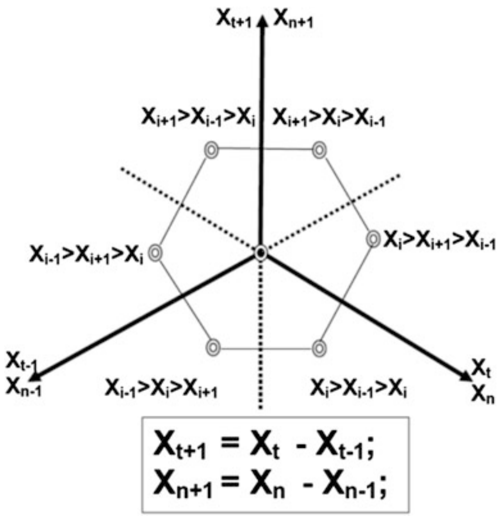


Fig. 8 The simple anticipatory recursive process dynamics (L.H. Kauffman)

Fig. 9 The vectorial recursive anticipatory process dynamics as fuzzy more-equal-less (M-E-L) logic procedures



Such vector systems carry out analysis and encoding of data as a summary of the main features of the values, of the factors of importance weights for data analysis and decision-making, and are sorted according to their size rank. The rank sequence is the main criterion for decision-making.

It seems that the existence of the simple biological systems are based on similar principles of cyclic dynamics. In this regard, it is worth pointing out the social amoeba and prokaryotic cell anticipatory self-control models.

4.3 The Biological Examples of Population and Genetics Anticipations

The different stages of the lifecycle of the primitive social amoeba *Dictyostelium discoideum* can be seen in Fig. 10. First, in the free-living growth stage, spores and food (bacteria) are enclosed within the *D. discoideum* population. The amoebae preserve their individuality and each amoeba has its own bacterium. In the next aggregation stage, the amoeba population form migrating sludge and migrate elsewhere top a new, rich food place and matures into fruiting bodies, spores, and bacteria. During the culmination stage, when the spores are produced, the bacteria pass from the cell to the sorus. Free-living amoebae seem to play a crucial role for persistence and dispersal of some pathogens in the environment. Agriculture seems to play a crucial role as anticipatory process for pathogen survival, since these can live and replicate inside *Dyctiostelium discoideum* [28].

All biological processes take place in controlled cellular genetic mechanisms. One of the simplest cells is the prokaryotic genetic operon system. Its functional organization is presented Fig. 11.

Operon is a specific biotechnological procedures system in the cell organized as an anticipatory FFM-FBM control system. It is made up of three main components: genetic memory to store information and for biotechnological reading of this (transcription); translator of the information suitable for production of materials;

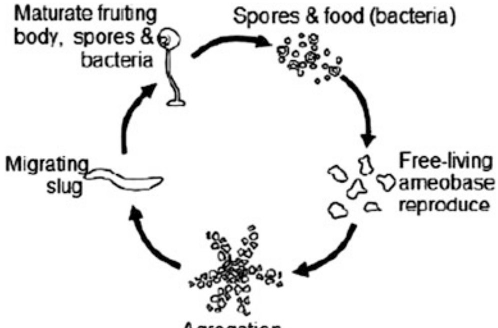


Fig. 10 Lifecycle of the primitive social amoeba *Dictyostelium discoideum* populations with genetic-bacterial anticipations

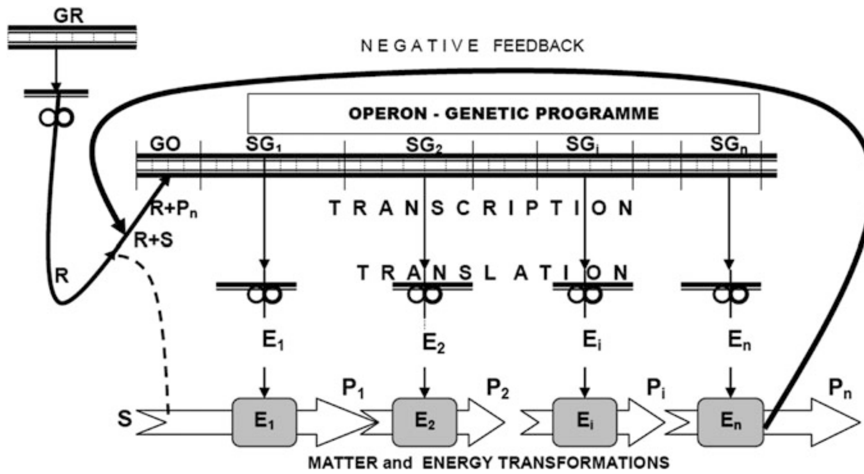


Fig. 11 The operon as composite—feedback-feedforward (FBM-FFM) genetic CL-CD anticipatory control in the procariotic living cells

and material production by a special enzyme or metabolic biotechnology procedures chain in which is the main process of the production.

But for understanding the more sophisticated anticipatory system organization and genesis, the origin of the informational models formation structures require the emergence of new opportunities. In this case, Bios: creative organization beyond CHAOS concept [24] can help.

4.4 BIOS: Creative Organization—Anticipatory A-by-S Genesis

In Fig. 12 shows the recursive process and equations (as simple mathematical models) that represent the essence of the possible evolution of the complex systems as CHAOS, emergence of self-reference structures, and progressive biological structures.

Kauffman's view (BIOS: Creative Organization-like principles) facilitates increasing coefficient **g** magnitude, starting from initially simple disorderly stable system, turning into auto-vibrating, moving to CHAOS, then forming self-referential and self-producing structures. The claim is that this aids in interpreting all bio-evolution. It is assumed that such a principle would form the structure of the CL-CD as a Kalman filter, the required learning and predictive control systems for optimal anticipatory activity [24].

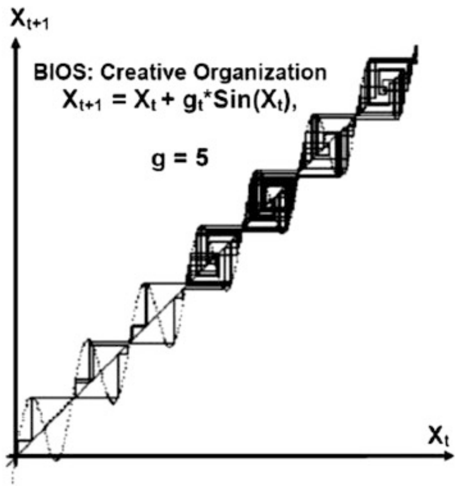


Fig. 12 BIOS: creative organization beyond CHAOS as qualitative development of the anticipatory control systems [24]

4.5 Kalman Filter as Anticipatory CL-CD Decision-Making System

The Kalman filter is needed for forecasting control systems (Fig. 13). The informational Kalman filter is a hierarchically organized, statistically learning structure of memory. A Kalman filter as CL-CD system is used to analyze sensor data in real time. This filter has a statistically integrating memory structure with a model-recall rate that is faster than the sensor's rate. It allows for model-based prediction, hypthesis testing, and decision making [29].

The Kalman filter is the first step in the information CL-CD structure, which has whole model-based anticipation. Such a completed system can be anticipatory along the line of the von Foerster-Kauffman non-trivial machine.

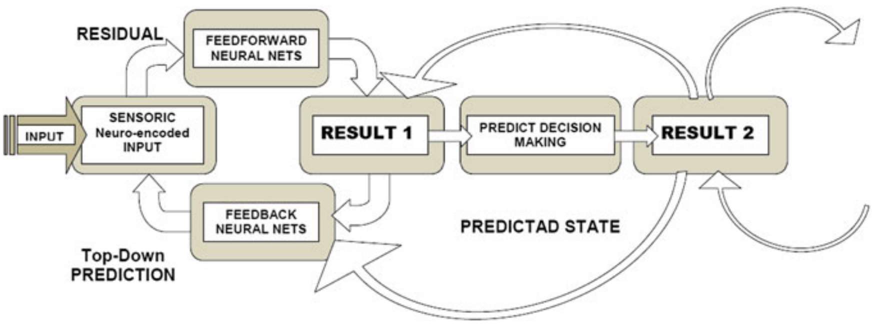


Fig. 13 Kalman filter as anticipatory CL-CD control system

4.6 Non-trivial Anticipatory CL-CD

Non-trivial Foerster-Kauffman machine is whole CL-CD anticipatory system (Fig. 14).

Foerster's non-trivial machine is a self-organizing FFM control system. Kauffman proposed another feedback-based FBM control system also on the non-trivial structure model. The convergence result can create a hybrid machine, which may open more possibilities for vertebrate animal and human brain anticipatory control [23, 30].

Assuming direct FFM and FBM feedback structures have phenomenal memory qualities (the memory is able to fully capture the entire life of the system epoch), then such a machine may satisfy human brain phenomenal opportunities. These information systems must function according to the analysis-by-synthesis (A-by-S) principles, which play a crucial role in human brain simulation, comparison, decision-making, and thinking processes.

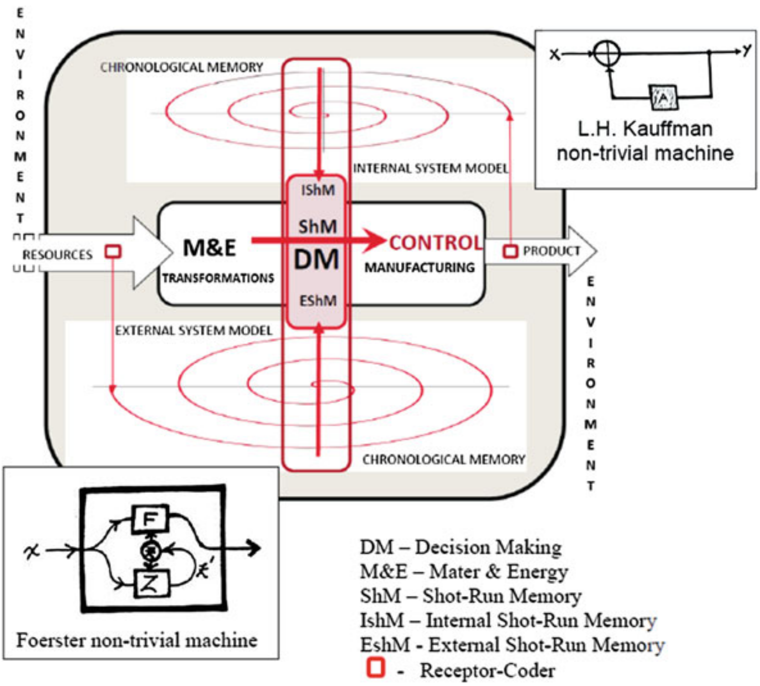


Fig. 14 Functional organization of the evolving anticipatory Foerster-Kauffman machine

5 The Brain as Model Based Anticipatory Hierarchic Organized Information A-by-S System

It is believed that cognitive information systems functional organization is based on A-by-S. This method is as result of the anticipatory CL-CD control systems evolution. It is LS of the nerve subsystem and, in particular, of the principles of brain function. They function best in birds, mammals, and especially in human brain mechanisms and behavior. Therefore, it makes sense to look at a summary of the human brain's functional organization concept.

5.1 A General Approach Regarding Human Brain Anticipatory Action

The current approach to functional organization of the human brain distinguishes five components that evolved with the appropriate functions. The lowest level of the brain is the reptilian nervous subsystem, which is responsible for the simple Perceptronic anticipation. Above that is the Paleo-limbic subsystem, which is characterized by the feedback anticipation. The next higher level is neo-limbic subsystem, which carries the anticipation via the Kalman filter approach. The highest level is the neocortex structure, which acts on the A-by-S principles (Fig. 15) [31].

The simulation hypothesis, or *simulism*, states that cognitive anticipatory control and thinking procedures consist of simulated interaction following three core assumptions: (1) internal models or simulation of actions, activating pre-motor areas in the frontal lobes in a way that resembles activity during a normal action,

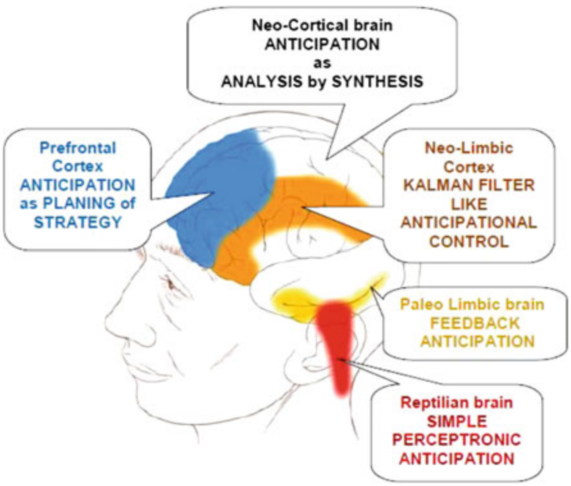


Fig. 15 Perceptual anticipation in the brain (cf. Lynch, http://ceciledemailly.files.wordpress.com/2010/09/es-anc-brain-territories.png

but does not cause any overt movement; (2) external models or simulation of perception (imagining that one perceives something is essentially the same as actually perceiving it, but the perceptual activity is generated by the brain itself rather than by external stimuli); (3) anticipation, with associative mechanisms of the brain neo-cortex that enable both behavioral and perceptual activity to elicit other perceptual activity in the sensory areas of the brain.

5.2 The Brain Neo-Cortex as Information Anticipatory A-by-S System

An overview of the neocortex functional organization is meaningful from positions of the perceptual activity visual analyzer. The generalized visual analyzer functional organization scheme is an anticipatory A-by-S system (Fig. 16).

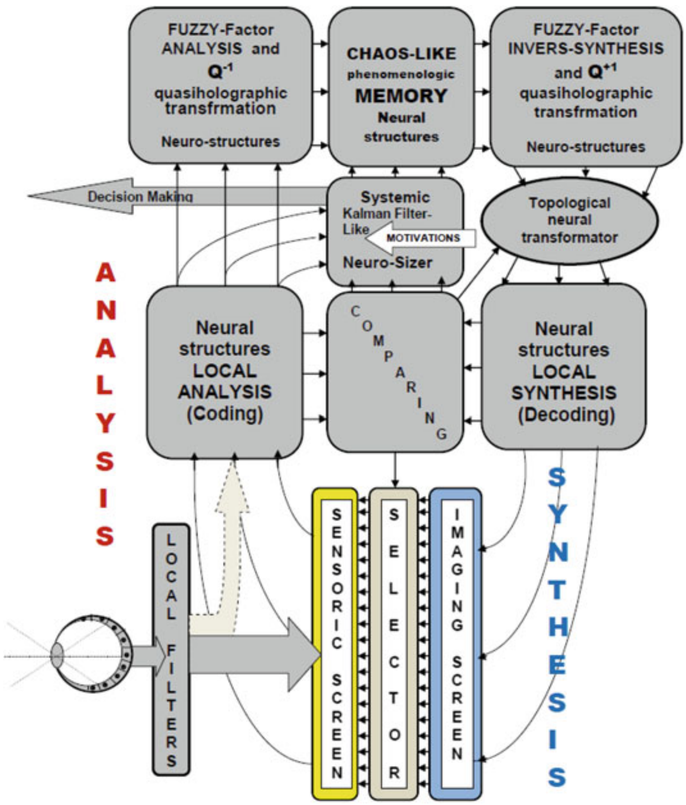


Fig. 16 Functional organization neuro-structures of the sensory neocortex for analysis by synthesis (A-by-S) or imitative closed-loop coding-decoding (CL-CD), that's carry out model-based anticipatory perceptions

It is supposed that a “sensory” neuronal screen (SS) and a “reconstruction” neuronal screen (RS) exist in the projection zone of visual cortex (*Area Striata* or V1). The functioning of the visual analyzer consists of the following intertwined operations: analysis of visual scenes projected onto SS; quasi-holographic “tracing” of images; preliminary recognition; quasi-holographic image reconstruction from memory onto RS; comparison of images projected onto SS with images reconstructed onto RS; and correction of preliminary recognition. The CL-CD procedure of A-by-S corresponds to visual procedures on mental images. It is supposed that the image “tracing” and reverse image reconstruction is based on Fuzzy-Factors Analysis and special memory mechanisms and on principles of brain neuronal organization as periodic CL-CD procedures.

It is proposed here that the neuronal structure implementing the quasi-holographic Fuzzy-Factors analysis-by-synthesis ought to possess at least ten functional layered complexes: (1) the receptor layer, where the retinal image is projected; (2) layer of local filtering; (3) local Hermite-Laguerre-like analyzer; and (4) local Hermite-Laguerre like synthesizer; with (5) comparisons among them. These structures are looped by quasi-holographic Fuzzy-Factor memory layered complexes (6, 7), with (8) special memory neural structure controlled by systemic Perceptron-like classifier (9) between them. The memory traces are extracted by means of the topological transformation structure (10) controlled by signals from the comparing function. The comparing function block collates the actual signal of local analysis and the mental image of local synthesis.

The synthesis can be accomplished by dedicated predictive structures driven by arbitrary motivations or preliminary expectations of events in the environment. Notice that the system described above resembles closed-loop coding-decoding, similar to the classic non-loop communication system of Shannon’s information theory, whereby analysis/decomposition and Fuzzy-Factor analysis is equivalent to the encoding step, and the reconstruction/synthesis with inverse Fuzzy-Factor analysis corresponds to decoding.

This model is based on both visual psychophysical and neurobiological data, interpreted in light of the theoretical solutions of image recognition and visual perception. It is believed that this model is applicable to the other neocortex perceptoric structures.

In this way it is possible to develop some of the human brain functional organization as anticipatory complex Perceptronic, Kalman filter and A-by-S structures (cf. Fig. 15). It remains a mysterious incomprehensible strategy of prefrontal brain anticipation and the mechanisms of phenomenal chronological memory. Scientific neopositivistic investigation is A-by-S anticipation too (Fig. 17).

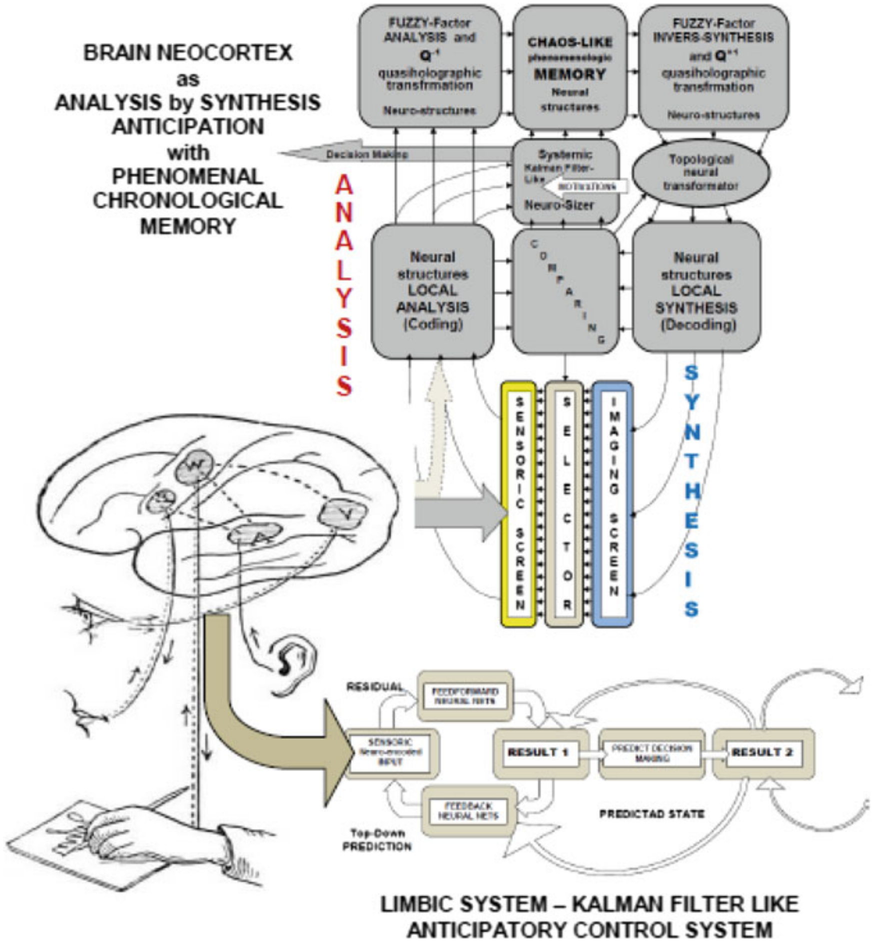


Fig. 17 The brain as hierarchically organized anticipatory Perceptronic, Kalman filter, CL-CD and A-by-S informational control system

6 Scientific Investigation as Anticipatory CL-CD or A-by-S Procedure

The neo-positivistic methodological scheme of the scientific investigations constructed according to Popper's theory perfectly correspond to A-by-S structure and CL-CD procedures (Fig. 18) [32].

This scheme, as an CL-CD structure, is constructed based on the experimental scientific inductive method, the creative imagination of deductive method of formulating hypotheses and models, comparison of the feature's reality with models, and further revising the formulation and execution of the experiment.

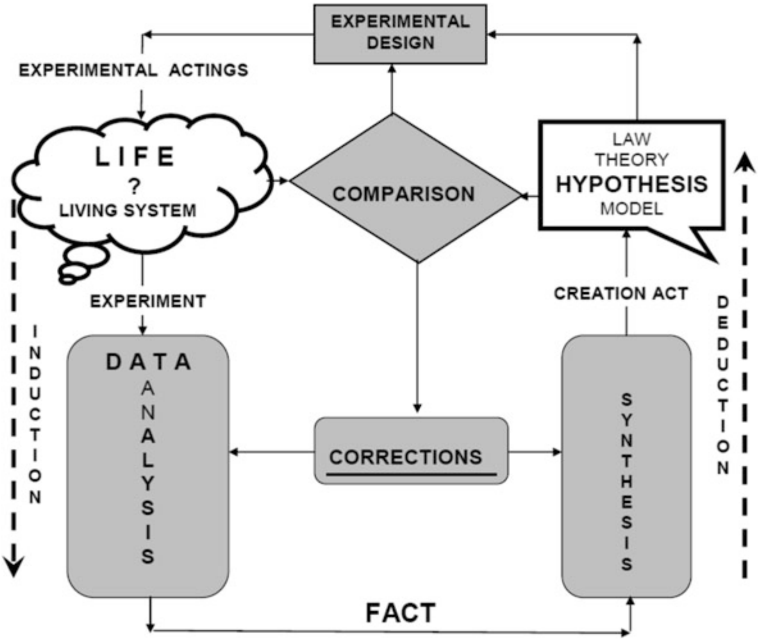


Fig. 18 Neopositivistic anticipatory methodology of the scientifique investigations

The scientific research methodology reflects the functional organization of the human brain thinking principles that corresponds to A-by-S. It is advisable to follow A-by-S principles when managing social systems and states.

7 The State Governance Accordingly Human Brain Anticipatory CL-CD and A-by-S Control System

Anthony Stafford Beer's Viable System Model of the state governance as brain-like anticipatory informational control system, with strategy and tactic anticipation, and the Chilean Cybersyn project of 1971–1973 correspond to CL-CD and A-by-S control principles (Fig. 19) [33].

This scheme clearly shows the need for tactical anticipation for separate structures (departments) of implementation and for strategic "brain-like" anticipation, such as the National Science & Technology Council (which already exists in some countries).

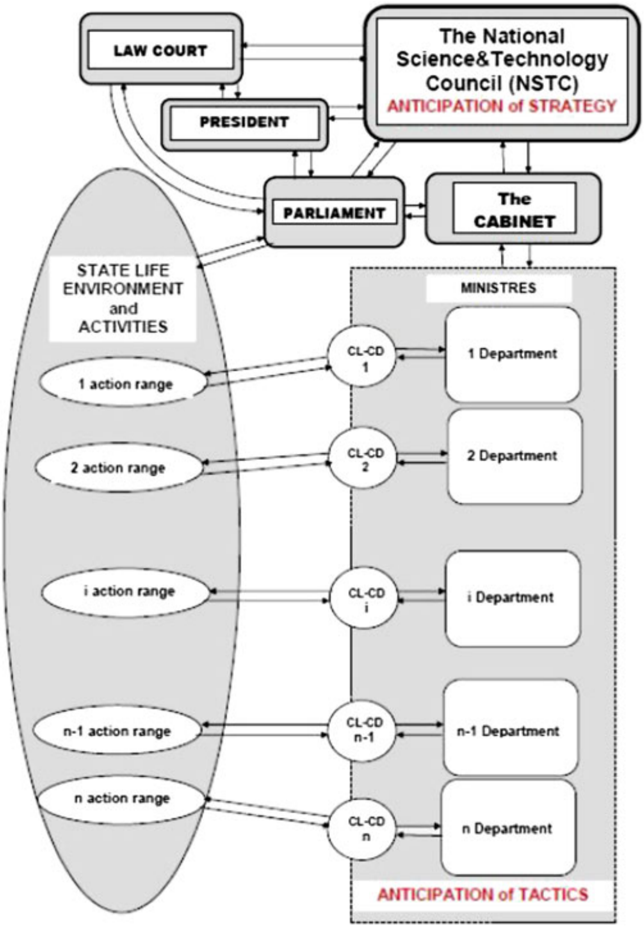


Fig. 19 The Viable System Model of the state governance as brain-like anticipatory informational control system with strategy and tactic anticipation

8 The Global Social Anticipation of the NOOSPHERE in the BIOSPHERE Evolution

Today the best strategic anticipatory S&T program is the USA's NSF 2013-2020 program "Convergence of Knowledge, Technology and Society: beyond Convergence of Nano-Bio-Info-Cognitive Technologies (CKTS-NBIC2)" (Fig. 20) [25] as "Enhansing Human Perfomance" in USA and "Making Perfect Life" in Europe [26].

Convergence of knowledge and technology for the benefit of society (CKTS) is the core opportunity for progress in the 21st century. CKTS is defined as the escalating and transformative interactions among seemingly different disciplines, technologies, communities, and domains of human activity in order to achieve

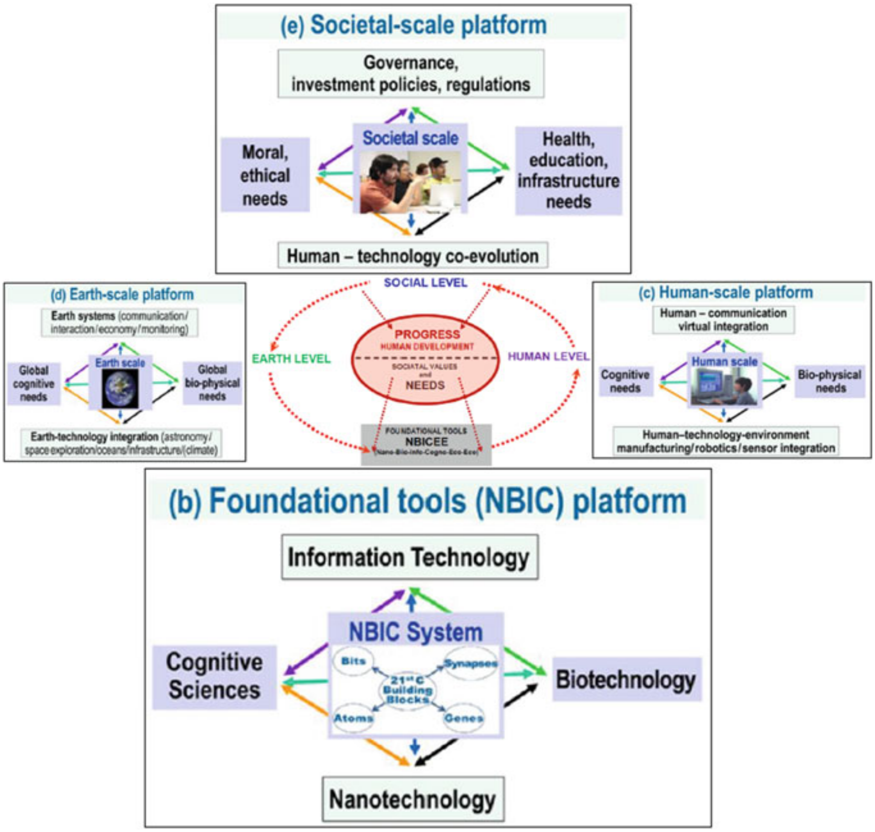


Fig. 20 Anticipatory USA NSF 2013-2020 program "Convergence of Knowledge, Technology and Society: beyond Convergence of Nano-Bio-Info-Cognitive Technologies (CKTS-NBIC2)" for "making perfect life in the Earth"

mutual compatibility, synergism, and integration. Through this process, added value is created and branches out to meet shared goals. Convergence has been progressing by stages over the past several decades, beginning with nanotechnology for the material world, followed by convergence of nanotechnology, biotechnology, information, and cognitive science (NBIC) for emerging technologies in future platforms on human, societal and planetary scales.

9 Conclusions

Analysis of the functional organization of living systems (LS) shows that:

1. The living system provides the best examples of the anticipatory systems (AS)
2. The evolution of living systems is the most obvious history of the development of AS

3. Information and memory technologies are the basic components of AS in their functional organization
4. The AS is formed by the convergence of the two different technologies
5. Material (matter-energy) transformation and information are mutually connected (hard-soft) technology
6. The convergence of the material (material-energy) and the information technologies implement special encoding and decoding technology tools
7. The higher memory capacity of the AS, the greater the potential of system adaptability
8. The Closed-Loop Coding-Decoding (CL-CD) concept is the fundamental principle of the functional organization
9. The CL-CD concept in the AS of higher levels (aviofauna, mammals, humans, and society) evolves into the structural analysis by synthesis (A-by-S) of the functional organization
10. The same CL-CD and A-by-S approaches apply to the interpretation of social systems, their creation, and improvement.

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The Imminence Mapping Anticipates

A.H. Louie

Abstract I present a new mathematical formulation of anticipation. A brief introduction to the theory of set-valued mappings culminates in a special specimen, the imminence mapping Imm_N of a natural system *N*. For each process *f* in *N*, the set $\mathrm{Imm}_N(f)$ encompasses all possible further actions arising from *f*, which one may consider the 'imminence' of *f*. The imminence mapping definitively characterizes *N* as a complex relational network of interacting processes and their entailed potentialities. A natural system *N* is an anticipatory system if it contains an internal predictive model of itself and its environment, and in accordance with the model's predictions antecedent actions are taken. Consequent manifestations of the internal predictive model of an anticipatory system are thus embodied in the system's imminence, whence the imminence mapping, among all that it entails, eminently anticipates.

Keywords Relational biology · (M,R)-system · Set-valued mapping · Imminence mapping · Anticipation

1 A Mathematical Theory of Anticipation

Robert Rosen's now-classic 1985 monograph *Anticipatory Systems* [1] has the subtitle *Philosophical, Mathematical, and Methodological Foundations*. Its back cover contains a summary of its premise:

> Presents the first detailed study of this most important class of systems which contain internal predictive models of themselves and/or of their environments and whose predictions are utilized for purposes of present control. This book develops the basic concept of a predictive model, and shows how it can be embedded into a system of feed-forward control. Includes many examples and stresses analogies between wired-in anticipatory control and

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Cognitive Systems Monographs 29, DOI 10.1007/978-3-319-22599-9_11

processes of learning and adaption, at both individual and social levels. Shows how the basic theory of such systems throws a new light both on analytic problems (e.g. understanding what is going on in an organism or a social system) and synthetic ones (developing forecasting methods for making individual or collective decisions).

In short, the book reveals a comprehensive theory of anticipation.

In this chapter, I continue the theme of studying anticipation *itself*, and present a new mathematical formulation in terms of the set-valued mapping *imminence*. This is in some contrast to most of the chapters in the present collection of papers presented at the 'Anticipation Across Disciplines: The Interdisciplinary Perspective' workshop at Hanse-Wissenschaftskolleg, comprising a cornucopia of subjects and each chapter showing how anticipation specifically arises or is used therein. To proceed from particular instances to the general concept is of course a very common procedure in mathematics. One example, to mention but one analogy, is that 'symmetry' appears abundantly in nature and in every subject of human endeavour; in the minds of mathematicians the study of symmetry itself is generalized into group theory.

Robert Rosen was a mathematical biologist. Anticipation is a *necessary* condition of life: a living system anticipates. This connection ultimately explains how Rosen, in his lifelong quest of general principles that would answer the question 'What is Life?', happened to write, en passant, 'the book' [1] on anticipation. For an expository introduction to Robert Rosen's anticipatory systems, the enthused reader may like to consult [2].

2 Relational Biology

A living system is a material system, so its study shares the material cause with physics and chemistry. Reductionists claim this, therefore, makes biology reducible to 'physics'. *Physics*, in its original meaning of the Greek word *φύσις,* is simply (the study of) *nature*. So in this sense it is tautological that (the study of) every natural system is reducible to physics. But the hardcore reductionists, unfortunately, take the term 'physics' to pretentiously mean '(the toolbox of) *contemporary* physics'.

Contemporary physics that is the physics of mechanisms reduces biology to an exercise in molecular dynamics. This reductionistic exercise, for example practised in biochemistry and molecular biology, is useful and has enjoyed popular success and increased our understanding life by parts. Practitioners of this exercise want to feel that they have solved their problems when they isolate a particular set of parts and try to assert that from this set of parts will flow the understanding of everything that they really want to know about life. But it has become evident that there are incomparably more aspects of natural systems that the physics of mechanisms is *not* equipped to explain. The overreaching reductionistic claim of genericity is thus a misrepresentation and renders it into a falsehood.

Any question becomes unanswerable if one does not permit oneself a large enough universe to deal with the question. The failure of presumptuous reductionism is that of the inability of a small surrogate universe to exhaust the real one. Equivocations create artefacts. The limits of mechanistic dogma are very examples of the restrictiveness of self-imposed methodologies that fabricate non-existent artificial 'limitations' on knowledge. The limitations are due to the nongenericity of the methods and their associated bounded microcosms. In short, limits pertain to methods, to ways of knowing, but not to knowledge itself. One learns something new and fundamental about the universe when it refuses to be exhausted by a posited method.

Biology is a subject concerned with organization of relations. Physicochemical theories are only surrogates of biological theories, because the manners in which the shared matter is organized are fundamentally different. Hence the behaviours of the realizations of these simple mechanistic surrogates are different from those of complex living systems. This in-kind difference is the impermeable dichotomy between *predicativity* and *impredicativity*.

The issue at hand is the mode of analysis. Reductionism offers one particular way of decomposing a complex system into simpler subsystems. In molecular biology this way has to do with isolating fractions that are simpler physiochemical subsystems, looking at those in isolation, and then trying to recover properties of the original system from which the fractions came. The assertion of reductionism is that this is universally adequate, that these are the only kinds of system decompositions that one ever needs to use. But fractionation does not describe *all* activities: for each activity one gets a separate dynamics and a separate way of simplifying, while missing all the other activities and their mutual interactions. So, it is not a matter that one cannot analyse, but that the form of analysis is determined by the activity that one is trying to understand.

Stated otherwise, each way of looking at a complex system requires its own description, its own mode of analysis, its own decomposition of the system into parts. It is the *relation* of these different and nontrivial descriptions that is going to be a source of enrichment. Biological systems provide a rich source of insight one may have into *organization* itself.

Relational biology is the study of biology from the standpoint of 'organization of relations'. It was founded by Nicolas Rashevsky (1899–1972) in the 1950s, thence continued and flourished under his student (and my mentor) Robert Rosen (1934–1998). The essence of reductionism in biology is to keep the matter of which an organism is made, and throw away the organization, with the belief that, since physicochemical *structure implies function*, the organization can be effectively reconstituted from the analytic material parts. Relational biology, on the other hand, keeps the organization and throws away the matter; *function dictates structure*, whence material aspects are synthetically entailed.

To better acquaint with the premises of the Rashevsky–Rosen school of relational biology (and for a comprehensive illustration of the powers of our approach to the study of life), the reader is cordially invited to read the two books that I have (so far) written on the subject. The exploratory journey begins with the monograph *More Than Life Itself: A Synthetic Continuation in Relation Biology* [3] (henceforth denoted by the canonical symbol *ML*—the notation '*ML*: m.n' shall refer to Section m.n, in Chapter m, of *More Than Life Itself*), and continues with the monograph *The Reflection of Life: Functional Entailment and Imminence in Relational Biology* [4] (*RL*). The theme of *ML* is 'What is life?'; the theme of *RL* is "How do two lifeforms interact?".

The cast and crew of mathematical and biological characters in *ML* include partially ordered sets, lattices, simulations, models, Aristotle's four causes, graphs, categories, simple and complex systems, anticipatory systems, and metabolism–repair [(M,R)-] systems. In *RL*, the cast and crew are expanded to employ set-valued mappings, adjacency matrices, random graphs, and interacting entailment networks. The imminence mapping, a special set-valued mapping, equips the further investigation of functional entailment in complex relational networks. Imminence in (M,R)-networks that model living systems addresses the topics of biogenesis and natural selection. Interacting (M,R)-networks with mutually entailing processes serve as models in the study of symbiosis and pathophysiology. The formalism also provides a natural framework for a relational theory of virology and oncology.

Γνῶσις, s*cientia*, *σοφία*, *sapientia*: Human knowledge and wisdom are the tools and servants of human aspiration (*cf. ML*: 5.1). Their centrifugal tendency has led to a partition into 'cultures' (arts, science, mathematics, …), each further fragmented into 'disciplines' (literature, performing arts, visual arts, physics, chemistry, biology, algebra, analysis, topology, …). These fragments then interact in 'interdisciplines', cross-pollinations that mutually relate and illuminate (e.g., biophysics, mathematical drama, music psychology, …). But one must not lose sight, among the disciplines' infinite diversity in infinite combinations, of their centripetal unity. There is but one gnosis. A true theory of the organism requires new physics and new epistemology. Biology does not reduce provincially to physics; biology, rather, buttresses and extends physics. An expansive notion of science is crucial in handling the kinds of emergence problems that also arise on the human level, embracing cognitive and social systems. A relational approach to *science*, in its original sense of 'knowledge', restores to our fragmented disciplines the kind of integration they possessed in an earlier time, when scientists regarded themselves as Natural Philosophers.

3 Natural Law and the Modelling Relation

I shall include herein some background material on relational biology to make this paper (more or less) self-contained. To this end, let me first identify Aristotle's four causes as components of a mapping $f : X \to Y$ (*ML*: Chap. 5). The mapping f may alternatively be considered as a set of ordered pairs $f \subset X \times Y$, with the property that if $(x, y) \in f$ and $(x, z) \in f$, then $y = z$. The traditional concept of a mapping is that which assigns to each element of a given set a definite element of another given set; i.e., a 'point-to-point' map. That is, to each input element $x \in X$, by definition there corresponds a *unique* output element $y \in Y$ such that $(x, y) \in f$. In the 'point-pairing'(x, y), y is called the *value* of the mapping f at the source x. The collection of all the sources (which is conventionally the whole set X) is the *domain* of f, and the collection of all the values (a subset of Y) is the *range* of f. They are symmetrically defined thus:

$$\begin{aligned} \operatorname{dom}(f) &= \{x \in X : \exists y \in Y\ (x,y) \in f\}, \\ \operatorname{ran}(f) &= \{y \in Y : \exists x \in X\ (x,y) \in f\}. \end{aligned} \tag{1}$$

The relation between x and y in $(x,y) \in f$ is usually denoted $y = f(x)$. To trace the path of an element as it is mapped, one uses the 'maps to' arrow and writes

$$f : x \mapsto y. \tag{2}$$

The input x is the *material cause*, and the output y is the *final cause*. The mapping f itself (the *process* that pairs each $x \in X$ with its unique $y \in Y$) is the *efficient cause*, and the morphic structure, '$\bullet : \cdot \mapsto \circ$' is the *formal cause*. The processor (efficient cause) and output (final cause) relationship may be characterized '*f entails y*', which may then be denoted using the entailment symbol $\vdash$ (*ML*: 5.5, *RL*: 6.1) as

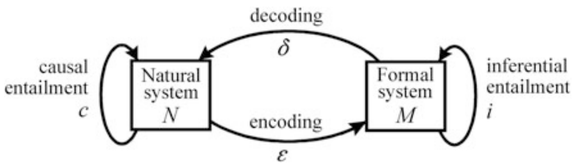
$$f \vdash y. \tag{3}$$

Note that the processor f is *that which entails* (symbolically '$f \vdash$ '), and the output y is *that which is entailed* (symbolically ' $\vdash y$').

Causality is the principle that every effect has a cause, and is a reflection of the belief that successions of events in the world are governed by definite relations. *Natural Law* posits the existence of these *entailment* relations *and* that this causal order can be *imaged* by implicative order (*ML*: 4.7).

System is a basic undefined term, a primitive. It takes on the intuitive meaning of 'a collection of material or immaterial things that comprises one's object of study'. In relational, hence non-material, terms, a system may be considered as a *network of interacting processes*.

A *modelling relation* is a commutative functorial (in the category-theoretic sense; *ML*: A.10) encoding and decoding between two systems. Between a natural system (an object partitioned from the physical universe) N and a formal system (an object in the universe of mathematics) M, the situation may be represented in the following diagram (*ML*: 4.14):



(4)

The encoding ε maps the natural system N and its causal entailment c therein to the formal system M and its internal inferential entailment i; i.e.,

$$\varepsilon : N \mapsto M \quad \text{and} \quad \varepsilon : c \mapsto i. \tag{5}$$

The decoding δ does the reverse. The entailments satisfy the commutativity condition that, in diagram (4), tracing through arrow c is the same as tracing through the three arrows ε, i, and δ in succession. This may be symbolically represented by the 'composition'

$$c = \delta \circ i \circ \varepsilon. \tag{6}$$

Thence related, M is a *model* of N, and N is a *realization* of M. In terms of the modelling relation, then, Natural Law is an *existential declaration* of causal entailment c and the encodings $\varepsilon : N \mapsto M$ and $\varepsilon : c \mapsto i$.

A formal system may simply be considered as a *set* with additional mathematical structures. So the mathematical statement $\varepsilon : N \mapsto M$, i.e., the posited existence for every natural system N a model formal system M, may be stated as the axiom

$$\textit{Everything is a set}. \tag{7}$$

Causal entailment in a natural system is a network of interacting processes, i.e., a network of mutually entailing efficient causes. The mathematical statement $\varepsilon : c \mapsto i$, i.e., the functorial correspondence of morphisms, between causality c in the natural domain and inference i in the formal domain, may thus be stated as an epistemological principle, the axiom

$$\textit{Every process is a mapping}. \tag{8}$$

Together, the two axioms (7) and (8) are the mathematical foundation of Natural Law. These self-evident truths serve to explain "the unreasonable effectiveness of mathematics in the natural sciences". They also serve to alternatively characterize a system as a network of interacting mappings.

The prototypical modelling relation (4) may be generalized, so that the systems N and M may both be natural systems or both be formal systems, and the entailments c and i are corresponding efficient causes; i.e., (4) may simply be a commutative diagram between 'general systems' (*ML*: 4.9). The general modelling relation has multifarious manifestations: e.g., category theory, analogies, alternate descriptions, similes, metaphors, and complementarities (*ML*: 4.16–4.20).

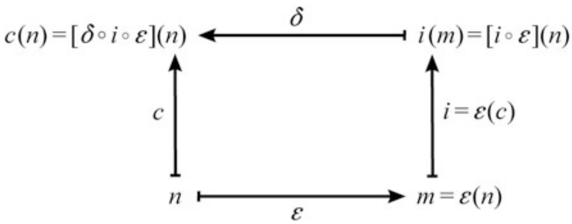
4 The Many Levels of the Encoding Functor

The collection of all models of a system N is denoted $\mathbf{C}(N)$ (*ML*: 7.27). $\mathbf{C}(N)$ is a lattice (*ML*: 7.28) as well as a category (*ML*: 7.29). Let $\kappa(N)$ be the collection of all efficient causes in N. An entailment network that models N may be denoted $\varepsilon(N) \in \mathbf{C}(N)$; the collection $\kappa(\varepsilon(N))$ of all efficient causes in the model network $\varepsilon(N)$, in view of the commutativity (6), may be represented by the encoding $\varepsilon(\kappa(N))$. Natural Law is the statement

$$\forall N \ \exists \varepsilon \ \exists M \in \mathbf{C}(N) \ : \ M = \varepsilon(N) \ \wedge \ \forall c \in \kappa(N) \ \exists\, i \in \kappa(M) \ : \ i = \varepsilon(c). \quad (9)$$

True to its category-theoretic taxonomy as a *functor*, the encoding ε maps on many levels (likewise for the decoding functor δ). The assignment $\varepsilon : N \mapsto M$ is a *choice mapping* (*RL*: 0.20) that singly selects, as a specific model of the natural system N, the formal system M from the set $\mathbf{C}(N)$. But in addition to this *set-pairing* $(N, M) \in \varepsilon$, ε also functions on the *point-pairing* level as a mapping $\varepsilon : N \to M$ *from one set into another*—to each input element (*material cause*) $n \in N$, there corresponds a unique output element (*final cause*) $m \in M$ such that $(n, m) \in \varepsilon$; i.e., $\varepsilon : n \mapsto m$.

The mapping $\varepsilon : c \mapsto i$ is a functorial correspondence of morphisms $\varepsilon : \kappa(N) \to \kappa(M)$. This *process-pairing* $(c, i) \in \varepsilon$ functions on a higher hierarchical level than point-pairing, because now the output is *itself* a mapping $i = \varepsilon(c) \in \kappa(M)$, whereas the former output $m = \varepsilon(n) \in M$ is a point. In $\vdash i$, the final cause itself acts as an efficient cause, while in $\vdash m$ the output is relayed as a material input of another efficient cause. The commutativity condition (6) may be drawn as the element trace



(10)

For a mapping $f : x \mapsto y$, 'that which is entailed' $\vdash y$ may take on a secondary role, when f *composes* with another mapping. In the *sequential composite* $g \circ f$ (*ML*: 5.13), the output y of f is used as input (material cause) by another mapping $g : y \mapsto z$ (in the material relay $x \mapsto y \mapsto z$), whence $\vdash y$ is called *material entailment* (*RL*: 6.10). In the *hierarchical composite* $f \vdash y \vdash$ (*ML*: 5.14), the output y of f is itself (the efficient cause of) a mapping $y : u \mapsto v$ (i.e., that which is entailed is a functional process), whence $\vdash y$ is called *functional entailment* (*RL*: 6.14). In both compositions, the final cause y of one mapping participates in further entailment involving other mappings. The encoding functor ε, in particular, encompasses the two levels of entailment in its effects: $\varepsilon \vdash m$ is material entailment, while $\varepsilon \vdash i$ is functional entailment.

The category **S** of formal systems is the subject of Chap. 7 of *ML*. An **S**-object is a pair $\langle X, \mathrm{K} \rangle$, where X is a set and K is a collection of mappings on X (*cf.* axioms (7) and (8)). The many operational levels of the encoding functor ε are succinctly embodied in its role as an **S**-morphism $\varepsilon : \langle N, \kappa(N) \rangle \to \langle M, \kappa(M) \rangle$.

5 Metabolism and Repair

Robert Rosen, a stalwart in relational biology, devised a class of relational models called (M,R)-systems. Indeed, Rosen introduced (M,R)-systems to the world in 1958, in his very first published scientific paper [5]. The M and R may very well stand for 'metaphorical' and 'relational' in modelling terms, but they are realized as 'metabolism' and 'repair'. The comprehensive reference is [6] (see also *ML*: Chaps. 11–13 and *RL*: Chap. 7).

Relational biology has a functional view of life, expressed in terms of processes that organisms manifest, independent of the physical substrata on which they are carried out. An organism, being a system open to material causation, must have processes that are modes of interaction with the world. It must have inputs from the world, typical material inputs which supply energy and which provide the capacity for renewing the structure of the organism, whatever it might be. So it is a *sine qua non* that one has to have a *metabolic* apparatus. The word *metabolism* comes from the Greek *μεταβολή*, 'change', or *μεταβολισμός*, 'out-throw'; i.e., an alteration or a relay of materials. Metabolism, in its most general form, is thus a mapping $f : x \mapsto y$ in which $\vdash y$ is material entailment. An organism must also have a *genetic* apparatus, information carriers that tell how the products of metabolism are to be assembled. The genetic apparatus serves two functions: to produce the metabolic apparatus of the organism and to *re*produce it. Rosen called the genetic processes *repair*, which, in its most general form, is a mapping $f : x \mapsto y$ in which $\vdash y$ is functional entailment.

The English word 'repair' comes from the Latin *re* + *parare*, 'make ready again'. It is, of course, a word in common usage, and means 'restore to good condition or proper functioning after damage or loss'; 'renovate or mend by replacing or fixing parts or by compensating for loss or exhaustion'; 'set right or make amends for loss, wrong, or error'. Rosen defined the technical usage of the term 'repair' in relational biology, precedently back in the beginnings of (M,R)-systems in the 1950 s, to mean a hierarchical process for which 'the output of a mapping is itself a mapping'. This is the general telos of 'repair', that of an action taken to generate another action. The entailed process may possibly be previously existing, but repair does not have to be a 'return to normalcy' or 'restore to original condition'; the goal of 'the fix works' is more important. It is unfortunate (but ultimately irrelevant) that the technical term now, alas, suffers semantic equivocation because of its usage in molecular biology to insularly mean biochemical repair of a specific molecule, that of 'DNA (and sometimes RNA) repair'. This restricted usage is a very example of the meagre appropriating the generic. Since the word 'repair' is not a specially coined word, its biological definition is not entitled to a universal decree. And in the absence of a default, Humpty Dumpty's rule applies: "When I use a word, it means just what I choose it to mean—neither more nor less."

To recap, our Unabashed Dictionary of Relational Biology defines

$$\begin{aligned} \textit{metabolism} &= \text{material entailment}, \\ \textit{repair} &= \text{functional entailment}. \end{aligned} \tag{11}$$

Anything that one would want to call 'alive' would have to have at least these two basic functions of M and R. A self-contained (in the very specific sense of *closed to efficient causation*, a topic into which I shall not dwell here; for exploration see, e.g., *ML*: 6.23 and *RL*: 7.1–7.3) network of metabolism and repair processes is an (*M*,*R*)-*system*. (M,R)-systems began as a class of metaphorical, relational paradigms that define cells. It is, however, not much of a hyperbole to declare that all of Rosen's scientific work—his lifelong quest being the answer to the question "What is life?"—has arisen from a consideration of topics related to the study of (M,R)-systems. This is because of the

Postulate of Life. A natural system is an *organism* if and only if it realizes an (M,R)-system.

(*ML*: 11.28, *RL*: 8.30) Here, the word 'organism' is used in the sense of a general living system (including, in particular, cells). Thus an (M,R)-system is the very model of life; and, conversely, life is the very realization of an (M,R)-system.

A union of interacting (M,R)-systems (or better, their *join* in the *lattice* of (M,R)-systems; *cf. ML*: 2.1 & 7.28) is itself an (M,R)-system. A multicellular organism has a life of its own, apart from the fact that the cells that comprise it are alive. Similarly, in some sense an ecosystem of interacting organisms is itself an organism. In particular, a symbiotic union of organisms may itself be considered an organism (*RL*: 11.12).

6 Set-Valued Mapping

Part I of *RL* is a pentateuchal exploration of the algebraic theory of set-valued mappings (*RL*: Chaps. 1–5). It also contains the motivations and other natural philosophical reasons on why I consider them congenial and congenital morphisms for relational biology. The enthused reader is invited to consult *RL* for further details on this much-neglected topic in mathematics. My exposition of set-valued mappings culminates in the *imminence mapping*, which equips the further investigation of functional entailment in complex relational networks. In what follows I am taking the brachistochrone to this plateau, before I proceed to discuss its connection to anticipation.

A *set-valued mapping*

$$F: \ X \mathrel{-\!\!\sqsubset} Y \tag{12}$$

from set X to set Y is a set of ordered pairs $F \subset X \times Y$. The *domain* of F is the set X, denoted by $\mathrm{dom}(F)$. I have invented in *RL* the special 'forked arrow' $\mathrel{-\!\!\sqsubset}$ to denote set-valued mappings, in distinction from $\rightarrow$ for a standard (single-valued) mapping $f : X \rightarrow Y$.

For each $x \in X$, define

$$F(x) = \{y \in Y : (x, y) \in F\} \ \subset \ Y. \tag{13}$$

Note the *point-to-set* nature of a set-valued mapping, as opposed to 'point-to-point' for a standard mapping. The 'value' $F(x)$ may contain more than one element, and it is possible that for some $x \in X$, one has $F(x) = \varnothing$. The *corange* of F is the subset of its domain X containing those points that are mapped to one or more elements in Y:

$$\mathrm{cor}(F) \ = \ \{x \in X : F(x) \neq \varnothing\}. \tag{14}$$

A standard (single-valued) mapping $f : X \rightarrow Y$ may be considered a very specialized set-valued mapping $F : X \mathrel{-\!\!\sqsubset} Y$ such that, for each $x \in X$, the value

$$F(x) = \{f(x)\} \tag{15}$$

is a singleton set. Indeed, one can make the formal definition: a set-valued mapping $F : X \mathrel{-\!\!\sqsubset} Y$ is called *single-valued* if, for *each* $x \in X$, $F(x)$ is a singleton set. A 'single-valued set-valued mapping' $F : X \mathrel{-\!\!\sqsubset} Y$ therefore defines a 'standard' mapping $f : X \rightarrow Y$ by $f : x \ \mapsto$ the single element in $F(x)$. For a single-valued mapping, $\mathrm{cor}(F) = \mathrm{dom}(F) = X$.

The same symbolic representations suffice for the other arrow diagrams; context determines the nature of the final cause, whether it is an 'element', a 'set', or some other entity. Thus, for $x \in X$ and $E = F(x) \subset Y$, in the set-valued mapping's element-tracing form, one may write

$$F: \ x \ \mapsto \ E. \tag{16}$$

The processor and output relationship may likewise be characterized '*F entails E*', which may then be denoted using the entailment symbol $\vdash$ as

$$F \ \vdash \ E. \tag{17}$$

The input of F is, as for a standard mapping, still a point $x \in X$, but now the output of the mapping F at the element x is a *set* $E = F(x) \subset Y$. The source (material cause) and the value (final cause) of a set-valued mapping are thus different in kind from each other, they belonging to different hierarchical levels (‘point’ versus ‘set’). The property of ‘that which is entailed’ is inherited by elements from their containing set: if F entails E, F also entails every member of E. This is the logical statement

$$F \vdash E \quad \Rightarrow \quad \forall\, y \in E \quad F \vdash y. \tag{18}$$

7 Metabolism Bundle and Imminence Mapping

Consider two formal systems $\langle H, \kappa(H) \rangle$ and $\langle S, \kappa(S) \rangle$; that is, systems H and S (e.g., (M,R)-networks) with their respective collections $\kappa(H)$ and $\kappa(S)$ of efficient causes. Two systems *interact* when a process in one system affects another system. Stated otherwise, an interactive connection $S \rightarrow H$ happens when the final cause of a process in $\kappa(S)$ is further relayed in H. The theme of *RL* is “How do two lifeforms interact?”. One ubiquitous biological interaction is symbiosis (*RL*: Chap. 11), between a *host* and a *symbiont*. This is the source of the symbols H and S. One may use host–symbiont interaction as a running example of the system interactions now under consideration.

The set-valued mapping

$$\mathrm{Met}_{S \to H} : \ \ \kappa(S) \multimap\!\sqsubset \kappa(H) \tag{19}$$

defined by

$$\mathrm{Met}_{S \to H} \ = \ \{\, (f, g) \in \kappa(S) \times \kappa(H) \ \ : \ \ \mathrm{dom}(g) \cap \mathrm{ran}(f) \neq \varnothing \,\} \tag{20}$$

is called the *metabolism bundle of the interaction* $S \rightarrow H$. (Recall that metabolism is material entailment; for an explanation of the usage of the term ‘bundle’, see *RL*: 10.5). If $(f, g) \in \mathrm{Met}_{S \to H}$, then a material relay $x \mapsto f(x) \mapsto g(f(x))$ may be defined on $X_g = \{\, x \in \mathrm{dom}(f) : f(x) \in \mathrm{dom}(g) \,\}$, but this restriction $g \circ f\,|_{X_g}$ may not necessarily be expandable to the sequential composite $g \circ f$ on all of $\mathrm{dom}(f)$, and it may not be in the existing collections $\kappa(H)$ or $\kappa(S)$ of processes. The mapping $g \circ f\,|_{X_g}$ arises from the interaction $S \rightarrow H$. If one denotes the effects of S on H (i.e., the collection of processes in the interaction $S \rightarrow H$) by $\kappa(S \rightarrow H)$, then $g \circ f\,|_{X_g} \in \kappa(S \rightarrow H)$.

Another set-valued mapping

$$\mathrm{Imm}_{S \to H} : \ \ \kappa(S) \multimap\!\sqsubset \kappa(H) \tag{21}$$

may be defined, by, for a mapping $f \in \kappa(S)$,

$$\mathrm{Imm}_{S \to H}(f) = \kappa(H) \cap \mathrm{ran}(f). \tag{22}$$

Hierarchical composition $f \vdash g$ occurs for $f \in \kappa(S)$ and $g \in \kappa(H)$ if and only if

$$g \in \kappa(H) \cap \operatorname{ran}(f) = \operatorname{Imm}_{S \to H}(f) \neq \varnothing. \tag{23}$$

$\operatorname{Imm}_{S \to H}(f)$ contains all the processes in the system H that may be functionally entailed by the process $f \in \kappa(S)$ of the system S. In other words, the set $\operatorname{Imm}_{S \to H}(f)$ contains all possible further actions in the system H arising from interacting with $f \in \kappa(S)$. This 'global' manifestation of the 'local' functional entailment may be termed the *imminence* of *f*. I have, therefore, given the set-valued mapping Imm the natural name of *imminence mapping* (which explains the use of the expression 'Imm' as the symbol for this set-valued mapping). This is a key concept in *RL*. Functional entailment is repair in its most general sense, whence the inter-network imminence $\operatorname{Imm}_{S \to H}(f)$ may be considered a *repair effect* in the interaction $S \to H$, whence $\operatorname{Imm}_{S \to H}(f) \subset \kappa(S \to H)$.

The analogy between Imm and Met is more apparent if I recast the set-valued mapping $\operatorname{Imm}_{S \to H}$ also as a subset of $\kappa(S) \times \kappa(H)$:

$$\begin{aligned} \operatorname{Imm}_{S \to H} &= \{(f, g) \in \kappa(S) \times \kappa(H) \ : \ g \in \operatorname{ran}(f)\} \\ &= \{(f, g) \in \kappa(S) \times \kappa(H) \ : \ \{g\} \cap \operatorname{ran}(f) \neq \varnothing\}. \end{aligned} \tag{24}$$

Now compare (20) and (24).

The two systems H and S need not be disjoint; it may very well happen that $H \cap S \neq \varnothing$. Indeed, one system may be a subsystem of the other, that $S \subset H$. When H and S are the same system, i.e., when $H = S = N$, one may define the set-valued mapping $\operatorname{Met}_N = \operatorname{Met}_{N \to N}$, the *metabolism bundle of the system N*. The subset $\operatorname{Met}_N \subset \kappa(N) \times \kappa(N)$ is the domain on which 'metabolism' *within* the system N may proceed, containing pairs of processes (f, g) that may participate in the internal material relay $x \mapsto f(x) \mapsto g(f(x))$. Hence Met_N embodies the material entailment structure in N. The *imminence mapping of the system N* (also the *imminence mapping on* $\kappa(N)$) is the set-valued mapping $\operatorname{Imm}_N = \operatorname{Imm}_{N \to N}$. The set $\operatorname{Imm}_N(f)$ is the collection of all efficient causes of N that lie in the range of $f \in \kappa(N)$, i.e., all the f-entailed entities in $\kappa(N)$. The imminence mapping Imm_N on $\kappa(N)$ is thus the functional entailment pattern of the system N.

The two subsets Met_N and Imm_N of $\kappa(N) \times \kappa(N)$, i.e., *metabolism* and *repair* in the system N, are themselves not necessarily disjoint. The range of a mapping may contain both materially-entailed and functionally-entailed entities. A single output set of a set-valued mapping may itself already contain both species. It may also happen that a single output entity takes on *dual roles* of being materially entailed in one interaction and functionally entailed in another.

Final causes of processes are not ends in themselves; they are simply the multifarious entailed outputs of interacting processes. The more significant final causes in the entailment network $\kappa(N)$ of a system N are those that are further relayed as material and efficient causes. The entailment network $\kappa(N)$ is completely described by its processes in composition, whence by the two special set-valued mappings defined on it: the metabolism bundle Met_N generates products through material entailment, and the imminence mapping Imm_N generates effects though functional entailment. Every process in $\kappa(N)$ may function as either 'metabolism' or 'repair', even when N is not necessarily a metabolism–repair network per se; indeed, every system $\langle N, \kappa(N)\rangle$ may be formulated as an (M,R)-network. Together, Met_N and Imm_N may be taken as the very definition of the entailment network of the system N.

It is how Met_N and Imm_N on $\kappa(N)$ interact that determines the nature of the nature of the system N. If no closed path of efficient causation exists in N, then it is a *simple system* (*ML*: Chap. 8); otherwise it is a *complex system* (*ML*: Chap. 9). In a closed to efficient causation (*clef*) system (*RL*: 7.3), every efficient cause is functionally entailed; this may be completely characterized in terms of the inverse Imm_N^{-1} of the imminence mapping (*RL*: 9.2).

8 Synthesis

When two formal systems $\langle H, \kappa(H)\rangle$ and $\langle S, \kappa(S)\rangle$ interact, their entailment networks connect to become the *join* formal system $\langle H \vee S, \kappa(H \vee S)\rangle$ (*RL*: 13.2). The material base set of $H \vee S$ is quite straight-forwardly $H \cup S$, but the collection $\kappa(H \vee S)$ of join processes is more than the union $\kappa(H) \cup \kappa(S)$. This is because in addition to the processes $\kappa(H)$ and $\kappa(S)$ within the two systems, join processes in $\kappa(H \vee S)$ must also include the mutual interactions between H and S: the effects $\kappa(S \rightarrow H)$ of S on H, and the effects $\kappa(H \rightarrow S)$ of H on S. Thus

$$\kappa(H \vee S) = \kappa(H) \cup \kappa(S) \cup \kappa(S \to H) \cup \kappa(H \to S). \tag{25}$$

Interactive processes between H and S may be *synthesized* from the set-valued mappings Met and Imm. Note that

$$\begin{array}{ll} \mathrm{cor}(\mathrm{Met}_{S\to H}) \subset \kappa(S), & \mathrm{cor}(\mathrm{Imm}_{S\to H}) \subset \kappa(S); \\ \mathrm{cor}(\mathrm{Met}_{H\to S}) \subset \kappa(H), & \mathrm{cor}(\mathrm{Imm}_{H\to S}) \subset \kappa(H). \end{array} \tag{26}$$

The corange

$$\mathrm{cor}(\mathrm{Met}_{S\to H}) = \{ f \in \kappa(S) \; : \; \exists g \in \kappa(H) \;\; \mathrm{dom}(g) \cap \mathrm{ran}(f) \neq \varnothing \} \tag{27}$$

contains all the processes in $\kappa(S)$ that produce metabolism effects in H. Likewise, $\mathrm{cor}(\mathrm{Imm}_{S\to H})$ contains all the processes in $\kappa(S)$ that produce repair effects in H. Every process may function as either 'metabolism' or 'repair' (or a combination thereof), so the union of material entailment and functional entailment $\mathrm{cor}(\mathrm{Met}_{S\to H}) \cup \mathrm{cor}(\mathrm{Imm}_{S\to H})$ completely describes the effect of $\kappa(S)$ on $\kappa(H)$. Let me introduce the notation

$$[\kappa(S) \dashv\sqsubset \kappa(H)] \;=\; \mathrm{cor}(\mathrm{Met}_{S\to H}) \cup \mathrm{cor}(\mathrm{Imm}_{S\to H}). \tag{28}$$

Conversely, $\mathrm{cor}(\mathrm{Met}_{H\to S})$ and $\mathrm{cor}(\mathrm{Imm}_{H\to S})$ are the metabolism and repair effects of of $\kappa(H)$ on S, whence

$$[\kappa(H) \dashv\sqsubset \kappa(S)] \;=\; \mathrm{cor}(\mathrm{Met}_{H\to S}) \cup \mathrm{cor}(\mathrm{Imm}_{H\to S}). \tag{29}$$

Our best approximation of the collection of join processes in $H \vee S$ is then the union of the *active* processes in $\kappa(H)$ and $\kappa(S)$ with these four coranges:

$$\begin{aligned} \kappa(H \vee S) \;\approx\; & \kappa(H) \;\cup\; \kappa(S) \\ & \cup\; \mathrm{cor}(\mathrm{Met}_{S\to H}) \;\cup\; \mathrm{cor}(\mathrm{Imm}_{S\to H}) \\ & \cup\; \mathrm{cor}(\mathrm{Met}_{H\to S}) \;\cup\; \mathrm{cor}(\mathrm{Imm}_{H\to S}) \;; \end{aligned} \tag{30}$$

that is,

$$\kappa(H \vee S) \;\approx\; \kappa(H) \;\cup\; \kappa(S) \cup\; [\kappa(S) \dashv\sqsubset \kappa(H)] \;\cup\; [\kappa(H) \dashv\sqsubset \kappa(S)]\;. \tag{31}$$

The set-valued mappings Met and Imm are mappings of *potentiality*. They trace the possible material and functional *entailments* arising from a system, i.e., the system's possible metabolism and repair *effects*. This propensity for the emergence of material and functional entailments inherent in Met and Imm is what allows the synthetic continuation from $\kappa(H)$ and $\kappa(S)$ to $\kappa(S \to H)$ and $\kappa(H \to S)$. Note, however, that one can only reconstruct the interactive processes between H and S from processes that already exist (but are *dormant*) in the partitioned $\kappa(H)$ and $\kappa(S)$. Note the containments (26); if a process in $\kappa(H \vee S)$ becomes *extinct* in the fractionation of $\kappa(H \vee S)$ into $\kappa(H)$ and $\kappa(S)$, then it cannot be recovered through Met and Imm. Stated otherwise,

$$[\kappa(S) \dashv\sqsubset \kappa(H)] \;=\; \mathrm{cor}(\mathrm{Met}_{S\to H}) \cup \mathrm{cor}(\mathrm{Imm}_{S\to H}) \;\;\subset\;\; \kappa(S \to H) \tag{32}$$

and

$$[\kappa(H) \dashv\sqsubset \kappa(S)] \;=\; \mathrm{cor}(\mathrm{Met}_{H\to S}) \cup \mathrm{cor}(\mathrm{Imm}_{H\to S}) \;\;\subset\;\; \kappa(H \to S), \tag{33}$$

and both containments may be proper. Thus the unions (30) and (31) are only an *approximation* of the union (25), but it is the *best* effort in the synthesis of the latter sum from the analytic parts $\kappa(H)$ and $\kappa(S)$. (For a thorough discussion of the amphibology of analysis and synthesis, see *ML*: 7.43–7.49.)

9 Internal Predictive Model

In Sect. 6.1 of [1], Rosen gave the following

Definition An *anticipatory system* is a natural system that contains an internal predictive model of itself and of its environment, which allows it to change state at an instant in accord with the model's predictions pertaining to a later instant.

An anticipatory system is complex, and an (M,R)-system is anticipatory; I have demonstrated these inclusions in Chap. 10 of *ML* and in [7].

True to the spirit of relational biology, the crux in this definition is not what an anticipatory system itself *is*, but what it *does*. The entailment *process* of anticipation is embedded in its defining component, its

$$internal \cdot predictive \cdot model \tag{34}$$

I now explicate these three keywords in some detail.

9.1 Model

Let the anticipatory system be $\langle N, \kappa(N) \rangle$. The system N partitions the universe U into *self* (N itself) and non-self that is its *environment*, $N^c = U \sim N$ (*ML*: 4.1–4.2). What does N's having a *model of itself and of its environment* entail? 'N itself and its environment' is the whole universe: $N \cup N^c = U$. A model is, however, by necessity incomplete, so it cannot be a model of the 'whole universe' U.

Let $W \subset U$ be the proper subsystem that is actually being modelled. That W is part of 'N itself and its environment' implies it straddles the self | non-self boundary: $H = W \cap N \neq \varnothing$ and $S = W \cap N^c \neq \varnothing$. While $W = H \cup S$, its collection $\kappa(W) = \kappa(H \vee S)$ of processes is (as explained in Sect. 8 above) more than the union $\kappa(H) \cup \kappa(S)$. More than the internal processes $\kappa(H) \subset \kappa(N)$ and the environmental processes $\kappa(S) \subset \kappa(N^c)$ are involved in the anticipation inherent in N; one must also consider $\kappa(S \to H) \subset \kappa(N^c \to N)$ (environmental effects on N) and $\kappa(H \to S) \subset \kappa(N \to N^c)$ (how the system N affects its environment).

Thus anticipation in N entails the existence of a model $M \in \mathbf{C}(W)$ and an encoding functor $\varepsilon : \langle W, \kappa(W) \rangle \to \langle M, \kappa(M) \rangle$. We have already encountered (in Sect. 4 above) the multilevel entailments of ε. In particular, one has material entailment

$$\varepsilon : W \to M \tag{35}$$

and functional entailment

$$\varepsilon : \kappa(W) \to \kappa(M). \tag{36}$$

9.2 Predictive

In common English usage, 'predict' means 'foretell, make a statement about the future', thus temporal succession is implicit. The word comes from the Latin *prae*, 'before', + *dicere*, 'say'. Note, however, the 'before' that the Latin prefix *prae*- (and *pre*-) predicates does not necessarily have to refer to time; it may also be before in place, order, degree, or importance. It is with this general sense that one may distinguish three temporally different classes of 'predictions': (i) *extenders*, pre-dictions that are time-independent; (ii) *portents*, predictions that relate simultaneous events; and (iii) *transducers*, predictions that convert information about the world at a given instant into information about the world at some later instant. Time-independent predictions (i) concern a system's *constitutive parameters*, while time-dependent predictions (ii) and (iii) concern a system's *dynamics*.

A model M is a *reflector* of its realization W. The functorial images $\varepsilon : W \to M$ and $\varepsilon : \kappa(W) \to \kappa(M)$ above all serve to archive a copy of $\langle W, \kappa(W) \rangle$ in $\langle M, \kappa(M) \rangle$. An important purpose of modelling is that through the study of the alternate description $\langle M, \kappa(M) \rangle$, one produces explanations that decode to help in one's understanding of $\langle W, \kappa(W) \rangle$. A good model should *augur*, i.e., suggest specified outcomes and generate conclusions that are more than the building blocks used in the construction of the model. A model predicts. To whichever class a prediction belongs, what shapes the consequents is not what the encoding ε supplies to the model, but, rather, what the decoding δ extracts from the model.

The internal predictive model in an anticipatory system augurs future events; i.e., its predictions belong to class (iii), transducers. One notes that in order to fulfill its purpose of making predictions about the future, a model M must have a 'faster dynamics' than its realization W. Tersely, this translates to the predictive model M operating on a faster internal timescale than the system N; I shall have an expanded explication later. The enthused reader may consult Chap. 4 of [1] for a thorough exposition of the encodings of time.

9.3 Internal

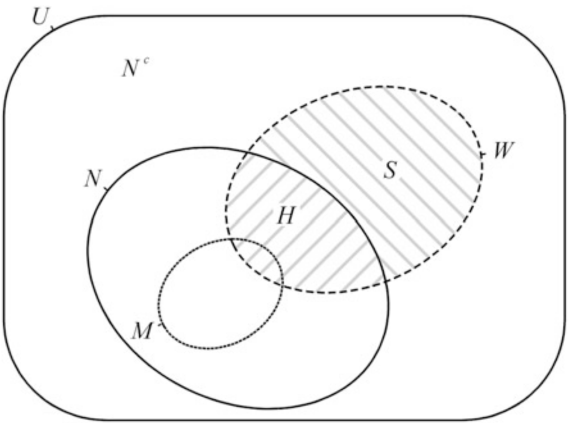
The predictive modelling activity of an anticipatory system is self-contained. That the predictive model is *internal* means

$$\langle M, \kappa(M) \rangle \subset \langle N, \kappa(N) \rangle; \tag{37}$$

that is to say,

$$M \subset N \quad \text{and} \quad \kappa(M) \subset \kappa(N). \tag{38}$$

A summary of the sets and their relationships in their *mille verba* is in order:



(39)

The encodings (35) and (36) imply

$$\varepsilon(W) \subset M \quad \text{and} \quad \varepsilon(\kappa(W)) \subset \kappa(M). \tag{40}$$

Together with (38), one has

$$\varepsilon(W) \subset N \quad \text{and} \quad \varepsilon(\kappa(W)) \subset \kappa(N). \tag{41}$$

The encodings (35) and (36) also immanently entail (*ML*: 5.18) the corresponding decoding

$$\delta : M \to W \tag{42}$$

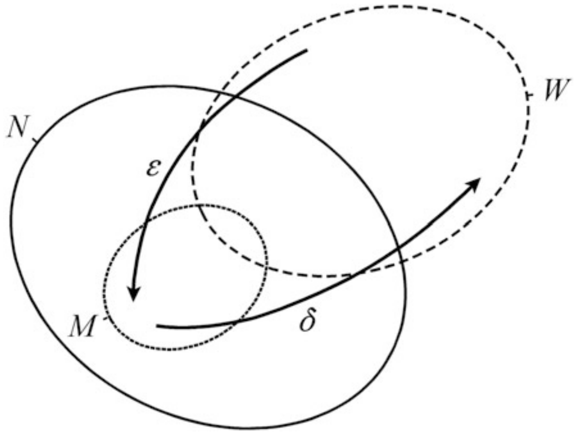
and

$$\delta : \kappa(M) \to \kappa(W), \tag{43}$$

whence

$$\delta(M) \subset W \quad \text{and} \quad \delta(\kappa(M)) \subset \kappa(W). \tag{44}$$

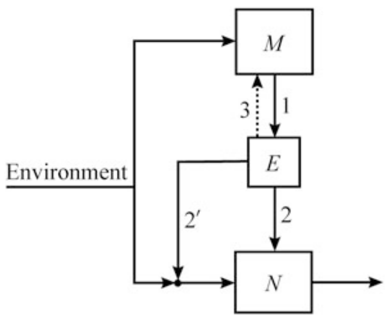
These inclusions are succinct summary statements of the embodiment of anticipation, the internal predictive model:



(45)

10 Imminent Anticipation

The now-iconic Fig. 1.1.1 in [1] is the definitive block diagram of Robert Rosen's anticipatory system. Therein the object system, the predictive model, and the set of effectors are represented, respectively, by the symbols S, M, and E. I am now replacing S with my N, since the symbol S has been otherwise defined as 'the symbiont' $S = W \cap N^c$. I am also eliminating the circles around the numerical labels of the arrows, and relabelling the two number-2 arrows as 2 and $2'$. After these mutations, Rosen's anticipatory system is



(46)

It is crucial to remember that what defines an anticipatory system N is not just the *existence* of the internal predictive model—there are *two* indispensable ingredients: (*a*) internal predictive model M and (*b*) *response* E to the prediction. The telos of anticipation is for the system N 'to change state at an instant in accord with the model's predictions pertaining to a later instant'. The central importance of this telos effected by E is reflected in the largest number of influent and effluent arrows among the blocks in diagram (46).

In [7], I have explicated how the triumvirate *receptor*, *controller*, and *effector* from control theory manifest themselves in (M,R)-networks and anticipatory systems. Here and now it suffices to summarize that, in an (M,R)-network, the controller controls metabolism processes while the effector effects repair functions; and, in an anticipatory system, the controller is the internal predictive model M while the effector E carries out the actual response arising from the anticipation process.

The controller, the model M, sets the system response in motion by functionally entailing the effector E. This entailment is represented by the arrow 1 in (46), and is contained in the effects $\kappa(M \to N)$ of M on N. As explained in Sect. 8 above, with only $\kappa(M)$ on hand, the best approximation of these effects is the union of the coranges of the metabolism bundle and imminence mapping:

$$[\kappa(M) -\!\!\sqsubset \kappa(N)] \;=\; \mathrm{cor}(\mathrm{Met}_{M\to N}) \cup \mathrm{cor}(\mathrm{Imm}_{M\to N}) \;\subset\; \kappa(M \to N). \tag{47}$$

The set $\mathrm{Imm}_{M\to N}(f)$ contains all possible further actions in the system N arising from interacting with $f \in \kappa(M)$. The response E of the anticipatory system N to predictions of the model M, the arrow 2 in (46), therefore comprises $\mathrm{cor}(\mathrm{Imm}_{M\to N})$.

Entailments within the model M are decoded back into the realization W (the arrow 2′ in (46)), whence the response E also includes $\delta(\kappa(M))$. Thus

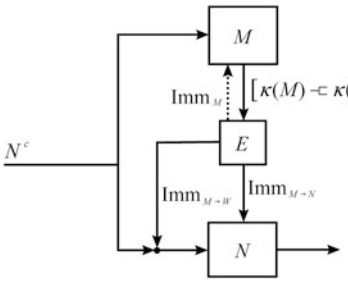
$$E = \mathrm{cor}(\mathrm{Imm}_{M\to N}) \cup \delta(\kappa(M)) \;\subset\; \kappa(M \to N) \cup \kappa(W). \tag{48}$$

Further,

$$\delta : \kappa(M) \to \kappa(W) \quad\Rightarrow\quad \delta \;\subset\; \mathrm{Imm}_{M\to W} : \kappa(M) -\!\!\sqsubset \kappa(W). \tag{49}$$

The dotted arrow 3 represents the updating function. The effector E must be able to reset the model M according to the controls that have been exerted on the system N. The details of this iterative 'remodelling' process may be found in [7]. The model M entails E which subsequently entails a renewal of M. This is the self-contained imminence Imm_M on $\kappa(M)$.

Diagram (46) may now be completely relabelled in terms of the metabolism bundle and the imminence mapping:



(50)

11 Anticipatory Imminence

An anticipatory system has to have more than one inherent dynamics, more than one thing that one may consider 'time' ('real time' or otherwise). To have anticipation of the system's own subsequent behaviour, something in the system must be running 'faster than real time'. This last phrase is an abbreviation, a terse summary that is interpreted thus: if the trajectories of the system *N* are parameterized by real time, then the corresponding trajectories of the model *M* are parameterized by a time variable that goes faster than real time. That is, if *N* and *M* both start at time t_0 in equivalent states, and if (real) time runs until $t_1 > t_0$, then *M* will have proceeded further along its trajectory than *N*. It is in this way that the behaviour of *M predicts* the behaviour of *N*: by looking at the state of the model *M* at 'present time' t_1, the system *N* gets information about its own state at some 'future time' $t_2 > t_1$.

It should be clarified that 'anticipation' in Rosen's usage does not refer to an ability to see or otherwise sense the immediate or the distant future—there is no prescience or psychic phenomena suggested here. Instead, Rosen suggests that there must be information about self, about species, and about the evolutionary environment, encoded into the organization of all living systems. He observes that this *information*, as it behaves through time, is capable of acting causally on the organism's present behaviour, based on relations projected to be applicable in the future. Thus, while not violating time established by external events, organisms seem capable of constructing an internal surrogate for time as part of a model that can indeed be manipulated to produce anticipation. The predictive model in an anticipatory system must not be equivocated to any kind of 'certainty' (even probabilistically) about the future. It is, rather, an assertion based on a model that runs in a faster time scale. The future still has not yet happened: the organism does not have definitive knowledge of future itself, but has a *model* of the future from which to act accordingly. An anticipatory model may be wrong, and wrong models often have disastrous consequences. Rosen's theory of anticipation is a general qualitative theory that describes *all* anticipatory systems. It is not a quantitative theory of *single* systems for which the lore of *large number* of systems, hence statistical reasoning, would ever enter into the picture. In other words, this theory has nothing to do with stochastics. «Je n'avais pas besoin de cette hypothèse-là».

Each imminence mapping in diagram (50) engenders its own time scale. This is because the imminence mapping verily defines a system's functional entailment pattern, through which emerge its faculties of simultaneity and temporal succession, which in turn characterize the system's inherent time scale. Inherent time scales thus arise from system decomposition, and different time scales imply the capability of nonequivalently fractioning a system into different component subsystems. Degrees of freedom in manifesting internal models allow 'internal surrogates of time' their multi-scaling and reversibility to produce new information. The idea that one has to have more than one scale of time in an anticipatory system generalises to alternate modes of system partition, and these lead to the wider notion of complexity (*ML*: Chap. 9).

In Sect. 3 above, we have encountered Aristotle's four causes as components of a mapping. Aristotelian analysis can be applied to any entailment structure κ, simply by asking, as Aristotle did, "Why κ?" (*ML*: Chap. 5). In any formalism, there is a natural flow from axioms to theorems, similar to the unidirectional flow of time. Consider an exemplary entailment that is the conditional statement '$p \to q$' (*ML*: 0.5). In it, the antecedent p is always *earlier* than the consequent q (this fact being reflected explicitly in the Latin prefixes *ante-* and *con-*). If there is a proof of q with p as hypothesis, then q must come *later* than p. The "arrow of time" is graphically illustrated in the corresponding arrow '$\to$ ' governing inferential entailments.

Inferential entailments do not have to occur in 'real time'; but they always characterize a time sense of *simultaneity* and *temporal succession*, whence function as portents and transducers (predictive classes (ii) and (iii) discussed in Sect. 9.2 above). Simultaneity and temporal succession are *ordinal* aspects of time that define *precedence*. Qualitative, ordinal time is the Greek concept of *καιρός* (*kairos*), moments marked along a timeline that is a totally ordered set (*cf. ML*: Chap. 1). In contrast, stretches of time-passing and waiting time are *cardinal* aspects of time that define *duration*. Quantitative, cardinal time is the Greek concept of *χρόνος* (*chronos*), lengths of time that can be measured. Chronometers—clocks and watches—do just that; they measure time intervals. *Kairos* is the algebra of ordinal time; *chronos* is the analysis (in the mathematical sense) of cardinal time. Cardinal numbers are *special* ordinal numbers, an illustration that quantitative is a *meagre* subset of qualitative (*ML*: 2.25). The traditional view of reductionism is (among other things) that every perceptual quality can and must be expressible in numerical terms. In our relational view, the features of natural systems in general, and of biological systems in particular, that are of interest and importance are precisely those that are unquantifiable.

The modelling relation establishes analogies between the natural and formal worlds, in particular those between causality and inference. When decoded, the inferential emergence of time from $p \to q$ becomes a cause-and-effect phenomenology. The three causal categories of material, formal, and efficient always respect this flow of 'formal time', because 'cause' p always precedes 'effect' q in 'natural time'. The material, formal, and efficient causation answers to the question "Why q?" require nothing further than *the entailment of* q. Final cause, however, requires something more of its effect q. The Greek term *τέλοζ* (*telos*, translated into *finis* in Latin), meaning 'end' or 'purpose', covers two meanings: the end considered as the object entailed (*i.e.*, q *itself*), or the end considered as the entailment of the object (*i.e.*, the *entailment of* q). To say that something is a final cause of q is to require that q *itself entails something*; indeed, a final cause of q must entail *the entailment of* q *itself* (*ML*: 5.18 & 10.3). This peculiar reflexive character of final causation leads to its anomalous temporal position, that it appears to be acting back on its own generating process. Final causation gives the appearance that that the 'future' is actively affecting the 'past'. In short, the ends entail the means.

A final cause of an effect is defined in terms of something entailed by the effect. In the Newtonian paradigm, a state can only entail *subsequent* states, which are necessarily *later* in time than present states. The presence of *time* as a parameter for state-transition chronicles then translates into *causes must not anticipate effects*. The rejection of finality in Newtonian derivative science is usually cast in this temporal context, in the form of a 'Zeroth Commandment' (*ML*: 10.5): "Thou shalt not allow the future to affect the present." Chapter 7 of [1] is an in-depth argument on why such rejection is misguided.

In the relational formulation of systems as networks of interacting processes, there is no (cardinal) time parameter. There are only mappings and their organizations in entailment networks. As noted above, the (ordinal) time sense is implied by the inherent directionality from cause to effect. Three out of the four Aristotelian categories of causation manifest the flow from past causes to future effects. In a mapping $f \vdash y$, 'that which entails' $f \vdash$ precedes 'that which is entailed' $\vdash y$. In the exceptional category of final cause, functional entailment $y \vdash$ (i.e., that y is in the imminence of f, $y \in \mathrm{Imm}(f)$) may be interpreted as an action of the future on the present. This paradoxical appearance of 'acausality' may be resolved by noting that prediction is simply the anticipation of future events from past ones that entail them, and that, in the first place, is precisely what causality itself is about.

We have discussed natural law and the modelling relation in Sect. 3 above. We have now also seen that the notions of causality, inference, and entailment are tied to imminence, a sense of determination and inevitability. When reformulated in terms of the sense of time, determination and inevitability of effects from causes translate temporally not only into *postdictability*, the entailment of past from present, but also into its reverse *predictability*, the entailment of future from present. Stated yet otherwise, natural law entailment makes the present serve as a surrogate for both past and future.

Through the imminence mapping Imm, functional entailment pulls the future into the present, creating the capacity for *anticipation*. Imminence lets a system use its entailment pattern to predict something about what will happen to it later. The internal predictive model in an anticipatory system *augurs future events*. Thus equipped, an anticipatory system can access its present and its future at a common instant of real time, allowing it to control its present actions in the light of the predicted future.

The imminence mapping anticipates.

To see a world in a grain of sand
And a heaven in a wild flower,
Hold infinity in the palm of your hand
And eternity in an hour.

—William Blake (1803)
Auguries of Innocence

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Synapses in Digital Medium: Computational Investigations of Neural Basis of Anticipation

Slawomir J. Nasuto and Yoshikatsu Hayashi

Abstract Anticipation is an emerging concept that can provide a bridge between the deepest philosophical theories about the nature of life and cognition on one hand and the empirical biological sciences steeped in reductionist and Newtonian conception of causality. Three conceptions of anticipation have been emerging from the literature that may be operationalised in a way leading to a viable empirical programme. The discussion of the research into a novel dynamical concept of anticipating synchronisation lends credence to such a possibility and suggests further links between the three anticipation paradigms. A careful progress mindful to the deep philosophical concerns but also respecting empirical evidence will ultimately lead towards unifying theoretical and empirical biological sciences and may offer progress where reductionist science have been so far faltering.

Keywords Strong anticipation · Delayed differential equations · Neuron models

1 Introduction

The received wisdom of dominant natural sciences methodologies, inspired by successes of XIX century physics, is based on a narrow, Newtonian interpretation of causality, where every system or phenomenon is entirely reducible to some mechanism, in which instantaneous state changes are fully determined by concurrent and past interactions with the environment. This implies in turn that any system can be fully described in mechanistic, i.e. deterministic and computable, terms. However, anticipation appears to be a fundamental property of living systems as much as forming a basic feature of cognition [1, 2]. It seems to pervade throughout

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the biota and hallmarks of anticipatory behaviour have been observed in unicellular organisms [3] and in plants [4]. In general, it is referring to the ability of even the simplest organisms to orient themselves to the future or, in other words, to modify their state at some time instant as if taking into account information from some later time instant. Its importance stems in part from recognition that both living and cognitive processes share in common the capacity for active pursuit of environmental conditions of their choice, in contrast to inanimate objects or systems which are purely mechanistically reactive to immediate and past external forces or influences and have no inner potential to systematise the regularities of the mutual interactions with the environment. Such potential, if it exists within a system such that it prolongs the system's existence, is at the heart of a circularity easily recognised in the definitions of life put forward in theories proposed by many researchers, for example Maturana and Varela [5], Rosen [2] or Nadin [6]. Rosen and Nadin implied in their definitions that the living system, i.e. a system exhibiting a capacity to anticipate, as a whole must possess sufficient complexity, rendering it effectively noncomputable.

That is not to say though, that system components cannot be described in mechanistic, i.e. effectively computational, terms. Consistent with above, the definition of anticipation as stated above is insufficient. It should be further operationalised by identifying the supporting mechanisms and their organisational structures. This is necessary in order to present a viable attempt at closing the gap between such theoretical constructs and empirical science, dominated by methods geared solely towards identification of mechanistic accounts, and to avoid the accusation of postulating some unexplained phenomena of the kind that plagued the discussions between the vitalists and proponents of mechanistic science [7].

However, before the steps towards such operationalisation could be outlined, given the growing wealth of research and empirical evidence [8, 9] and plurality of ways in which anticipation has been characterised in the literature, there is a need to clarify first the landscape of conceptions of anticipation. This is subject of Sect. 2. Section 3 will overview research on anticipating synchronisation, one of the mechanisms that may subserve anticipatory processes in the nervous system. Section 4 considers the computational evidence for possible neural realisations of anticipating synchronisation before concluding the paper.

2 Anticipation—Definition, Types

Out of a number of researchers aiming at characterisation of life, Rosen was among the first to concentrate on the notion of anticipation as one of the most fundamental characteristics of living systems [2]. Louie quotes the original definition provided by Rosen [10] of an anticipatory system as such natural system that contains an internal predictive model of itself and its environment allowing it to determine the change of current state taking into account the predicted future state. Rosen goes to great length to define precisely what he means by a modelling relation and to distinguish it from mere simulations (computational models). As Louie succinctly states, simulations lack an important property of models, in which the inferential entailments represent the causal entailments present in the modelled process.

Dubois introduces the concept of strong and weak anticipation [11, 12]. Anticipation is strong if the system determines its current state change using past and present states as well as explicitly anticipated future states of the system itself. Anticipation is weak if the current state change depends, in addition to past and present states, on future states anticipated from a predictive model of the system. Dubois' definition of strong anticipation depends on a concept of incursive (implicit recursive) equations.

Stepp and Turvey, after Dubois, also propose to consider weak and strong categories of anticipation although their definitions of these categories seem to differ somewhat from Dubois' [13]. According to Stepp and Turvey, weak anticipation does entail use of model-based predictions in determining the current state changes, whereas strong anticipation does not rely on explicit internal (formal) model but on dynamic coupling with the environment and systemic lawfulness.

Freddolino [3] introduced the notion of predictive dynamics, whereby the organism's internal dynamics are coupled to an environmental variable, which is temporally correlated with future values of another variable that the internal dynamics anticipate.

Finally, Bickhard's account of anticipation rests on the system's ability to anticipate the flow of interaction [14].

It is interesting to consider the relationships between these various accounts of anticipation. Dubois considers Rosen's definition as of weak anticipation type. Dubois's strong (incursive) anticipation may be interesting from a formal perspective but is unrealistic as a vehicle for biological modelling, as it requires explicit use of future states of the system and thus is inconsistent with causality. No other conception of anticipation discussed here is inconsistent with causality. That is true even for Rosen, as effectively his account of Aristotelian final cause is by use of a forward model but otherwise is causal in a reactive, but not strictly Newtonian, sense. Rosen's anticipatory system definition entails Freddolino's predictive dynamics.

Stepp and Turvey discuss the difference between weak and strong anticipation by considering an outfielder problem. In many ball games, a player is required to catch a thrown ball, so he must coordinate his movements so that his trajectory on the ground will intersect the trajectory of the ball flying through the air in such a way that will allow him to intercept the ball. According to Stepp and Turvey, the model based approach would posit an explicit calculation of the ball trajectory using Newtonian mechanics and some assumption (or measurement) on the ball initial conditions. This knowledge of the trajectory can then allow timely arrival at the position of the predicted impact point.

Their conception of weak anticipation conflates the model and simulation based means of anticipating the future. This is evident in their recapitulation of many criticisms raised in cognitive science related to the problem of representations and symbols typically levelled at computationalism, which poses unresolved philosophical difficulties amounting to a lack of grounding and an inability to account for organism sense-making. This, however, does not recognise the power of the definition of a model introduced by Rosen. Rosen introduced his definition of anticipatory systems in order to capture what he perceived to be a fundamental characteristic of living. Although the use of a model by the anticipatory system postulated by Rosen is similar to that considered by Stepp and Turvey (to provide information about future state), he nevertheless considers it in a very specific way, imposing constraints not only on the systematic relationship between the model states but also on the way model state transitions relate to the evolution of the natural system being modelled, see Fig. 1.

Such formal definition of a model capturing a specific set of physical couplings existing within a subsystem (the model) and their casual couplings to the system it is supposed to model differentiates it from a simulation, where the internal simulation entailments and causal entailments in the natural system being modelled may be related in a different way. However, it is the latter conception of a 'model', but merely a simulation in Rosen's nomenclature, that underpins the computationalism. Stepp and Turvey also tacitly assume that Rosen's definition must refer to modelling a natural system based on fundamental physical laws governing it. In fact, any phenomenon may be modelled in various ways, depending on which characteristics are captured, and, as Rosen posits, the model is never a complete description because it is blind to changes in natural system behaviour due to characteristics not present in the model [2]. In fact, a model can only be identified in any organism within a subset of causal, physical interactions between some of its constituents which are casually affected by the sensory inputs, these in turn casually linked to the characteristics of the system being modelled. Thus, modelling relation can only be concerned explicitly with the natural system characteristics that are casually interacting with an organism (what is not perceived/measured is not modelled). Not perceived characteristics of the natural system can only be reflected in the model implicitly, and only in so far as they are coupled to the perceived (and hence modelled) characteristics by systemic lawfulness of the natural system. In the ball catching example the outfielder has no access to the forces acting on the ball. In fact, the only information he obtains about the ball is carried by light reflected off the ball and causing activation pattern changes in his retinas. Thus, it is the changes in some characteristics caused by the ball motion in the image plane that could be explicitly reflected in a model according to Rosen.

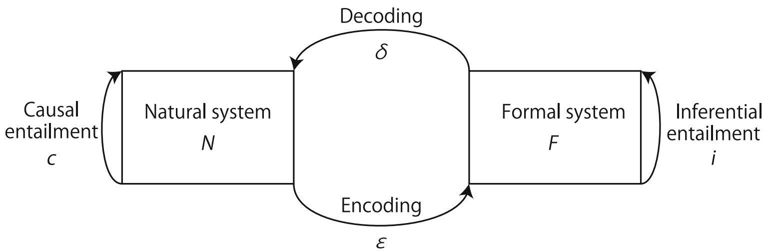

Fig. 1 Diagrammatic representation of Rosen's modelling relation

It is interesting to note that it is exactly such characteristics that serve Stepp and Turvey's first example of strong anticipation, which they argue is an appropriate account of anticipation in cognition. They posit that accounts based on the immediate coupling of environmental variables (changes in ball position) with internal variables, optical acceleration or optical trajectory, via simple control laws, which impose that coupling, are most appropriate of cognitive capacity. The actual point of contention between Rosen's and Stepp and Turvey's concepts of anticipation seems to be not the use of a model (given Rosen's definition and considering that even in Stepp and Turvey's example, the optical variables can be considered as models of ball movement) but the way it is used. For Rosen would use 'model' as a predictive forward model, explicitly relating to the future states, whereas Stepp and Turvey use it only to provide an instantaneous coupling driving the system dynamics. That the distinction between their positions is not clear cut may be reflected in the fact that both frameworks would embrace Freddolino's predictive dynamics as consistent with their postulations. Indeed, it seems that whether the environmental variable is used by a predictive internal model that triggers a change in gene expression, or by driving a fast dynamics accounting for the gene expression change, is a matter for empirical investigation rather than a paradigm shift. Such issues could be investigated, and settled on a case by case basis. In some, evidence may be indeed in favour of explicit prediction and in others, a form of direct dynamic coupling can be more consistent with the evidence.

Interestingly, Stepp and Turvey's strong anticipation is akin to the form of couplings required by direct perception postulated in ecological psychology. It seems also fully consistent with Bickhard's interactivist model [14].

In fact, the way anticipation is conceived by Rosen is also consistent with Bickhard, as for the living system, its internal model itself must be realised within the closure to efficient causation [2]. Although not introduced in the definition of anticipatory systems, we can invoke the closure to efficient causation, because anticipatory systems definition of living simply emphasises a particular characteristic of an organism, the final cause. The complementary definition also introduced by Rosen, an (M,R) system, of which closure to efficient causation is an essential characteristics, captures the properties of living (metabolism, repair and reproduction), which Bickhard characterised in nonequilibrium thermodynamic terms. That is, as far as the anticipatory system definition is concerned, the inferential entailments within the model are themselves causal entailments within the closure to efficient causation of the living system.

The second example of strong anticipation discussed at length by Stepp and Turvey is a relatively new dynamical phenomenon of anticipating synchronization introduced by Voss in [15]. It is based on dynamic (causal) coupling where a master is driving a slave system, which uses its own past states in order to determine master's state change. It is distinct from all the forms of anticipation discussed so far. It uses lags as opposed to leads of the incursive models of Dubois, and as Dubois remarked, incursive systems are not reducible to delayed systems by a simple change of variables [12]. It is also different from the predictive dynamics of Freddolino or the anticipatory system concept of Rosen, in that its anticipatory capability comes from its own delayed dynamics, rather than from environmental systemic lawfulness or a feedforward anticipatory model. Nevertheless, it is also based on couplings and is reactive, consistent with the conceptions of anticipation put forward by Rosen, Bickhard or Freddolino. It is important to note that it is not a complete system, in which anticipation might be linked with a purposeful behaviour but simply an anticipatory mechanism. Thus, its ability to anticipate has no relationship to any final cause or fulfilling any specific intrinsic purpose; indeed examples of the physical realisation of anticipatory synchronization have been demonstrated in optic and electronic systems [13, 16]. Its anticipatory characteristics stem from the fact that it is an example of a delayed dynamical system.

It is interesting to compare how the anticipatory mechanisms discussed acquire their ability to react to the future, see Fig. 2. Of these, only the incursive mechanism proposed by Dubois is acausal as it assumes direct access to future states in order to determine the present state change. Rosen's predictive model concept delegates the acquisition of the information about the future states to the model; given the model output, it is reactive to the information available at present. The remaining mechanisms are also reactive and acquire their anticipatory characteristics by appropriate couplings to the environment or existence of memory mechanisms.

Of particular interest here is the concept of anticipating synchronisation. Its constituent characteristics, dynamic couplings, recurrence and delays, make it a plausible candidate that could account for at least some cases of anticipatory behaviour in biology and cognition. In particular, the nervous system is abundant in recurrent coupling at different levels, with recurrent loops formed locally between excitatory primary neurons and inhibitory interneurons and with feedforward connections between any two regions most often accompanied with feedback pathways [17]. Interestingly, it is such a countercurrent architecture that plays a pivotal role in Deacon's argument linking, at the systems level, the dynamic interactions subserving information processing to thermodynamic principles [18]. Deacon's elaborate theory grounding living and meaning in thermodynamics of neural processes is again very consistent with Bickhard's interactivism [14].

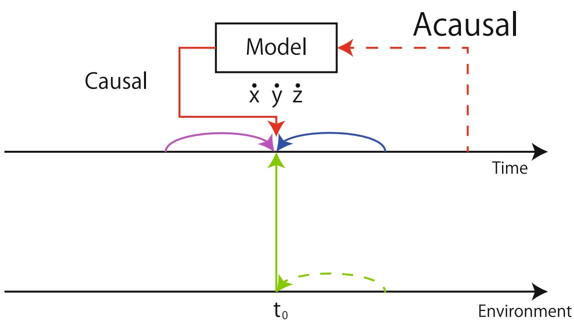

Fig. 2 Diagrammatic representation of how different anticipatory mechanisms relate to causality. *Blue*—incursive systems by Dubois; *Red*—predictive model by Rosen; *Magenta*—anticipating synchronisation by Voss; *Green*—predictive (acausal) dynamics by Freddolino

The consequence of finite propagation speeds of action potentials is that any neural system embedded in such recurrent feedback loops will inevitably receive the effects of its own activity after some delay, which is the basic structural requirement necessary for anticipating synchronisation to occur. Thus, it is a viable hypothesis that the nervous system could support internal organization corresponding to anticipating synchronisation and consistent with the model requirements of Rosen or interactive coupling of Bickhard.

In the next section, we will briefly review some literature on anticipating synchronisation with a particular emphasis on works attempting to explain how it could be realised in the nervous system and point to some empirical evidence that may support such a hypothesis.

3 Anticipating Synchronization

Anticipating synchronisation is a relatively new phenomenon introduced in 2000 by Voss [15]. It can manifest itself in systems with memory, which in dynamical systems amount to delay differential or difference equations. Anticipation appears in unidirectionally coupled dynamical systems with a master providing input into a slave system. In the first scheme, the master is a system with memory and the slave is memoryless,

$$\dot{x} = -ax + f(x(t-\tau)) \tag{1}$$

$$\dot{y} = -ay + f(y) \tag{2}$$

The system is asymptotically stable and converges, after some initial transient period, to a globally stable synchronisation manifold $x = y(t-\tau) := y_\tau$. This implies that $y(t) = x(t+\tau)$, i.e. on the synchronisation manifold the slave anticipates the future dynamics of the master. This phenomenon is not dependent on the form of the systems dynamics, f. Thus, it should also be valid for highly dimensional chaotic master with memory. It is interesting because it indicates a potential for anticipation of systems whose behaviour has an appearance of a stochastic process [15].

Voss also introduced another system where master has no memory, which instead is present in the slave system, Fig. 3.

$$\dot{x} = f(x) \tag{3}$$

$$\dot{y} = f(y) + K(x - y_\tau) \tag{4}$$

Voss discussed the existence of the invariant synchronisation manifold and numerically analysed its stability, demonstrating that indeed the slave will stably anticipate the master for suitable combinations of coupling strength, K, and delay, τ.

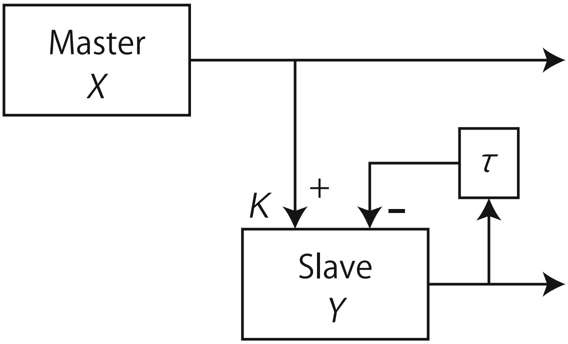

Fig. 3 Diagram of an anticipating synchronisation, in which master system is driving unidirectionally the slave system

Voss recognised that the anticipating synchronisation, due to its simplicity, may play an important role in natural systems, specifically suggesting that it may augment the models of neural information processing based on arrays of phase locked oscillators. Elaborating this idea further in another paper he showed that an array of unidirectionally coupled slave systems with memory can achieve anticipation on time scales exceeding the characteristic times scales of the chaotic dynamics [19], Fig. 4.

The equations for a chain of m unidirectionally coupled slave systems are

$$\dot{x}_1 = \mathbf{f}(x_1) \tag{5}$$

$$\dot{x}_i = \mathbf{f}(x_i) + \mathbf{K}\left(x_{i-1} - x_{i,\tau}\right), i = 2, \ldots, m + 1 \tag{6}$$

The anticipatory behaviour in chains of coupled oscillators is even more striking than in two coupled systems, amplifying the apparently noncausal behaviour, with the signal travelling against the causal direction with the last slave not being causally connected to the master. It is important to stress that this behaviour is solely due to delays occurring in the coupling terms. All the equations defining systems in the chain are causal, i.e. no knowledge of future states, predicted or derived from the systems, is necessary in order to calculate the instantaneous change of the state in such systems. In some cases such chains of oscillators have similar stability properties to the analogous chains of identically synchronising oscillators.

Pyragas and Pyragienè investigated the effect of the coupling scheme on the anticipation time in anticipating synchronisation [20]. They proposed a new coupling scheme that, for two systems, achieves stable anticipation times comparable to the characteristic times of the chaotic dynamics of the master system, by taking into account the topology of its strange attractor. The phase lag compensating coupling works for Rossler-like chaotic systems, in which a strange attractor is dominated by a 2D unstable spiral manifold and a 1D stable manifold formed around a saddle focus. The anticipation time is much longer than the corresponding characteristics of the original coupling scheme proposed by Voss.

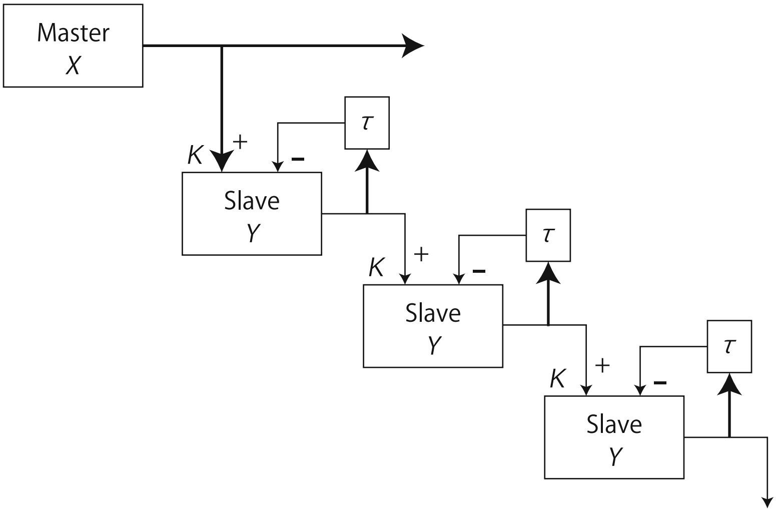

Fig. 4 Cascade of anticipating synchronisation systems

Calvo et al. analysed anticipating synchronisation in the case of linear systems to emphasise the fundamental properties of this phenomenon [21]. They stress that the nonlinearity of the dynamics does not play a role in achieving it, indeed it may make it more difficult to attain, presumably due to decay of the correlation between $y(t)$ and $y(t-\tau)$ for higher τ, which makes the adjustments to $\dot{y}(t)$ difficult to drive towards anticipating manifold [13]. The control perspective is particularly interesting, as it casts the anticipating synchronisation as a servo mechanism control with the delayed term $y(t-\tau)$ playing the role of an error signal and $x(t)$ as the reference signal. The assumed linearity and time invariance of the dynamics allows for recasting the equations in terms of the transfer functions, feedforward and feedback gains and calculation of the stability condition in the (k, τ) parameters plane. The stability region obtained in this way agrees in form with numerical simulations performed by Voss and others for nonlinear dynamics, illustrating a universal nature of the tradeoff between coupling gain and delay.

Ciszak et al. review the numerical and analytic research concerning anticipating synchronisation in excitable systems [16]. They also were one of the first groups demonstrating anticipating synchronisation in electronic hardware. The numerical investigations of the stability region of an anticipating manifold for such excitable systems driven by common and uncommon forcing noise illustrate robustness of the phenomenon. The uncommon forcing noise case is particularly interesting as it corroborates the claim that anticipating synchronisation need not require an exact match of the master and slave dynamics [13]. The authors also observe that the cascading of slaves proposed by Voss [19] improves anticipating synchronisation in excitable systems subject to uncommon forcing.

Stepp and Frank complement the numerical investigations of driven anticipating synchronisation by providing an empirical approach for estimating the parameters of anticipating synchronisation, k and τ, and the variance of forcing noise [22]. Considering the linear coupling term ('force') as a first-order approximation of a nonlinear coupling in a Taylor expansion, allows them to consider nonlinear coupling by analogous first-order approximation of 'force' expansion in a different basis. Interestingly, their parameter estimation method is also applicable in such a case.

Stepp and Turvey provide a further overview of anticipating synchronisation properties in their argument in favour of basing it at the heart of a discourse on anticipation and representation in cognitive science [13]. They illustrate that it is easy to obtain an array of anticipating times by simply coupling with a single master a number of mutually independent slaves, each with a different delay in the coupling term. A shift of rhythm can also be generated by switching the coupling of the slave between different masters, and the slave tends to remain anticipatingly synchronised with the master even after switching off the coupling. The above characteristics are representative of predictive homeostasis, involved in control of phenomena related to circadian synchronisation. They also consider Pavlovian conditioning, one of the most fundamental forms of adaptation and learning proposed in psychology, as a special case of anticipating synchronisation.

4 Anticipating Synchronisation in Neural Systems

Given the case presented by Stepp and Turvey for considering anticipating synchronisation as a putative example of representation-less predictive mechanism that may underpin cognitive processing, of particular interest are the studies investigating existence and properties of anticipating synchronisation in neural systems. Ciszak et al. in their investigation of anticipating synchronisation in excitable media in fact discuss two dynamical model neuron classes, corresponding to different dynamical mechanisms of spike generation and different neural excitability modes [16]. Class One, an integrator, represented by Adler or Morris-Lecar models, generates a spike via a saddle-node bifurcation on an invariant circle, whereas Class Two, a resonator (Hodgkin-Huxley or Fitzhugh-Nagumo), achieves action potential via a Hopf bifurcation. Numerical results indicate that both types can function within anticipating synchronisation arrangement also in case of various forms of forcing.

Pyragienè and Pyragas [23] further demonstrate that anticipating spike synchronisation may occur under rather weak conditions, with mismatched dynamics of master and slave neurons and even with no self-delay in the slave system; the main requirement being that the mean autonomous firing frequency of the slave neuron is greater than that of the master neuron.

The studies discussed above relax the requirements of the original anticipating synchronisation scheme of identical dynamics of master and slave. They also show that dynamics of excitable systems, which is a hallmark of neuronal excitability, is also amenable to such coupling.

The study by Matias et al. [24] brings anticipating synchronisation a step closer to biological reality by demonstrating that it can be exhibited by a canonical microcircuit composed of excitatory and inhibitory neurons coupled by chemical synapses. The problem they address is how to achieve the anticipating synchronisation effect without an explicit self delay in the slave neuron. Although inclusion of such self delay term in differential equation is a common approach in models of systems with memory or delays, it is nevertheless a simplifying abstraction, which may have no obvious structural or functional counterpart in the modelled physical system. Matias shows that its effect can be achieved using ingredients commonly encountered in the nervous tissue. In many brain structures, including the cortex, the neurons can be divided into two main classes. The excitatory neurons are considered to be the main drivers of the information processing, receiving nonlocal inputs and sending the outputs to distal regions. The interneurons, which are predominantly inhibitory, typically form local connections, receiving inputs from nearby cells and making inhibitory synaptic contacts on local excitatory neurons. Matias used such canonical microcircuit of excitatory slave neuron reciprocally connected with an interneuron in order to implement a self delay of slave neuron. Although there are no explicit delays in their model, the underlying principle is qualitatively similar to a finite dimensional approximation of pure delayed system via a cascade of ordinary differential equations. The effect is achieved due to individual time constants of equations modelling the canonical microcircuit components amounting to the slower response times tracking the varying input from the slave neuron. With an appropriate choice of synaptic strengths within the circuit, an anticipatory synchronisation can be achieved. In fact, depending on the synaptic strengths these authors observed a smooth transition between delayed and anticipating synchronisation.

Given the computational studies of anticipating synchronisation and its attractive properties, including explorations of existence of such dynamic behaviour in models of neural circuitry, what evidence could corroborate its existence and shed light on its putative role in the brain?

As mentioned earlier, the nervous system is abundant in reciprocal connections at multiple levels and the resulting signal propagation delays [17] and the work by Matias et al. indicated the possibility of achieving anticipating synchronisation within neural circuits coupled with chemical synapses. The same group further explored the interplay between anticipating synchronisation and the spike timing dependent plasticity (STDP) [25]. STDP has been proposed as a biologically plausible learning rule that incorporates Hebbian learning postulate for spike trains. Within a single rule it encompasses long term potentiation (LTP), if the presynaptic neuron fires a couple of milliseconds before the postsynaptic one, and long term depression (LTD), if the temporal order of pre- and postsynaptic spikes is reversed. Although there are still discussions within the neuroscience on the scope of STDP as a universal synaptic plasticity mechanism [26], the empirical evidence suggests that temporally sensitive learning rules are widespread, if diverse, within a single mammalian brain and across species. The transitions between delayed and anticipatory synchronisation within a canonical microcircuit investigated in [25] can have a stabilising effect on neuronal dynamics in addition to other forms of homeostatic plasticity [27]. Indeed, Matias et al. report that anticipating synchronisation together with STDP rules lead to a synaptic weights distribution consistent with empirical findings in the cortex.

It is interesting to note the work by Matias et al. in this context [28]. They concentrated on the data from Brovelli et al. [29], who recorded data from somatosensory and motor cortices in monkeys engaged in a cognitive task. The authors estimated phase synchronisation of Local Field Potentials between different areas as well as directionality of influence, measured by Granger causality. Their data indicated that a clear interaction asymmetry between two somatosensory cortical areas may be accompanied by either positive or negative delay, as measured by a phase difference. Matias et al. demonstrated the emergence of anticipating synchronisation in two unidirectionally coupled neural populations, extending their neural canonical microcircuit model with synaptic inhibition [24]. The model qualitatively reproduced time lags, coherence and Granger causality spectra consistent with corresponding experimental data estimates. This is one of the first studies demonstrating experimental evidence for anticipating synchronisation in the brain. Interestingly, together with the computational studies reported in this section and focusing on micro-level information processing, it also suggests that this dynamic phenomenon may span different levels of information processing from micro- through meso- to macro-level.

5 Conclusions

Taking anticipation seriously in research offers an exciting opportunity to bridge the gap between, on one hand, experimental biology—a dominant modus operandi of biological sciences, firmly entrenched within reductionist and Newtonian interpretation of causality and, on the other hand, the theoretical works mindful of pitfalls and philosophical vacuity of computational accounts [1, 14].

We have presented a brief overview of some of the main characterisations of anticipatory mechanisms and tried to highlight their putative similarities and differences. The emerging common ground entails the importance of interactive coupling between internal processes closed to efficient causation, and the environment. When the emerging characteristic of such coupling is that it is oriented towards the future, i.e. anticipatory, this may give rise to normative function, as such anticipation may be correct or wrong, and this in turn may give rise to the proper grounding and ultimately, sense making. The flip side of anticipation is that, as it inherently must account for the future, in the context of organism survival, it must be involved in the organism's purposeful behaviour. Thus, anticipation seems to provide the common mechanism integrating such concepts as sense making and teleology. Although they have been recognised separately as important characteristics of living systems, they so far have eluded a unified treatment, which would also allow for formulating an effective empirical research programme.

We have seen some evidence in the form of computational and empirical studies that point to the possible signatures of anticipatory mechanisms in the nervous system, with a focus on anticipating synchronisation. Study of such mechanisms must by default be interdisciplinary and mindful of the deep theoretical constraints and philosophical considerations, lest it should turn into yet another strand of reductionist endeavour.

Three mechanisms put forward in literature seem to be complementary and consistent with philosophical arguments from first principles. They share in common that they account for the future by using information about future state (explicitly or implicitly) in determining a present state change. Nevertheless, they are otherwise quite consistent and viable accounts of causality, albeit extending beyond the Newtonian conception of it.

The three anticipatory modes—feedforward model anticipation, predictive dynamics and anticipating synchronisation appear to be complementary although some commonalities have been already highlighted within the strong anticipation framework [13]. Anticipating synchronisation can be easily incorporated within the anticipatory system framework—with a slave with delayed self-feedback serving as a model of future environment behaviour. In turn, whether the delayed self-feedback is needed or not could depend on the nature of the coupling between the system and the environment, and the spatiotemporal correlations within the latter. The more regular temporal dependencies are between different environmental variables, the less the self-feedback delay is required to predict the future behaviour. Thus, the predictive dynamics and anticipating synchronisation may turn out to be two ends of a continuous spectrum of anticipatory couplings, indexed by the amount of utilised self-feedback delay. Moreover, Dubois showed [12] that at least some classes of systems with delayed self-feedback can be equivalently represented as dynamical models using only current time state and no delay, and appropriately rescaled time constant; as if their evolution were running on a faster time scale. Thus, at least for such systems, predictive model or self delay based anticipating synchronisation may in fact be equivalent formulations.

A similar conclusion can be derived from the control theoretic reformulation of anticipating synchronisation presented in [21], indicating that a feedforward model may or may not be actually needed to account for final cause. Rather, it may be an empirical question as to which formulation is appropriate, given the structural and causal entailments within the represented system. So it may be up to the experimentalist to consider this on a case by case basis and establish, in any given system, which of the two—feedforward predictive model or anticipating synchronisation—is a model (in the sense of Rosen) or simply a description (a simulation).

In any case, anticipating synchronisation can only be a building block, not the whole story. As follows from the original abstract formulation and demonstrations of the phenomenon in physical systems, anticipating synchronization clearly is not restricted to cognitive systems, not even biological ones. In order to form a foundation accounting for such fundamental notions as normativity, purposeful behaviour or sense making it must emerge as a coupling within a system closed to efficient causation. Some steps investigating the putative role of anticipating synchronisation have been undertaken already at the behavioural level [30]. The recently introduced animat platform, a robotic system controlled in a closed loop by cultures of biological neurons, will also provide a suitable paradigm to start addressing questions about the nature of anticipation and its constituent mechanisms [31]. It offers a constructive way towards naturally spanning the divide between empirical sciences and theoretical or philosophical accounts, as it brings to the foreground questions that clearly have implications for both. To sum up, the emerging picture points to an exciting, albeit a complex path forward. Time will tell if we are on the right path to start answering some of the most fundamental questions troubling us about our own place within the physical, inanimate world. We can only anticipate the future.

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Representation and Anticipation in Motor Action

Thomas Schack, Christoph Schütz, André Frank Krause and Christian Seegelke

Abstract This paper introduces a cognitive architecture model of human action, showing how it is organized over several levels and how it is built up to connect the anticipation of future states and related action execution. Basic Action Concepts (BACs) are identified as major building blocks on a representation level. These BACs are considered cognitive tools for mastering the functional demands of movement tasks. Different lines of research, ranging from complex action to manual action, are presented that provide evidence for a systematic relation between the cognitive representation structures and the actual motor performance. It is concluded that such motor representations provide the basis for action anticipation and motor execution by linking higher-level action goals with the lower-level perceptual effects in the form of cognitive reference structures.

Keywords Representation structure · Anticipation · Motor hysteresis · End-state comfort · SDA-M · Motor hysteresis

1 Introduction

Almost all of our daily activities require that we plan, execute, and control our movements in a skillful manner. Strictly speaking, movement provides the only means by which we not only physically interact with the world, but also actively

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operate on this world. Consequently, and somewhat exaggerated, it has been proposed that the entire purpose of the brain is to produce movement, and all sensory and cognitive processes can be regarded as inputs for future motor outputs [1, 2].

Typically, our motor behavior seeks to achieve action goals related to the environment. Thus, given a certain action goal, the motor system's task is to generate a movement that will attain this goal, and hence, bring about a change in the sensory environment. This applies not only to rather complex movements such as in sport contexts, but to manual actions as well.

Bernstein [1] as one of the first scientists already acknowledged the fundamental role of sensory feedback processing in the control of voluntary movements, and pointed out the goal-directed character of motor actions. He explicitly emphasized the importance of anticipation in realizing any type of goal-directed motor act, and that any voluntary motor action cannot be initiated without a model of what should result from the planned action. This idea is expressed in his 'model of the desired future' (i.e., a model of what should be) which is supposed to play an important role in motor control. Consequently, such a model must possess the capability to form a representation of future events by integrating information from past (i.e., memory) and present (i.e., sensory) events in order to generate motor commands that transform the current state in the sensory environment into the desired state (i.e., achieving the action goal). Bernstein's model reflects the idea that motor control is based on cognitive representations, which serve goal-directed motor planning, and that these representations reflect the functional movement structure.

Building on this general idea and more recent research by Hoffmann, Rosch, Prinz, Jeannerod and others [3–7], Schack and colleagues have proposed a cognitive architecture model (see Table 1) which views the functional construction of actions on the basis of a reciprocal assignment of performance-oriented regulation levels and representational levels [8–10]. According to this view, basic action concepts (BACs) are thought to serve as major representation units for movement control. Analogous to the well-established notion of basic concepts for objects [6], BACs are considered the mental counterparts of functionally relevant elementary components or transitional states (body postures) of movements. BACs are based on the cognitive chunking of body postures and movement events concerning common functions in realizing action goals. In contrast to basic object concepts, they do not refer to behavior-related invariance properties of objects, but to perception-linked invariance properties of movements. Consequently, BACs can be understood as representational units in memory that tie together the functional and

Table 1 Cognitive architecture (levels) of motor action (modified from [9, 10])

Code	Level	Main function	Tools
IV	Mental control	Regulation	Symbols strategies
III	Mental representation	Representation	Basic action concepts
II	Sensorimotor representation	Representation	Perceptual representations internal models
I	Sensorimotor control	Regulation	Motor primitives Basic reflexes

sensory features of movements. The integration of sensory features refers to the perceptual movement effects, whereas the functional features are derived from the action goals. Taken together, such movement representations provide the basis for action anticipation and control by linking higher-level action goals with the lower-level perceptual effects in the form of cognitive reference structures.

The integration of BACs into higher-order representation structures has been investigated and simulated with a number of different methods [9, 11, 12]. One way to ascertain cognitive representation structures is provided by the *Structural Dimensional Analysis—Motoric* (SDA-M [13]). The SDA-M procedure determines relational structures in a given set of concepts, and has been applied in a number of different studies such as complex action in sport contexts [14, 15], manual action [10], and rehabilitation settings [16]. Importantly, this method allows for a psychometric analysis of the structures without necessitating participants to give explicit statements regarding their representation, but rather through means of knowledge-based decisions in an experimental setting. In general, results of these studies have provided convincing evidence for a mutual overlap between the representation structures and the actual motor performance. In the following, examples of such studies are presented to demonstrate the broad spectrum of potential applications of this approach.

2 Representation Structures of Complex Motor Action

Schack and Mechsner [14] demonstrated differences of representation structures between skilled athletes and novices in the tennis serve. In skilled athletes, representation structures had a distinct hierarchical organization, were remarkably similar between individuals, and were well matched with the functional and biomechanical demands of the task. In comparison, representation structures in novices were organized less hierarchically, exhibited a higher variability between individuals, and were less well matched with task demands. This systematic relationship between mental representation structures and expertise has been successfully reproduced in a number of complex actions, such as golf, soccer, wind surfing, volleyball, gymnastics, and dancing [17–21].

While these differences between skilled athletes and novices suggested that representation structures changed as a function of skill level, experimental evidence for a change of the representation over the course of learning was lacking. Frank and colleagues [22] therefore investigated the effects of movement practice on representation structures during early skill acquisition. To this end, novice golfers were randomly assigned into a practice and a control group. Participants in the practice group were asked to perform a total of 600 golf putts over a period of 3 days. Using the SDA-M method, representation structures of the practice and the control group were measured before and after this acquisition phase. Results showed that the structures of the practice group had changed between tests, while the structures of the control group had not. The structural changes in the mental representation of the practice group resulted in the formation of functionally meaningful clusters and, over the course of learning, rendered the mental representation more similar to an expert structure. These findings indicate that practice results not only in a better motor control and anticipation of future states but furthermore in functional adaptations in the mental representation of complex actions.

Bläsing and colleagues [23] used the measurement of mental representation structures to study the interaction of the body schema and multiple, effector-specific actions. The body schema was defined as the multimodal representation of the body that integrates somatosensory, proprioceptive, vestibular, and visual information. The authors measured the cognitive representations of body parts and actions of two patients with congenitally absent limbs (one with, one without phantom sensations) and compared those to the representation structures of a group of paraplegic participants and two healthy control groups. Structures of the control groups and the paraplegic group revealed a clear separation of upper body, lower body, fingers and head, as well as a clear clustering of the different actions with their respective effectors. The representation structure of the patient with phantom limbs closely resembled the structures of the control groups, whereas the structure of the patient without phantom limbs exhibited no modularity of the body schema. However, actions were still clustered with the action-specific effector of the patient (i.e., the right toe). These results provided evidence for a link between motor actions and their respective effectors on the level of mental representation.

To study the functional link between representation and motor execution Land et al. [8] measured the representation structures and the kinematic structures of the full swing in golf. The authors asked to what extent the output at the kinematic level was governed by processes of anticipation and representation at the level of motor control. To this end, the *Spatio-Temporal Kinematic Decomposition* (STKD) was introduced, which could calculate the hierarchically-organized kinematic structure of a movement in different spatio-temporal scales. The authors measured the overlap between the representation structure of a movement and its kinematic structure. Results showed that the hierarchical kinematic structure was closely related to the representation structure of the movement across participants, with various degrees of skill on a complex motor movement (see Fig. 1). This finding supports the idea that representation and motor execution are closely linked. The STKD approach might also be used to distinguish the extent to which humans, but also artificial cognitive systems like robots, efficiently represent and guide complex actions [8].

3 From Representation to Anticipation

Further evidence for the close link between mental representation and action was found in a recent study on the visual processing of complex stimuli [24]. The authors used an unconscious response priming paradigm to investigate whether

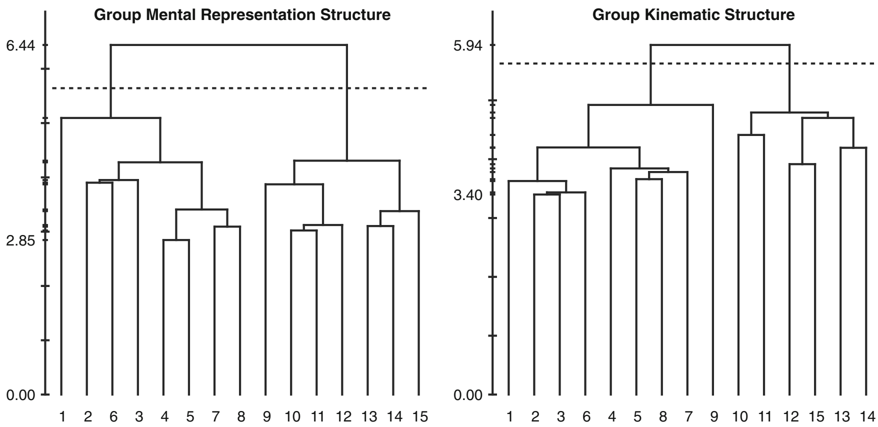

Fig. 1 Mean hierarchical structures over all participants for the mental representation (*left*) and movement kinematics (*right*) of the golf swing. The numbers on the horizontal axis relate to the concept number, the numbers on the vertical axis display Euclidean distances. The lower the Euclidean distance between two concepts in feature space, the stronger the link between these concepts. The horizontal dotted line marks the critical distance d_{crit} for a given α-level ($d_{crit} = 5.64$, $\alpha = .001$): links above this line are considered statistically irrelevant, whereas concepts linked below this line are clustered together. Concepts: (*1*) head, (*2*) chest, (*3*) left shoulder, (*4*) left elbow, (*5*) left hand, (*6*) right shoulder, (*7*) right elbow, (*8*) right hand, (*9*) hips, (*10*) left thigh, (*11*) left knee, (*12*) left foot, (*13*) right thigh, (*14*) right knee, (*15*) right foot. The two structures show that both the mental and kinematic structure are split into two main clusters pertaining to the upper and lower body (adapted from [8] with friendly permission of Frontiers in Computational Neuroscience)

skilled athletes and novices differed in the visual perception of actions: Participants had to decide to which phase of the high jump (approach vs. flight) a presented target picture belonged. Before the target picture, a picture from the same or different movement phase, masked by two scrambled versions of the stimulus material, was presented briefly (17 ms) on screen. The prime and target picture were either presented in a natural (reflecting the temporal sequence of the movement) or reversed order. Results showed that skilled athletes had faster reaction times for prime-target pairs that reflected the natural movement order, indicating a facilitation of the visual processing. The authors hypothesized that, in skilled athletes, the represented BACs of the high jump also contained information about anticipated future aspects of the movement, facilitating the processing of the subsequent target picture in a natural prime-target order.

Similar anticipation of future movement states has been described by Marteniuk and colleagues [25] for the hand trajectory in a reach-to-grasp movement. Participants had to grasp a disk and either (1) throw it or (2) place it into a tight-fitting well. The authors showed that the relative length of the deceleration phase of the initial reach-to-grasp segment depended on the subsequent movement: If the object had to be placed in a tight-fitting well, the deceleration phase was prolonged. This result supported the hypothesis that subsequent movements were anticipated and movement plans were optimized according to the final goal of the task.

Rosenbaum and Jorgensen [26] extended these previous results to grasp posture planning. In the first of two experiments, participants were asked to grasp a horizontal bar and place its left or right end onto a target disk on the table. When asked to place the right end on the target disk, participants used an overhand grasp, to end the movement sequence in a comfortable, thumb-up posture. When asked to place the left end of the bar on the target, however, participants used a less comfortable, underhand grasp, to again end their movement in a comfortable, thumb-up posture. This tendency to accept uncomfortable initial postures in order to avoid awkward postures at the end of the movement has been termed *end-state comfort effect* [26, 27]. Since its original description, the end-state comfort effect has been reproduced in a variety of different experiments [28–33] and taken to support the notion that people represent future body postures and select initial grasps in anticipation of these forthcoming postures.

4 The Link of Anticipation and Cognitive Cost

In the second experiment of their study, Rosenbaum and Jorgensen [26] demonstrated that posture selection not only depended on anticipated future, but also on previous movement states. A demonstration of this behavior was provided by Weigelt and colleagues [34]. Participants had to open a column of slotted drawers in a sequential order, using either an over- or underhand grasp for each drawer. Results showed that the point-of-change between grasp types shifted depending on the movement direction: In ascending sequences, participants tended to keep their initial underhand grasp for the central drawers, whereas they stuck to an overhand grasp in the descending sequences. This tendency of the motor system to switch from one state to another at different values depending on its history was termed motor hysteresis. Motor hysteresis is not limited to binary state changes, but can also be observed in sequential tasks with continuous hand rotation [35]. Rosenbaum and colleagues [36] hypothesized that motor hysteresis effects resulted from the cognitive costs of movement planning. In a sequential task, planning costs could be reduced by the reuse of a former movement plan instead of the creation of a new plan from scratch for each movement. A number of studies support the cognitive cost hypothesis [34, 37, 38].

Weigelt and colleagues [34], for example, provided evidence for the interaction of motor execution and working memory in a combined sensorimotor and verbal memory task. In their study, participants had to retrieve a cup from each drawer and memorize the letter from the inside of the cup. Under these dual-task conditions, one of the most reliable effects in memory research was eliminated, namely, the tendency to recall more recent items better than items encountered earlier (recency effect).

This outcome was not the result of an overall poor memory performance, as the tendency to recall initial items better than items in the middle of the sequence—the primacy effect—was preserved. Changing the difficulty of the memory task (free recall instead of serial recall) did not affect the loss of the recency effect. However, it did affect the transition of grasp type in the ascending and descending sequences. In the free recall task the range of indifference [26], within which grasp type selection depended on the movement history, increased in comparison to the serial recall task. These findings indicate that cognitive load modulates the motor execution and vice versa.

The interaction of motor planning and verbal memory was studied in detail by Spiegel and colleagues [39]. The authors combined a verbal memory task with a grasp-to-place task. Participants were asked to plan a placing movement to one of two target locations and subsequently memorize a 3 × 3 letter matrix. They then had to execute the pre-planned movement. In 20 % of the trials, an auditory cue informed the participants that the placing movement had to be executed to the alternative target. Results showed that the verbal recall performance was significantly reduced by the re-planning of the movement, indicating that movement planning and verbal working memory share common cognitive resources. In a subsequent study [40], the authors tested what kind of working memory processes were recruited for the storage and creation of a movement plan. To this end, either a verbal or a spatial memory task was used. Results showed that the storage of a motor plan disrupted spatial more than verbal memory, whereas re-planning reduced memory performance in both tasks in equal measure. These findings indicate distinct roles of working memory domains during the storage and creation of a motor plan.

Whereas the planning and re-planning of grasping movements obviously require the anticipation of a desired movement state, this requirement is less self-evident for the reuse of former movement plans. In a recent study, however, Schütz and Schack [37] argued that motor hysteresis also relies on the representation of future movement states. The authors hypothesized that, in a sequential task, the motor system does not seek to minimize the cognitive cost of movement planning, but the added cost of movement planning and movement execution. To test this hypothesis, participants were asked to open a column of drawers with cylindrical knobs in a sequential order. Results showed that, at the central drawers, participants assumed a more pronated posture in the descending sequences and a more supinated posture in the ascending sequences, thus showing motor hysteresis in a continuous posture space. After an initial pre-test phase, the mechanical cost of opening and closing a drawer in the sequence was increased for 10 trials. In the subsequent post-test, the size of the motor hysteresis effect was significantly reduced in comparison to the pre-test, indicating that the increased mechanical cost during the intervention phase was represented in participants' long term memory. Based on the original hypothesis, this result also supports the notion that both the cognitive and mechanical cost of the upcoming movement have to be anticipated in order to optimize the total cost of the movement.

5 From Anticipation to Representation—Developmental Aspects

The planning of grasping actions is not only related to physical features of the grasped object such as its shape [41] or size [42], but also depends on what the actor intends to do with the object [25, 43]. This anticipatory aspect of manual action has been termed second-order motor planning [27, 44]. A number of studies investigated the development of second-order motor planning on a phylogenetic (e.g., non-human primates [45]) and ontogenetic level (human children [46–48]). Weiss et al. [45], for example, showed that end-state comfort planning in New World monkeys (cotton top tamarins) was similar to human adults.

Weigelt and Schack [48], on the other hand, investigated end-state comfort sensitivity in young children (3, 4, and 5 year old). The children performed a dowel placing task, reaching for a horizontal dowel and inserting one of its ends into a target disc. If an initial overhand grasp was required to achieve end-state comfort, all children were able to perform the task successfully. If, however, an underhand grasp had to be selected, only 18 % of the 3-year-olds, 45 % of the 4-year-olds, and 67 % of the 5-year-olds were able to satisfy end-state comfort. These results show a distinct pattern of gradual improvement in children's sensitivity to reach end-state comfort across the three age-groups.

To compare anticipatory planning of manual actions between non-human primates and humans, Wunsch and colleagues [44] applied the motor task previously used for cotton-top tamarins [45] to pre-school children, primary school children and adults. Participants had to reach for a plastic cup that was vertically suspended in an upright or inverted orientation and retrieve a small toy from inside the cup. When the cup was presented in the inverted orientation, only adults consistently used the inverted grasp posture required to satisfy end-state comfort. The percentage of inverted grip amongst participants increased with age, indicating a gradual improvement of end-state comfort sensitivity. However, while the performance of adults was closely related to the performance of non-human primates, even children at approximately 10 years of age exhibited less end-state comfort sensitivity than the primates.

Convincing evidence that the gradual improvements in anticipatory motor planning in children are closely related to adaptations on a cognitive level was provided by Stöckel and colleagues [46]. Specifically, these authors examined links between motor planning (using the bar-transport task) and the development of cognitive representation of grasp postures in children aged 7, 8, and 9 years. In line with other studies on motor planning during childhood (see [49] for a recent review), end-state comfort satisfaction increased with age, and the 9-year old children had more distinct representation structures compared to the 7- and 8-year old children. Importantly, the sensitivity to comfortable end-states was related to the cognitive representation structure. Children with functionally well-structured representations exhibited a stronger preference for end-state comfort, thus supporting the notion that cognitive action representation provide a benchmark for anticipatory motor planning and behavior.

6 Computational Models

Computational frameworks of sensorimotor control based on parallel inverse and forward dynamic motor models (e.g., MOSAIC model [50]) are well established and are detailed enough to reason about neurological motor disorders in humans, such as musician's dystonia (i.e., involuntary muscle cramps during instrument playing that can become severe enough to end a professional career [51]). In the MOSAIC model, an efference copy of a motor command is used by predictor units to internally simulate the sensory consequences of a planned action. These predictor units can therefore be interpreted as the computational model´s counterparts of BACs. Further, the hierarchical MOSAIC model (HMOSAIC) [52]—having a top symbolic/representational level, a middle motor sequence level and a bottom sensorimotor control level—bears strong similarities to the 4-layer model of complex motor control described by Schack and Ritter [10] and can be used to explain action observation, imitation learning and social interaction.

MOSAIC uses parallel local modules to represent motor primitives. This local approach allows for sharp segmentation between learned motor patterns, but leads to poor generalization properties due to strong competition between local modules during learning. This 'conflict between generalization and segmentation' [53] limits the number of learnable motor patterns. A neural network based model proposed by Yamashita and Tani [53] avoids this problem by distributed storage of motor patterns within a single network. Furthermore, the network is able to implicitly establish functional hierarchies using neural units with multiple time scales. Yet, the model requires long training times and has limited motor pattern capacity because of known problems using a classical training method for recurrent neural networks (conventional back-propagation through time).

Echo State Networks (ESN) proposed by Jäger and Haas [54] are special variants of recurrent neural networks that circumvent the problems of gradient based learning methods. They offer high model capacity, fast learning and excellent prediction capabilities. The learning speed is high enough to combine them with evolutionary algorithms to optimize both reservoir weights and network structure in a motor pattern learning task [11]. The resulting, compact networks can smoothly switch between motor patterns and show an interesting emergent feature: the ability to morph between stored patterns [11]. A recent extension of ESNs adds neural filters called *conceptors* [55] that pull the network dynamics to defined subspaces. Conceptors bridge the gap between (1) low level neuronal processing and learning of static and dynamic patterns and (2) high level symbolic processing. Using conceptors, motor patterns can be smoothly switched, interpolated and combined by logical operations [55]. Again, conceptors can be interpreted as computational instances of BACs.

Cruse and Schilling [56, 57] argue that cognitive systems not necessarily have to be complex, but that already small, reactive neuronal systems like WALKNET [58] or ESN based approaches [11, 55] can be expanded in a bottom-up approach to show basic cognitive capabilities like planning ahead or discovering new actions to solve a given problem. The proposed cognitive architecture described in [56] consists of modules arranged in layers and columns, again bearing close similarities to the layered architecture of Schack and Ritter [10]. Internal body models based on grounded and embodied sensorimotor circuits provide the basis for internal simulation of given tasks. Such internal models can be employed as forward models to predict sensory consequences of planned actions, and at the same time, serve as inverse models for generating and 'inventing' new, task specific motor commands [59].

7 Implications for Robotics

Information about basic principles of anticipatory planning in humans such as the end-state comfort effect are relevant when designing robot architectures that are used to perform manual actions and interact with humans in an appropriate, age-dependent manner [60]. Robot technology has matured to the point at which it can approximate a reasonable spectrum of perceptual, cognitive, and motor capabilities, allowing us to explore architectures for the integration of these functions into robot action control. This gives us the opportunity to fit existing models of anticipation, representation, and decision making in humans to robotic architectures. Therefore research concerning anticipation in human motor control and the cognitive architecture of human motion is clearly linked to the ongoing field of cognitive robotics. The goal of cognitive robotics is to elevate the currently still rigid and rather narrow action repertoire of robots to a level where a robot can select and adjust its actions flexibly to highly varying contexts, maintain a shared focus of attention with a human instructor, and react to commands that are offered in a 'natural' format, such as speech and demonstration.

Our recent interdisciplinary research within the Center of Excellence 'Cognitive Interaction Technology' (CITEC) focused on the question of how motor anticipation and representation structures are established and changed step by step in compliance with task constraints. We wanted to investigate the relationship between goal anticipation, the structure of mental representations and the performance in manual actions in humans and robots. Therefore, we studied the development of structured representations (action templates) in human skill acquisition, and how these research results could be applied to robotics [10, 61]. In a next step, we translated our findings from studies of human movement into sufficiently specific models that permitted an implementation on robotic platforms [11, 12]. This research connection was used in both directions: insights gained from the attempt to validate the hypothesis about action and representation structures in the robot learning scenario have been used to change the design of experiments with human subjects. For instance, to learn about the granularity of cognitive building blocks in manual actions we tried to gain closer insight into the relationship between representation structures and motor execution, including situations in which actions resulted in errors.

An important link between cognitive architecture in humans and robots focuses on the cognitive reference structures of manual actions, especially the representations of objects and grasp postures. Therefore we investigated the hierarchical representation of objects under different task constraints and, complementary to this, the hierarchical representation of grasping movements (hierarchies of power and precision grips). The insights gained in these experiments have been implemented in robotic platforms and could be linked to different robot architectures [10, 61]. This kind of integrated (interdisciplinary) research allowed us to experimentally explore the interactions of action representation in memory (simulated with artificial neural networks) and motor skills in the context of real-world tasks. Based on present studies on anticipation, motor planning, and representation of grasp postures in humans and the corresponding experimental studies with uni- and bimanual robotic platforms we are going to refine robotic grasping step by step.

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Part IV
Anticipation in Engineering and Information Technology

Information Concepts in Anticipatory Systems

Tippure S. Sundresh

Abstract Anticipatory Systems involve intelligent information acquisition and processing. This presentation provides a combined information, communication, and computational perspective of these systems using an Information Engine model that leads to some fundamental definitions of intelligence. An Information Engine model represents the transformation of raw information to a form that is directly utilized by the target application just as a thermodynamic engine converts heat into mechanical work. Taking the analogy of Carnot's cycle, the area of the information cycle in the information-need and entropy coordinates of the Information Engine model is defined as logical work which is proposed here as a unified measure of intelligence that has the promise of capturing a variety of diverse systems ranging from natural to constructed and hybrid systems. This model provides a unified concept of the informational, computational, and intelligence aspects of anticipatory systems and hybrid intelligent systems across diverse implementations and applications.

Keywords Anticipatory systems · Information engine · Carnot's cycle · Logical work · Semiosis · Intelligence · Cooperative systems · Information generation efficiency · Information utilization efficiency

1 Introduction

An anticipatory System acts not only on the basis of past and present states but also on the anticipated future states of itself and the environment [1]. Anticipatory systems are complex and intelligent. As a result they present a great deal of

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challenge in understanding and even greater in attempting to construct them. So far, anticipatory systems, intelligent systems (AI) and a variety of natural systems such as biological, social systems, etc., have been studied separately and have resulted in separate treatments and analyses. These studies, although very rich and extensive (for an extensive list of related work see references in the compendium by Vladimir Arshinov and Christian Fuchs [2]), still need to help fill knowledge gaps in handling present day systems that integrate diverse elements. For example they involve cooperative working of several intelligent agents, or joint working of biological and mechanistic systems. It is generally known that the primary task in integrating such systems is to address the optimization of communication, computation, and information utilization; however, there is a need for models and methodologies that deal with all these aspects in a way that is transparent across different system types (e.g., machines, biological, social, etc.). Even within communication between similar entities, the merging of communication and computation has enabled distributed intelligent systems where communicating entities act on the basis of the "meaning" of information transacted thus dealing with the intent as opposed to the content. In general the important part played by communication among the various entities needs to be addressed from the perspective of meaning and intent rather than merely transmission and reception. In the work presented here we have drawn upon our past work [3–5] and attempted to utilize some of those concepts to unify the understanding and visualization of systems with diversified intelligence. The central model that facilitates this is the Information Engine concept. Our presentation begins with an overview of the information engine model and then we show how it applies in a simple fashion to various systems such as an anticipatory system, multi-agent system, hybrid brain-machine composite, etc. An important concept derived from the information engine mechanization is that of Logical Work that is used to define an intelligence metric that is meaningful across diverse systems.

2 Information Engine

An Information Engine is set up as consisting of an information source, a processing agent, and a sink. Detailed discussions of the Information Engine including optimality are available in our earlier work [3]. Here is a brief overview. This engine is modeled in a fashion similar to a heat engine where the engine takes heat from the source and converts some of it into mechanical energy and discards the rest of the heat to the sink, the mechanical energy is then used to drive external applications. The performance of the heat engine is analyzed in terms of physical parameters such as temperature, pressure, volume, entropy, etc. Modeling of the information engine is motivated by Carnot's engine of the second law of thermodynamics, which is known to be an optimal heat engine. Carnot's engine is characterized in terms of temperature and entropy. In order to formulate the information engine, we define a parameter Information-Need as analogous to temperature and assign the physical entropy (the sum of Shannon, i.e. the statistical entropy and the

Kolmogorov/Algorithmic entropy) to information fragments. Although metrization of information-need continues to be a research topic, some more details are discussed in our prior work [3]. This engine is seen to work between the information source and sink to transform the random ensemble entropy (Shannon entropy) of the source information to algorithmic entropy (Kolmogorov entropy), which gives the information needed to directly effect the action to drive the desired application in a way analogous to the conversion of heat to mechanical work by a heat engine working between a heat source and a heat sink. Considering Semiosis as the action of extracting meaning from the information ensemble, such an information engine is representative of a semiotic loop.

Consider two systems S1 and S2 that can communicate and work cooperatively. Further, consider that the system S2 is assigned an application task for which it has insufficient information that can be obtained from a source S1. The corresponding information engine cycle is shown in Fig. 1. The engine starts at the point d with S1 being a source and S2 being a processor of information. During the leg d–a S2 recognizes that it needs a certain fragment of information from S1 to proceed with the assigned task i.e., the target application. Data containing this information is obtained by S2 from S1 during a–b. This is followed by the leg b–c during which the acquired data is processed by S2 to generate the necessary algorithm or compacted information necessary for actuation. During b–c the processing converts some of the Shannon entropy that comes from the uncertainty in the acquired data to Algorithmic (or Kolmogorov) entropy that may be useful to the target application. The next leg c–d denotes the reduction of entropy due to selection of the algorithms generated in the processing during b–c and utilized by the system for actuation. The remaining Shannon entropy is discarded and the cycle restarts by evaluating further information need through the leg d–a. Thus the useful information made available by the system to the application is equal to the algorithmic entropy extracted by the system for use by the application as represented by the leg c–d.

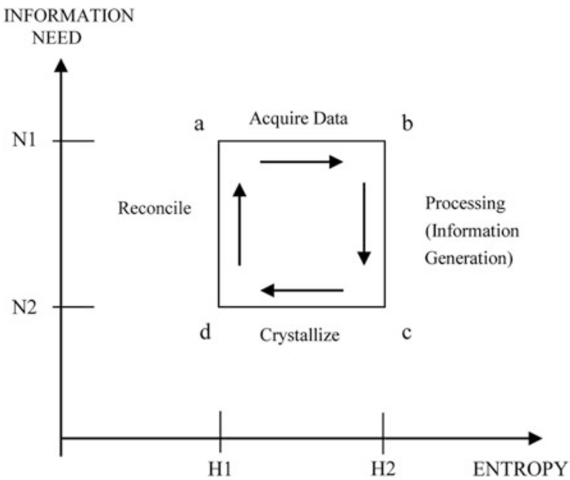

Fig. 1 Information cycle

3 Intelligent Systems

There is a large number of Intelligent Systems in existence today, their numbers as well as variety is increasing. A single system may consist of several diverse subsystems with various levels of capability and autonomy collaborating with each other. Architectural diversity is a fact of life. In general an intelligent system strives to extract useful information from the given raw information ensemble. The "intelligence" of system is characterized by the effectiveness with which it does the above extraction that in turn is concerned with the efficacy of information transactions and processing to enable taking an action.

An intelligent system can thus be modeled as an information engine which would transform the raw information to a form that can be directly utilized by the target application. As described in the previous section such an information engine would consist of four fundamental processes, recognition of information need, acquisition of data, processing of the data for information generation, and the separation of the algorithmic entropy and its use by the application for actualization of its need. These four processes when represented in the space of Entropy/Information Need, form a cycle analogous to a thermodynamic cycle (engine) represented in the Entropy/Temperature space. Since this engine is modeled in terms of fundamental notions such as Shannon and Kolmogorov entropy, using it to construct measures of intelligent processing of information in systems is very attractive. Analogy of the Information Engine with thermodynamic cycles prompts us to consider the area of the cycle that consists of the product of the Information Need and the Entropy to be the logical work performed by the information engine in driving the target application. Logical work becomes a representation of the value produced by the information engine and when normalized with respect to the information input into the system, it leads to a measure of intelligence.

4 Semiosis in Intelligent Systems

In intelligent systems actions are dependent upon meanings arrived at by interpretations rather than merely the raw data that is a priori available. Thus, semiosis as the process of meaning extraction plays a vital role in intelligent systems. Although there are some excellent expositions on semiotics in the context of complex systems that offer detailed discussions on semiosis, the information engine representation ties the concepts together in the form of a concise fundamental architecture. In discussions of Complex Semiotic Systems for example Cliff Joslyn [6] states that, "semiotically closed systems maintain cyclic relations of perception, interpretation, decision, and action with their environments". It is easily seen that these relationships are exactly those described by the four legs of our information engine. Howard Pattee [7] in his discussion of Semiotic Controls, has discussed the relationship and distinction between dynamics and semiotics as being similar to the formal and the functional and goes on to discuss the epistemic cut between them. Pattee says, “we must ask not what we mean by information but what the information itself means in the physical world”. This coincides with our approach that meaning is equivalent to action. Considering the end action to be the proof of the meaning, it is representative of the meaning itself. The information content of the meaning is such that it fulfils the need of the action. Meaning is purposive. The information engine combines the formal or dynamic effort of information collection and processing with the functional or purposive aspect of the algorithmic entropy and information need. Intelligent systems expend their dynamic effort towards purposive goals. This is accomplished through processing of information and selection of the results that are capable of neutralizing the need. All four legs of the information engine are essential for an intelligent system to function and therefore provide a good basis for modeling an intelligent system.

5 Logical Work Representation of Intelligence

Having said that an intelligent system is purposive, we can use this property to measure intelligence. Modeling an intelligent system by an information engine allows us to compare intelligence with the working efficiency of this engine. Although evaluating the efficiency of a real system is expected to be fairly complicated, studying an ideal cycle such as described above adds useful insights to the construction of measures of intelligence. In Carnot’s cycle of thermodynamics, which motivated our Information Engine model, the area of the rectangle describing the process in temperature-entropy space yields the mechanical work output by the engine [8]. In a similar fashion, the area of the rectangle representing the information engine process in the information need—entropy coordinates can be considered to be the Logical Work output of the information engine. This is justified by the following reasoning. Work performed by an information engine must identify with the functional value of the evolved algorithm to the specific target application and the intrinsic complexity of the algorithm itself. An information processing system that generates a piece of information with high complexity which is capable of satisfying a large portion of the information need is associated with a large measure of logical work. Thus the product of the neutralized information need and the Kolmogorov complexity of the algorithm generated is a suitable measure of the logical work output of the information engine.

There are three concepts of efficiency relating to intelligence that emerge from the above model. Two of these relate to information generation, and information utilization. The two together determine the third one that represents a measure of the system intelligence.

5.1 Information Generation Efficiency

The efficiency of information generation is the ratio of the algorithmic information generated to the total information input to the system. In terms of the corresponding entropies this may be written as Information generation efficiency:

$$L = (H2 - H1)/H2 = 1 - H1/H2 \tag{1}$$

5.2 Information Utilization Efficiency

The information utilized depends upon the utility of the generated information. Thus this is the product of the algorithmic entropy and the need that it satisfies.

$$U = (H2 - H1) \cdot (N1 - N2) \tag{2}$$

This is to be compared with the possible utilization had the total need of N1 been fulfilled. This would be:

$$V = (H2 - H1) \cdot N1 \tag{3}$$

Thus, Information utilization efficiency:

$$M = (N1 - N2)/N1 = 1 - N2/N1 \tag{4}$$

It is observed that the information utilization efficiency is similar to the efficiency of heat to mechanical work conversion in the Carnot's cycle. This points to the value of a piece of information for an application to be analogous to the mechanical work performed by a heat engine. For actuation an application always seeks meaning in the information.

5.3 Information System Efficiency

This is an indicator of the value of the algorithmic information generated to the application in relation to the information value that was provided in the raw data to the system. Information system efficiency:

$$J = (H2 - H1) \cdot (N1 - N2)/H2N1 \tag{5}$$

$$= \text{Info.Generation eff.X Info.Utilization eff.} \tag{6}$$

We consider Information System Efficiency to be an indicator of the measure of intelligence in a system. As seen above this can be factored into the capabilities of the system to generate algorithmic information and that to utilize from it what is needed.

As an example of such factorization consider a search engine that processes the enormous data available to narrow down to a set of information fragments that contain the supplied keywords. However, within the members of the generated set, one that is the best match to the context is figured out as part of the utilization.

As an observation of the information cycle diagram it is noticed that cycles described by tall rectangles would be associated with small generated entropy, characteristic of simple algorithms, however satisfying large needs. On the other hand, cycles described by broad rectangles are associated with handling large statistical entropies and that come up with relatively large algorithmic entropy and correspondingly complex action but satisfy modest needs. One must take cognizance of this composition while constructing intelligent systems.

6 Anticipatory Systems

Robert Rosen defines [1] an anticipatory system as “a system containing a predictive model of itself and of its environment, which allows it to change state in accord with the model’s predictions pertaining to a future instant”. Based on the information engine model we examine an anticipatory system to understand the relationship between its mechanics and the intelligence in its functioning. Rosen’s definition, as seen by his modeling relation, may be broken down into two major structural characteristics of an anticipatory system S2 working in cooperation with another natural system S1. First, S2 possesses a predictive model of S1, and second, at any instant, change of state occurs in S2 as a function of its predictions about S1. Since updates of the model of S1 in S2 necessarily involve communication with S1, it is seen that the cooperative working of S1 and S2 at once fits the information engine model. Various aspects of this model are discussed in detail in our previous work [4]. Here we would like to first highlight the way in which the anticipatory nature of the system is reflected in the information engine model. After this we discuss a high level architecture applicable to the construction of an anticipatory system.

6.1 Anticipation as the Final Cause

Referring to the diagram of information engine described in the section above, the system S2 obtains information from S1, which is the environment here, during the leg a–b. This is a data gathering process. However, it needs to be in consonance with the need to be fulfilled. Thus it depends upon goal related causality (Aristotle’s “final cause”) that is part of the leg d–a that projects the need. Once S2 has the raw data, it processes it in conformity with its goals and in association with the information that it may already possess about S1 in the form of a model of S1; this happens in the leg b–c by way of conversion of the Shannon entropy to Kolmogorov entropy. Then during the leg c–d, the separated algorithm is made available for anticipatory action; this is a part of the intelligence but one that does not involve anticipation. Anticipation depends upon the recognition and estimation of need, and this happens during the leg d–a. Optimality of the system is also closely tied with this function since for minimization of the data acquisition and processing effort, the data to be collected must be maximally useful for the final task.

6.2 Architectural View of Anticipatory Systems

Anticipatory Systems involve prediction, communication, processing and interpretation in a knowledge environment. In the past since all these individual areas progressed independently architecting the combined systems escaped serious attention. Here we touch upon a few aspects that are useful in engineering such systems.

As seen from the information engine representation, architecting an anticipatory system calls for engineering four broad categories of functions. It calls for estimating information needs, acquisition of data from all relevant sources, intelligent processing of information, and planning and commitment to appropriate actions. Estimation of information needs as well as intelligent processing of data require knowledge resources. Correspondingly, the total infrastructure may be factored into the following three categories:

1. Service plane: Sets up communication with all entities, acquires data as needed, registers service requests, etc.
2. Knowledge plane: Provides knowledge assets, carries out all cognitive processing, maintaining knowledge bases, and updates models of self and other entities.
3. Action plane: Does planning, decides on commitments, and effects actions.

This concept of the planes enables the infrastructure to be implemented using any combination of hardware, software, firmware, or network assets. This is similar to the control and user plane concepts used in present day telecommunication networks. The action plane can be thought of as part of control plane, however, we prefer to separate it because it has more of an AI flavor while a control plane is related more to data transport. Although the knowledge plane has been talked about [9], its use does not seem to be quite so prevalent yet. For an implementation example, the interested reader is referred to the analytics of the author's patent on an adaptive phone for users with dementia or other mental impairments that illustrates the use of knowledge plane involving cognitive processing [10].

Further to the resource categorization in the three planes, following aspects merit special attention while architecting for performance.

- Modeling of various system entities including external world representation necessary for estimation of information need, acquisition, and processing
- Efficient maintenance of knowledge databases and models in the system
- Use of domain ontologies consistent across the entire system
- Efficient information acquisition and interpretation using robust communication protocols
- Cognitive processing consistent with the task, data, and the knowledge bases.
- Efficient planning to commit from the outcome of cognitive processing
- Monitoring intelligence measures of the system

Discussions of the above considerations in relation to multi-agent systems are available in [5]. Further expansion in terms of actual design would depend upon the specific task situation.

7 Hybrid Cooperative Systems

Since machines are generally not considered as effective as natural systems in anticipatory capabilities, a composite working of machine and natural system can have significant merits over the two individually. In “The Limits of Intelligence” Douglas Fox [11] has projected an analysis to show that it is unlikely that human brain by itself may evolve considerably further and suggests that a good way to enhance intelligence would be through augmentation with internet. Undeniably, although presently difficult to implement, in the future it is quite conceivable that human brain could be closely coupled with a computing system or other machines to increase the total intelligence. Will it increase intelligence? And how to optimize the enhancement? To explore answers to this we must examine and analyze the information transactions and processing that are expected to occur in the composite system and then optimize the cooperative working. We cast this problem as a cooperative multi-agent system and apply the information engine model. Formal treatment of communication and cooperation among intelligent agents has been addressed by many authors, for example see Haddadi [12]. Reliability aspects of such systems are considered in [5]. Here we would like to consider the intelligence aspect of the cooperative working.

We consider the machine and the brain as two intelligent agents and set up an information engine between them to examine their cooperative working. To show that intelligence is increased, we need to observe that now logical work can be performed in both agents provided they both have the capability to a) identify their information need from the other and b) they can process the information received from the other to perform the global service. The contribution of each to the total will be equal to the logical work performed by each which in turn is determined by the product of the amount of raw information processed and the need fulfilled by each. The enhanced computational capabilities of present day and future machines with large processing capability suggest that they can make a large contribution to the logical work. However, according to the information engine model we see that this will happen only if the machine knows what its information need is. This can come either from the biological brain in the hybrid system or in a purely mechanistic AI system it would come from a proxy module. Thus in the hybrid system, the biological part could be assigned the executive function of factoring the information need of which it will process some and others would be passed to the machine. Notice that if the biological part were to pass all the information need for processing to the machine the two together will form only one information engine that is distributed over multiple locations. Although in either case the total logical work and correspondingly the intelligence may be increased, the multiple engine structure may be preferred from robustness and reliability perspective. Evidently much further work is needed in this open area of research.

8 Conclusion

In this paper we have examined the working of an anticipatory system as a semiotic loop involving information transaction as well as processing for meaning extraction in the context of an application task. For this analysis we used the information engine concept. Based on this we defined Logical Work, a notion of work in logical spaces that is analogous to the notion of mechanical work in physical systems. We proposed using logical work as the basis of a unified measure of intelligence that can be applied to diverse systems ranging from natural to mechanistic and hybrid systems. The system intelligence was shown to consist of two factors called the information generation efficiency and the information utilization efficiency. Each of these can be expressed in terms of the statistical entropy of the input data, the algorithmic entropy of the output information, and the information need that relates to the goal of satisfying the application. This kind of modeling demonstrates the epistemic cut between the dynamic and semiotic parts of the intelligent system; in fact the logical work output and therefore the intelligent system functioning itself requires both parts. The application of these principles to anticipatory systems and hybrid bio-mechanistic systems is illustrated.

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Anticipatory Behavior of Software Agents in Self-organizing Negotiations

Jan Ole Berndt and Otthein Herzog

Abstract Software agents are a well-established approach for modeling autonomous entities in distributed artificial intelligence. Iterated negotiations allow for coordinating the activities of multiple autonomous agents by means of repeated interactions. However, if several agents interact concurrently, the participants' activities can mutually influence each other. This leads to poor coordination results. In this paper, we discuss these interrelations and propose a self-organization approach to cope with that problem. To that end, we apply distributed reinforcement learning as a feedback mechanism to the agents' decision-making process. This enables the agents to use their experiences from previous activities to anticipate the results of potential future actions. They mutually adapt their behaviors to each other which results in the emergence of social order within the multiagent system. We empirically evaluate the dynamics of that process in a multiagent resource allocation scenario. The results show that the agents successfully anticipate the reactions to their activities in that dynamic and partially observable negotiation environment. This enables them to maximize their payoffs and to drastically outperform non-anticipating agents.

1 Introduction

In distributed artificial intelligence, software agents model autonomous entities which plan and perform their activities in multiagent systems. These autonomous agents are able to proactively select their actions, to react to changes in their environment and to interact with each other [31]. In the latter context, iterated negotiations are a well-established means for coordinating distributed systems containing multiple agents. The participating agents can negotiate on allocations of

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resources, delegations of tasks, as well as commissions of services. This enables them to identify appropriate partners which complement their own capabilities in order to meet their individual objectives [10, 23].

Nevertheless, a problem occurs if several of these interactions take place concurrently. In this situation, the participants' activities can mutually influence each other. That is, the outcome of each negotiation depends on those being performed simultaneously. This is particularly the case in joint negotiations of cooperating agents which require them to compromise about their desired agreements. In order to enable efficient and robust multiagent coordination, the agents have to take these interdependencies into account when selecting and evaluating their respective actions in iterated negotiations. That is, they must adapt their behavior to the activities of others.

In a competitive setting, a game theoretical equilibrium [19] denotes a combination of each individual agent's best response to the others' behaviors. However, acting in a partially observable environment, the agents are unable to explicitly compute such an equilibrium. Therefore, we propose to approximate it by means of agents adapting their activities to each other. Inspired by Niklas Luhmann's theory of social systems [15, 17], our approach enables these agents to anticipate the reactions of others to their own actions. Thus, they can select best responses to the expected behaviors of others. To that end, we apply distributed reinforcement learning to the agent decision-making in iterated multiagent negotiations. Using this technique, each agent learns a best response behavior to the others' activities without the necessity to observe them directly. This results in a self-organizing system of mutually interdependent activity selections in which social order emerges from the agents' concurrent learning efforts.

We structure this paper as follows. Section 2 elaborates on concurrent iterated negotiations and discusses their challenges as well as existing approaches to address them. Subsequently, Sect. 3 presents the main contribution of this paper which is threefold. Firstly, we model concurrent negotiations as repeated games and propose multiagent learning for coordinating them. Secondly, we discuss Luhmann's notion of self-organization in social systems and its adaptation for multiagent coordination. Thirdly, we introduce decentral decision-making criteria for terminating multiagent negotiations. Section 4 empirically evaluates this approach in a distributed resource allocation scenario. This evaluation confirms the ability of learning agents to successfully anticipate each other's behaviors and provides insights into the dynamics of that process. Finally, Sect. 5 concludes on the achievements of this paper and outlines directions for future research.

2 Iterated Multiagent Negotiations

Iterated multiagent negotiations denote a process of distributed search for an agreement among two or more participants [13]. This process consists of the negotiation objects, an interaction protocol, the participating agents, and their decision-making mechanisms. The negotiation objects determine the search space of potential agreements. In the process, the agents exchange proposals which their counterparts can either accept or reject. While the protocol defines the possible sequences of messages, an agent selects its actions among those possibilities by means of its decision-making mechanism. If the agents find a mutually acceptable agreement according to their individual preferences, the search returns this solution as its result. Otherwise, it terminates without success.

In the following, we further elaborate on these aspects of multiagent negotiations. In particular, Sect. 2.1 examines negotiation objects and protocols. This provides the foundations for discussing the challenges of agent decision-making as well as existing approaches to cope with these challenges in Sect. 2.2.

2.1 Negotiation Objects and Protocols

The negotiation objects define the topic on which the participating agents attempt to reach agreement [13]. They cover the target of a negotiation such as the desired service fulfillment or resource allocation. Moreover, they denote the cardinality of these items: Either single or multiple ones. In the latter case, the agents negotiate on possible combinations of the target products or services. Many-object negotiations require them to identify a mutually acceptable compromise out of the range of those combinations. In the following, we focus on many-object negotiations as they subsume the special case of single-object ones. Furthermore, they are equivalent to cooperative activities of several agents attempting to achieve common goals. In that case, several agents group together in teams [22, 25, 32]. These teams negotiate as composite entities in order to further their common objectives while competing with other teams or individual agents.

To structure the negotiation process, there are two basic protocol types for exchanging proposals [13]. In auction type negotiations, one or more agents exclusively propose potential agreements while the others only accept or reject them. An example for this is the Dutch auction in which the auctioneer repeatedly decreases the proposed price until one or more buyers accept the current offer. Contrastingly, in negotiations of the bargaining type the agents bilaterally exchange offers and counter-offers. Hence, they mutually attempt to steer the search in their individually favored direction. On the one hand, this increases the speed of reaching an agreement; on the other hand, it requires all participants to be capable of both evaluating and generating meaningful proposals [10]. In this paper we mainly focus on negotiations of the auction type. Nevertheless, in Sect. 3.3 we also suggest to adapt our approach to bargaining type interactions.

A well-known protocol for iterated auction type negotiations is the FIPA Iterated Contract Net [11] as depicted in Fig. 1. It is particularly suitable for situations in which a consumer agent attempts to find the best partner among the potential providers of a required service or product. In many-object negotiations, this can also be a set of agents if no single participant is able to fulfill the initiator's demands on its own. However, this approach requires the initiator to address all potential

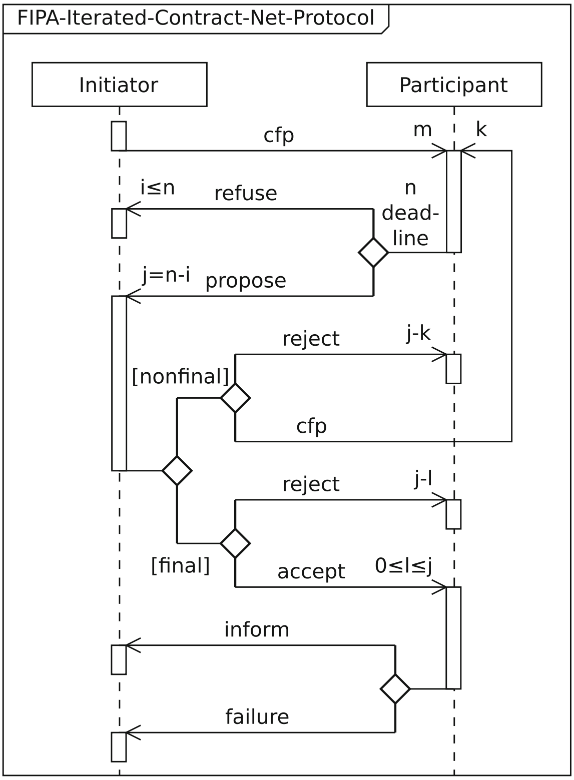

Fig. 1 The FIPA Iterated Contract Net interaction protocol (adapted from [11])

participants from the beginning on as there is no way to include additional agents during the process. If the initial selection is insufficient to fulfill the initiator's requirements, the whole negotiation will fail.

2.2 *Agent Decision-Making: Challenges and Related Work*

If there is exclusively one single initiator agent at any time, its decision-making in the aforementioned protocol is simple. It only requires to keep track of the participants' offers to identify the currently best agreement, *accept* it when no further improvements occur, and *reject* all other proposals. However, this is not the case if several of these interactions take place concurrently. In this situation, the participants receive several *cfp* messages simultaneously and their subsequent responses depend on all of these messages. Consequently, these interactions mutually influence each other's outcome as the initiator agents compete for the participants' limited capacities. In order to still achieve the best possible result of the negotiation, an agent must take the actions of all others into account. That is, it has to find a best response to its counterparts' behaviors.

To illustrate the aforementioned problem, Fig. 2 depicts a simple resource allocation example. This scenario consists of two consumer agents (A,B) acting as initiators of concurrent negotiations. They attempt to allocate resources from the provider agents (C,D) of which each has only enough capacity to fulfill the request of one consumer. If each consumer contacts both providers simultaneously, there are four different possible outcomes. Only two of those lead to a successful negotiation result for both consumers. In the other two cases, a single consumer receives two offers. Because it can only accept one of them, the other provider's resource remains unused due to its refuse message terminating the negotiation with the unsuccessful consumer agent. Hence, the agents have a 50 % chance of achieving an efficient overall coordination result.

In the general case of a set N of initiators and a set M of participants, an efficient allocation is equivalent with a surjective mapping (i.e., an onto function) from M to N. Consequently, the probability for achieving such a result is given by the possible number of these mappings [18, pp. 84–85;90] divided by the number of all possible interactions.

$$P_{eff} = \frac{1}{|N|^{|M|}} \cdot \sum_{j=0}^{|N|} \binom{|N|}{j} \cdot (-1)^j \cdot (|N| - j)^{|M|} \tag{1}$$

Figure 2 shows this probability for varying agent populations. As the number of consumers increases, a drastically higher supply of resources (i.e., number of providers) is necessary to ensure a near efficient coordination result. This holds for both the standard Contract Net protocol as well as its iterated version because in the latter, a *refuse* message terminates the interaction with its sender. Consequently, subsequent iterations can only refine the result of the first one which renders this protocol inadequate for concurrent negotiations.

To overcome the limitations of the Iterated Contract Net, we slightly modify the original FIPA protocol of Fig. 1. Instead of narrowing the set of participants to a subset of the initial receivers in each iteration, we allow for including alternative

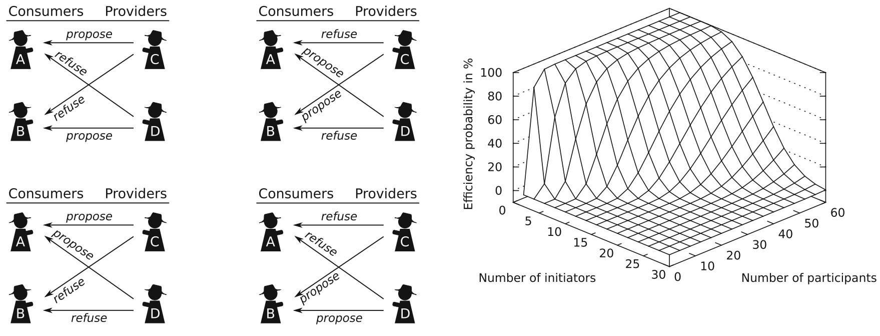

Fig. 2 Resource allocation options and probability of achieving an efficient outcome for varying agent populations in the (Iterated) Contract Net

ones while keeping their overall number constant. That is, the initiator selects a fixed number m of participants and replaces those $m-k$ which propose none or only unacceptable agreements (*refuse/reject*) with alternative candidates. Thus, it refills the set of receivers for the next iteration's *call for proposals* (*cfp*) with x new ones to a size of $k + x = m$. This enables an initiator to contact participants more than once, even if they refused their earlier allocation attempts.

Nonetheless, the agents must still find best responses to each other's activities in the modified Iterated Contract Net protocol. This is due to the fact that their activities can still collide which leads to suboptimal outcomes. While they have the ability to continue their negotiations despite failed allocation attempts, they must avoid these collisions in future iterations of the interaction. That is, they must *anticipate* their counterparts' behaviors and adequately respond to them to secure their intended negotiation results. This anticipation is crucial for achieving the desired outcomes because otherwise the agents would mutually disturb their efforts. To facilitate that end, the following concepts and methods for finding best responses are available from related work.

Determining best responses to other agents' activities is the subject of game theory [29]. If all agents pursue a best response strategy to the behaviors of the others, these strategies form a Nash equilibrium [19] in which no single agent can benefit from changing its current behavior. A Nash equilibrium denotes the agents' best possible activities in such a strictly competitive setting. Moreover, by approximating best responses to the others' behaviors, an agent maximizes its individual payoff, even if they fail to establish a corresponding best response in return. Therefore, each agent should select its actions in an iterated negotiation with respect to the others' activities.

Existing methods for computing an equilibrium of mutual best responses often evaluate the structure of the game and are computationally expensive [20]. Nevertheless, each agent only has to identify its own best strategy. Consequently, it requires a decision-making method for finding its most beneficial activities, given the actions of the others. A well-known technique for this is the *minimax* rule [28] of 2-player decision-making and its generalization for n-player settings [14]. By assuming the others to pursue their most beneficial courses of actions, this rule selects the best response to those behaviors. As a result, an equilibrium emerges from the agents' mutually dependent action selections.

However, in concurrent negotiations, the *minimax* approach requires an agent to be aware of the other participating agents, their possible actions as well as their preferences (i.e., their scoring functions for the interaction's outcome). For competitive distributed negotiations, disclosing these trade secrets is inappropriate [10]. Consequently, the agents act in a partially observable environment. In this environment, they must coordinate their negotiation behaviors while preserving the privacy of information. To achieve the latter, *combinatorial auctions* [8] provide a means for computing the best allocation of goods or services in a mediated interaction process. In these auctions, the participants express their preferences as bids on combinations of offered items. While such a bid represents the result of an agent's valuation of an offer, it hides the agent's private method for attaining that assessment. Moreover, combinatorial auctions are particularly suitable for many objects as the participants can express bids on arbitrary combinations. Nonetheless, the winner determination is a centralized process which creates a computational bottleneck [21]. This is undesirable in distributed systems.

To overcome this problem, agents should adapt their behaviors during a negotiation according to their experiences throughout that process [27]. Hence, we propose to enable the agents to learn best responses to each other's actions from observations of their personal performance. Deriving beliefs about successful behavior from the outcome of past interactions has been shown to enable the approximation of market equilibria in repeated trading activities [12]. That is, buyers and sellers determine mutually acceptable prices for the traded items by estimating the probabilities of reaching an agreement for potential price offers. Nevertheless, this requires the presence of a common currency to express those prices.

In order to allow for best responses according to generic utility assessments, we rather apply *reinforcement learning* [26] to multiagent negotiations. This technique enables the agents to anticipate the expected results of their actions by observing and learning from the outcome of their previous activities. By adapting their behavior accordingly, they can establish of social order within the negotiation through a process of self-organization. They implicitly generate interaction practices which reflect the identified best responses to the unobservable activities of their competitors. To accomplish this, an agent receives a reward when performing an action from which it learns an estimation of the expected reward for potential future actions. Subsequently, it can select the next action based on this estimation. Multiagent reinforcement learning [6] has been applied successfully to approximate best response behaviors in distributed coordination tasks [5, 7]. Therefore, it is a promising approach for determining an agent's most beneficial strategy in concurrent iterated negotiations.

3 Multiagent Self-organization in Iterated Negotiations

In the following, we apply multiagent reinforcement learning to concurrent iterated many-object negotiations. Section 3.1 interprets them as repeated games and provides a formal notation for the agents' decision-making environments and behaviors. Subsequently, Sect. 3.2 motivates our approach to social self-organization, introduces its sociological foundations, and applies a stateless version of the *Q-learning* approach to agent decision-making. Finally, Sect. 3.3 discusses criteria for determining acceptable offers to terminate such a negotiation.

3.1 Iterated Multiagent Negotiations as Repeated Games

In order to facilitate a better understanding of the interdependencies of concurrent agent activities in iterated negotiations, we formalize them using the terminology of game theory and reinforcement learning. From this point of view, a single iteration of a multiagent negotiation is a *static (stateless) game*. In such a game, each of the agents performs one action and receives a reward depending on all simultaneously executed actions. Its formal definition is as follows [6].

Definition 1 (*Static Game*) A static game is a triple $\left(N, \vec{A}, \vec{R}\right)$. N is a set of agents being indexed *1,..., n*. Each agent $i \in N$ has a finite set of atomic actions A_i. Thus, $\vec{A} = (A_1, \ldots, A_n)$. $\vec{R} = (R_1, \ldots, R_n)$ is the collection of individual reward functions for each agent *i*. Each $R_i : A_1 \times \cdots \times A_n \rightarrow \mathbb{R}$ returns *i's* immediate reward for the simultaneous execution of agent actions $a_1, \ldots, a_n$ with $\forall j \in N : a_j \in A_j$.

In a concurrently executed Contract Net, the set of agents N consists of the initiators of the simultaneous negotiations. Each of them selects a participant to send its *call for proposals* specifying the negotiation object. Thus, agent i's individual actions A_i contain all of these possible messages in conjunction with their respective receivers. Instead of distributing the rewards directly, the participants subsequently respond with a *proposal* or a *refuse* message. A participant's response depends on the entirety of messages it received in the current iteration. Each initiator can rate its individually received response by calculating its respective payoff (i.e., the negotiation's expected outcome if it accepts the received offer). Thus, an agent obtains the conditional reward for its action, even though it is unable to observe the actions of the others. Iterating this one-shot negotiation several times results in a *stage game* [6]. This repeated game describes the agents' decision-making environment during concurrent iterated negotiations. Only in its final iteration, an agent bindingly *accepts* or *rejects* its received offer. Until then, it can use the stage game to learn the most beneficial actions for that last static game.

In order to accomplish this learning, the agents repeatedly observe the payoff of their respective activities which enables them to reason about their expected reward in further iterations. A rational agent has the objective to maximize its personal payoff. Hence, it attempts to adopt a behavior which is a best response to the other agents' actions. In game theoretical terms, a deterministic best response strategy returns an action which maximizes an agent's payoff, given the actions of all others [6].

Definition 2 (*Best Response*) A best response of agent $i \in N$ to the other agents' actions $a_1, \ldots, a_{i-1}, a_{i+1}, \ldots, a_n$ is an action a_i^* which leads to the highest reward given those activities: $\forall a_i \in A_i : R_i\left(a_1, \ldots, a_i^*, \ldots, a_n\right) \geq R_i(a_1, \ldots, a_i, \ldots, a_n)$.

In a competitive environment, each agent strives to maximize its individual payoff on its own. Therefore, all agents mutually attempt to find a best response to each other's activities. Such a situation, in which no single agent can beneficially deviate from its current behavior, forms a Nash equilibrium [19]. For deterministic agent strategies, this is defined as follows.

Definition 3 (*Nash Equilibrium*) A Nash equilibrium is a vector $\left(a_1^*, \ldots, a_n^*\right)$, such that $\forall i \in N$, each action a_i^* is a best response to the others.

A Nash equilibrium does not ensure that the agents maximize their common payoff in the form of a social welfare optimum.[1] Nonetheless, it denotes each agent's best possible action relative to the others' activities if all agents attempt to maximize their individual payoff. The objective of each agent in concurrent iterated negotiations is to identify such a best response action in order to select it in its decision-making.

Additionally, there are negotiations in which not all agents compete with each other. If two or more agents pursue a common goal, they have to negotiate together in order to acquire the necessary resources or commission required services. In this case, these agents can group together in teams [23]. The set of those multiagent teams $MT \subset 2^N$ is a partition of the set of individual agents. The members of each team $mt \in MT$ cooperate in their interactions. To that end, they combine their individual rewards in a common *social welfare function*.

Definition 4 (*Social Welfare Function*) Asocial welfare function of team $mt \in MT$ maps all team members' rewards to a single value: welfare: $\mathbb{R}^{|mt|} \rightarrow \mathbb{R}$.

A team's welfare indicates the joint performance of its member agents by aggregating their individual rewards. Several different aggregation methods are available for implementing that function [9]. The most common of those is the *utilitarian welfare function* which returns the sum of the team members' rewards: $\sum_{i \in mt} R_i(a_1, \ldots, a_n)$.

In a negotiation, a team acts as a single initiator agent. That is, a particular member agent $mgr \in mt$ becomes the *team manager*. That agent sends cfp messages on behalf of all members and collects the respective rewards for the responses. Then, it aggregates them in the team's welfare function. This is equivalent to a single agent negotiating several objects. As a result, multiagent teams attempt to find joint best responses to other teams' as well as to individual agents' activities. This replaces the member agents' rewards in Definition 2 with the team's welfare. Consequently, a Nash equilibrium consists of the best combination of actions for the team given the non-members' best possible responses to those activities.

However, both individual agents and multiagent teams are unable to directly determine whether their concurrent activities form a Nash equilibrium. This is because there is no entity which can observe all of these behaviors. Instead, they must derive the best responses solely from their payoffs for the performed actions. If all agents and teams succeed in this endeavor, a Nash equilibrium emerges from their distributed efforts. To that end, the next section specifies our approach to *self-organizing negotiations* which relies on the anticipation and an adaptation of agent behaviors.

[1]A famous example for this is the prisoner's dilemma in which the equilibrium point is the only strategy combination not belonging to the Pareto frontier.

3.2 *Anticipation and Behavior Adaptation for Iterated Negotiations*

Niklas Luhmann's sociological theory of communication systems [15, 17] provides a fundamental inspiration for our approach to self-organizing negotiations. According to this theory, social order derives from actors mutually expecting each other's activities. These expectations emerge from the actors' interactions rather than reflecting static behavioral norms or fixed channels for communication. An actor observes his counterpart's behavior and selects his activities according to the other's expected reaction. Thus, an actor's action selection depends on observed activities of others and vice versa. This feedback loop of observation and expectation enables social structures to emerge from an initial state of ignorance [2] by means of interaction processes. These structures guide subsequent executions of those very processes. Luhmann refers to the generation of social structures by the term *self-organization* [16].

In previous work, we have applied expectations to the decision-making of software agents [1–5]. These agents memorize the observable effects of their own activities. Each time it has to select an action, such an agent evaluates its options according to its memory entries. That is, it searches for an action which it expects to predictably lead to an advantageous response. After executing the selected action, it observes the actual response by the addressed agent and updates its memory with that observation. That process either increases or decreases the agent's expectation for the selected activity depending on whether it under- or overestimated its outcome. This renewed expectation then becomes available for the anticipation of activity results in further interactions.

The aforementioned process enables a software agent to anticipate the outcomes of its activities without having to know their exact causes, the identities of its competitors, and their respective capabilities. To that end, it assumes its past observations to be representative for future events. It learns which of its potential interaction partners best to select in order to reach its goals. In a negotiation, this allows for an initiator agent to identify those participants which can offer the most advantageous deals. To achieve this effect, we model the process of generating expectations and selecting activities according to them by means of *reinforcement learning* [26]. In a stage game, this technique allows for the agent to learn from its experiences to increase its future performance.

A well-understood algorithm for the case of one single learning agent is *Q-learning* [30]. In its stateless form, this algorithm estimates expected rewards (action payoffs) as *Q-values* $Q(a)$ for each possible action a [7]. A learning agent

[2] In this state of *double contingency*, both participants are unable to act because each of their activities depends on the other's previous actions and they lack any existing expectations for selecting them. However, Luhmann notes that this is a highly unstable fixpoint of the interaction's dynamics which never actually occurs in real encounters [15, 17]. Instead, every slight action allows for generating initial expectations which facilitate the emergence of social order.

uses the following update rule to refine its estimation when observing a reward *R(a)* for action *a*.

$$Q(a) \leftarrow Q(a) + \lambda \cdot (R(a) - Q(a)) \quad (2)$$

If each action is sampled infinitely often, the agent's Q-values converge to the unobservable true values Q^* for every learning rate λ with $0 < \lambda \leq 1$ [7, 30]. This enables the learning agent to select its activities according to their expected payoff values. Hence, as the values converge, it can identify its individually optimal action.

However, in concurrent iterated negotiation processes, several initiator agents act simultaneously. This results in interdependent effects of their actions as formalized in the preceding section. In fact, the convergence property of single agent Q-learning does not hold for a distributed setting in which several agents simultaneously adapt their behaviors. This is because their interdependent activities result in non-stationary rewards. These rewards depend on the combination of all concurrently executed actions. Consequently, an agent can observe changing effects of its actions without being able to influence them or to identify the cause of these changes. For instance, if two agents attempt to allocate resources from two resource providers, the first initiator may receive offers or rejects of its attempts depending on the simultaneous actions of the other initiator. Even if the first agent always selects the same action, it will be unable to accurately anticipate the reaction because the second agent may change its behavior. Thus, an agent's interaction environment changes during its learning process which can render its existing expectations invalid.

The same situation arises in social systems. According to Luhmann, communications are guided by expectation structures in these systems [15, 17]. Through repeated changes and mutual adaptations, these structures stabilize themselves and social order emerges. The reason for this effect lies in the reciprocal nature of expectations. All actors simultaneously generate and refine their expectations. In this process, they narrow the range of actually occurring communications within the system. This increases the likeliness of communications being successful. Hence, the participating actors can mutually anticipate each other's reactions to their activities and act accordingly instead of arbitrarily changing their behaviors. While they retain the ability to react in an unexpected manner, this makes communications sufficiently predictable to facilitate goal-directed social coordination.

In the following, we transfer the preceding considerations to concurrent multi-agent negotiations. If all agents in that setting develop expectations about the outcomes of their activities and their actions depend on those expectations, those very outcomes become increasingly predictable. This is because they narrow the range of selected actions. If they also maximize the payoffs they receive from the corresponding responses, the agents establish a Nash Equilibrium of mutual best response activities. Nevertheless, conventional reinforcement learning is unable to bring about that effect. It suffers from several agents mutually disturbing their adaptation efforts by changing their behaviors. When an agent perceives an action to yield inferior outcomes, it has to change its selection and search for an adequate alternative option. This change can interfere with the activities of another agent. That agent is then also obliged to modify its behavior. Therefore, a chain reaction of adaptations can occur in which disturbances build up and the agents are unable to obtain social order. To avoid this and instead enable the interactions to converge to social order, the agents' action selection method must fulfill two additional conditions [5, 7].

1. At any time, every possible action of an agent must have a non-zero probability of being selected.
2. An agent's action selection strategy must be asymptotically exploitive.

Condition 1 ensures the infinite sampling of all agent actions for $t \to \infty$. An agent must always have the opportunity to explore alternative courses of action to be able to react to changes of other agents' behaviors which affect its own performance. Furthermore, that condition prevents the agents from executing strictly correlated explorations. That is, no combination of agent actions becomes impossible to occur. This is an extension of the infinite sampling requirement for single agent Q-learning: In a multiagent setting, each combination of actions must be executed infinitely often due to the payoff's dependence on all concurrently triggered other actions. Condition 2 requires the agents to pursue a *decaying* exploration strategy. This decreases the probability of concurrent exploration activities over time. Hence, the agents become less likely to disturb each other as their behaviors become increasingly predictable. As a result, their expectations can settle to stable social structures. Empirical evidence shows that these agents successfully establish mutual best responses in a variety of settings [5, 7].

In order to apply this technique to iterated negotiations, we construct the initiator agent's behavior as depicted in Fig. 3. This behavior extends the message passing activities as specified in the FIPA Iterated Contract Net protocol definition [11] with an initialization step as well as the following repeatedly executed activities.

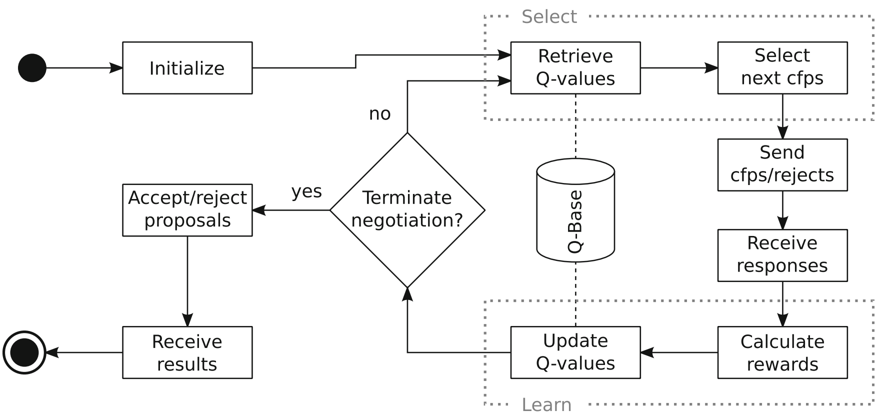

Fig. 3 Behavior of a learning initiator agent in the Iterated Contract Net

1. *Selecting* the receivers and contents for the next *calls for proposals*.
2. *Learning* from the observed responses.
3. *Deciding* on whether to terminate or continue the negotiation.

When entering a negotiation, each learning agent $i \in N$ initializes its Q-Base (i.e., its memory) Q_i in which it stores the expected payoffs $Q_i(a_i)$ for all its possible atomic actions $a_i \in A_i$. Its individual actions A_i consist of all *cfp* messages, given by their possible contents and receivers. The message contents depend on the agent's preferences toward the negotiation object and the receivers correspond to the possible providers of that object. In the case of a multiagent team, the team manager maintains such a memory for each of the member agents. The following considerations cover the decision-making of such a team manager because it subsumes the special case of an individual agent (being equivalent to a team with a single member).

Subsequently, the agent enters the iterated part of the negotiation. To select the next action, it considers all messages $a_i \subseteq A_i$ and looks up their stored Q-values $Q_i(a_i)$. A team manager does this for every member agent individually. In that case, maintaining a Q-base for the atomic actions instead of their combinations keeps the required storage space small when using a lookup table [5]. Nevertheless, this requires the corresponding rewards $R_i(a_i)$ to be mutually independent. This is because the team manager must aggregate those Q-values in the team's welfare function to identify the expectedly most beneficial message combinations $maxA_{mt} \in A_1 \times \cdots \times A_{|mt|}$.

$$maxA = \arg \max_{A_{mt} \in A_1 \times \cdots \times A_{|mt|}} \left(\sum_{i \in mt} Q_i(a_i) \right) \tag{3}$$

with $a_i \in A_{mt}$ being the selected action for team member i

Choosing an action set from $maxA_{mt}$ corresponds to a greedy strategy which maximizes the team's expected payoff based on its experiences so far. For that purpose, Eq. 3 computes the utilitarian welfare of the expected action outcomes. This method maximizes the average payoff of the team's members without favoring particular ones over others as long as the expectations accurately anticipate the actual outcomes. However, a team manager is unable to guarantee this because it is initially unaware of the available deals in the negotiation and other agents can change their behaviors which may provide potentials for improving its performance. Hence, in order to find out whether there is an even better option, the agent also has to explore alternative actions.

To this end, we propose to use an ε-greedy strategy. That is, in iteration t of the negotiation, the manager selects the next actions $A_{mt,t}$ from $maxA_{mt}$. with a probability of $1 - \varepsilon$ (with $0 < \varepsilon \leq 1$). If there is more than one best option, it chooses randomly among them. Alternatively, with a probability of ε, the agent selects $A_{mt,t}$ at random out of all action combinations in $A_1 \times \cdots \times A_{|mt|}$. Moreover, to ensure the aforementioned asymptotically exploitive selection with non-zero probabilities, it employs a decaying ε-greedy strategy. This requires a sequence ε_n with $\lim_{t \to \infty} \varepsilon_t = 0$ and $\forall t \in \mathbb{N} : \varepsilon_t > 0$. An example meeting these requirements is the following quence: $\forall t > 0 : \varepsilon_t = \frac{1}{\ln(t+2)}$. This sequence leads to high exploration rates in the beginning of the negotiation which decrease over time. Once an agent has identified a highly rated combination of actions, it increasingly tends to stick to those actions as time proceeds.

After selecting the next actions, sending the chosen messages, and collecting the respective responses, the team manager proceeds with the learning part of its behavior. To assess the usefulness of the selected actions $A_{mt,t}$, it evaluates the response messages $result(a_i, t)$, $\forall a_{i,t} \in A_{mt,t}$ for each member agent $i \in mt$ by means of an individual utility measure $U_i : \{result(a_i) | \forall a_i \in A_i\} \to [0, 1]$. It uses the result of this calculation as the action's immediate reward $R_i\left(a_{i,t}\right)$.

$$R_i\left(a_{i,t}\right) = U_i\left(result\left(a_{i,t}\right)\right) \tag{4}$$

As the response messages depend on the concurrent actions of all agents participating in the negotiation, their utility implicitly reflects these actions as well. Thus, it is sufficient for the team manager to evaluate only the observable responses instead of receiving a conditional reward for all simultaneous activities. In order to learn from this observation, it subsequently applies the standard update rule as in Eq. 2 to modify its stored Q-value $Q_i\left(a_{i,t}\right)$ for all performed actions $a_{i,t} \in A_{mt,t}$. In the succeeding iteration, the refined entries in the Q-Base serve as the new Q-values for these actions.

According to the aforementioned convergence property of the Q-learning rule, an infinite number of these iterations will lead to each agent and multiagent team learning to anticipate the best response to the others' activities. Hence, a Nash equilibrium will emerge from these distributed learning processes in concurrent negotiations. Nonetheless, an infinite negotiation never comes to a final result. To avoid this, each negotiation initiator must decide after an iteration either to accept its received response messages as the result and terminate the negotiation or to continue it in the attempt to reach a better outcome. That is, while learning the best behavior for the repeated interaction process, it must eventually apply its findings to one single iteration to bring about a result of the negotiation. To facilitate this decision-making, the next section discusses individual tactics for terminating iterated negotiations.

3.3 Termination of Iterated Negotiations

A learning agent as specified in the preceding section is unable to determine whether it has already developed a best response behavior or not. Furthermore, it cannot guarantee that stable social structures have emerged among all negotiating agents. This is because it would have to know all other agents' possible actions as well as their actual selections, the participants' respective responses, and the agents' utility measures for evaluating these responses.

However, disclosing this information is inappropriate for competitive negotiations (cf. Section 2.2). As an alternative, negotiation *tactics* enable reaching individually acceptable agreements without requiring additional information. These tactics model an agent's bidding behavior in bargaining type negotiations consisting of offers and counter-offers. They can depend on the amount of *time* or other *resources* being available as well as on the observable bidding *behavior* of the negotiation opponents [10]. Such a tactic provides a function which approaches the agent's private *reservation value* in the course of the negotiation. This value denotes the minimal offer it is willing to accept. Thus, unless the agents come to a better agreement at some time during the negotiation, the reservation value denotes its last offer on which it insists until the end of the negotiation. If at some point in time neither agent concedes any further, the negotiation terminates without success.

In contrast to bargaining negotiations, in auction type mechanisms like the Iterated Contract Net it is unnecessary to generate counter-offers. Instead, the initiator agents only require a decision function which indicates whether or not one or more received proposals are acceptable. To this end, an agent must consider the payoff of the current offers. These values are already available from the reinforcement learning algorithm (Eq. 4). Thus, we define agent i's decision function in dependence of its utility measure U_i for evaluating the perceived results of its actions (with the manager of a multiagent team using the utility measures of all member agents). In analogy to the bargaining tactics, the agent has a *reservation level* of utilities U_{res}. This is the minimum utility it will accept for the *last offers* of the negotiation. If the reservation level turns out to be unreachable, it will terminate the negotiation without coming to an agreement.

However, in order to maximize its payoff, the agent must explore alternative actions in the course of the negotiation. Therefore, it should abstain from choosing the first option exceeding its reservation level as the final one. Only if it fails to achieve a better result, the agent should accept the current offer. To this end, we introduce an agent's *acceptance level* of utilities U_{acc} which denotes the minimum utility for the *current offer* to be acceptable. In the case of a multiagent team, the common welfare of the member agents denotes that utility. As the team manager attempts to maximize the members' joint payoff, it has to compare the team's welfare to the acceptance level in order to evaluate whether the outcome for the team is acceptable or not. Varying over time during a negotiation, the acceptance level resembles an agent's tactic in bargaining: It consists of a function describing the agent's behavior of conceding to its reservation level. To enable the agent to benefit from its learning ability, this function starts from a sufficiently high value and decreases monotonically over time. As a result, the agent rejects all but the best offers in the early iterations. Nevertheless, it becomes increasingly inclined to compromise about that utility during the negotiation process.

Following from these considerations, a team manager successfully terminates a negotiation in iteration t if the received offers' aggregated utility exceeds the current acceptance level: $U_{acc,t} < \sum_{i \in mt} U_i\left(result\left(a_{i,t}\right)\right)$ with $a_{i,t} \in A_{mt,t}$ being the selected action for team member i. That is, the team manager computes the welfare of the whole team and decides whether the result is acceptable as the negotiation's outcome. Furthermore, it terminates the process without success if the acceptance level falls below the reservation level: $U_{acc,t} < U_{res}$. In the latter case, the team failed to reach an agreement with its interaction partners under the least acceptable conditions. Figure 4 depicts these termination criteria for a range of acceptance level functions. Analogously to the concession behaviors in bargaining negotiations, these functions tend toward either the well-known *Boulware* or the *Conceder* tactics [10]. While the former attempts to reach a highly valued agreement as long as possible, the latter quickly approaches the reservation level.

To implement these tactics, we modify the polynomial time dependent function presented in [10] according to the aforementioned considerations. In the resulting function, the acceptance level $U_{acc,t}$ in iteration t ranges between the initial value $U_{acc,0}$ and the reservation level U_{res} as long as t adheres to a given deadline t_{max}. Moreover, the acceptance level is strictly monotonically decreasing if $U_{acc,0} > U_{res}$ and t_{max} is constant.

$$U_{acc,t} = U_{acc,0} - \left(U_{acc,0} - U_{res}\right) \cdot \left(\frac{t}{t_{max}}\right)^{\beta} \tag{5}$$

According to this equation, the negotiation is guaranteed to terminate for all $t_{max} < \infty$. The parameter β controls the agent's concession behavior: While it pursues a Boulware tactic if $\beta > 1$, each $\beta < 1$ leads to a Conceder behavior. The intensity of these tactics increases the more β deviates from 1 (with $\beta = 1$ denoting the neutral linear tactic).

By means of Eq. 5, an agent controls its negotiation behavior. Setting t_{max} to a fixed point in time allows for modeling situations in which the agents must finish their negotiation before some deadline exceeds. In conjunction with the

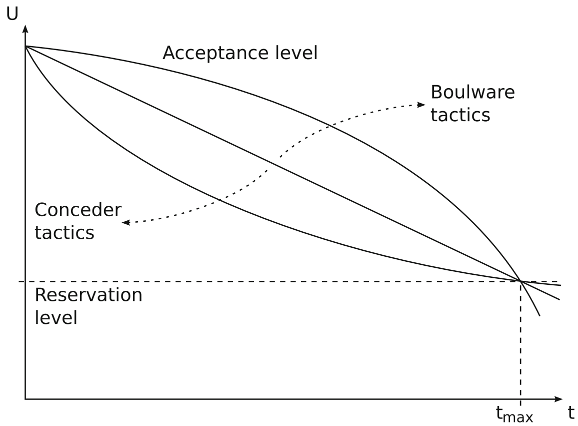

Fig. 4 Termination criteria based on acceptance and reservation utility levels

reinforcement learning technique, this termination method enables agents in concurrent multiagent negotiations to adjust their behaviors according to each other's distributed activities. While the learning approach facilitates an agent's anticipation of best responses to the unobservable behaviors of others, the termination criteria control the negotiation's duration. Moreover, deriving from negotiation tactics in bargaining, the latter even offer the possibility to transfer this approach to bilateral negotiations. As the acceptance level denotes the minimum utility for an agreement, an agent can invert its utility measure to generate counter-proposals to the perceived offers. If a common currency is used, this is easy to accomplish by mapping the learned values to price offers [12]. However, we leave this adaptation as well as the analysis of its requirements and implications to future research.

4 Evaluation

In this section, we evaluate our approach to self-organizing multiagent negotiations in a multiagent simulation. This evaluation covers the dynamics of the agents' learning efforts as they establish expectations to anticipate the behaviors of their interaction partners. In the following, Sect. 4.1 describes the design of the simulation experiments while Sect. 4.2 presents and discusses the results.

4.1 Experiment Design and Setup

In order to evaluate the proposed learning approach in iterated multiagent negotiations, we apply it to a distributed resource allocation problem using the simulation system PlaSMA [24]. Our scenario is an abstraction from a kind of problems occurring frequently in real-world applications like production scheduling and logistics [5]. This scenario contains a set N of resource consumer agents which concurrently negotiate with the resource providers in set M as depicted in Fig. 5. The member agents of these sets are indexed $1,\ldots,n$ for the consumers and $1,\ldots,m$ for the providers. In addition, the set of consumers is partitioned into n teams of size k. Consequently, only every kth consumer takes an active part in the negotiation as a team manager. Each consumer team requires k resource units while every provider

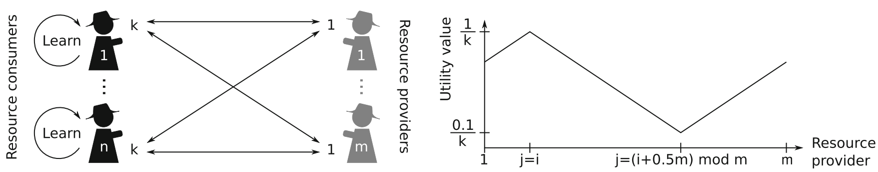

Fig. 5 Many-object resource allocation scenario with n consumers and $m = n{\cdot}k$ providers

has exactly one unit available. Because $|M| = |N|$, there is sufficient supply for fulfilling that demand. Thus, the agents have to find an appropriate bijection between the set of consumers and the set of providers. In this case, each consumer allocates its required amount of resources without interfering with the others.

To approximate a mutual best response allocation in that setting, the team managers act as initiators of a concurrent iterated negotiation. In each iteration, a manager selects k providers for a *call for proposals*, one for each team member. If a provider still has its resource unit, it sends an offer for the allocation; otherwise it sends a *refusal*. In the case of a provider receiving two or more allocation attempts, it randomly selects one consumer for its offer and *refuses* all other *cfps*. The initiators evaluate these responses by means of the following utility function for each team member.

$$U_i\left(ra_{i,t}\right) = \frac{1}{k} \cdot \begin{cases} \frac{|0.5m - |i-j||}{0.5m} \cdot 0.9 + 0.1 & \text{if } ra_{i,t} \text{ is a } \textit{propose} \text{ message} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

with

$$\forall a_{i,t} \in A_{mt,t} : ra_{i,t} = result\left(a_{i,t}\right)$$

According to Eq. 6, each agent $i \in N$ has an individual utility function. If the response to the selected action is an offer, its utility ranges between $\frac{0.1}{k}$ and $\frac{1.0}{k}$ depending on the respective sender. Otherwise, it is zero. Hence, the usefulness of the different provider's resources varies for each consumer. Figure 5 depicts the resulting function. There is only one provider offering an optimal payoff. Because these providers differ for all consumers, there is exactly one optimal resource allocation (namely that allocation which maps all consumers to the providers with the same index). Being unaware of the described scenario and the actions of other agents, this optimum is difficult to achieve for the team managers. In its attempts to maximize its performance, a team manager has to find the best activities for each of its members while competing with the managers of other teams for those results. This requires it to search for resource providers which reliably offer high payoffs. The agents must anticipate these outcomes in order to maximize their performance because an arbitrary selection of actions and mutual disturbances will lead to poor coordination results.

Our evaluation assesses the capability of the proposed approach to approximate an allocation with the aforementioned properties. It focuses on the agents' learning dynamics in order to evaluate the impact of their self-organization during the course of a negotiation. To this end, we test it in a scenario with a set of 1200 consumer agents which we subdivide into 20 teams of 60 members each. We vary the team managers' learning rates λ between zero and one in order to evaluate their impact on the learning dynamics. In this context, $\lambda = 0$ means that an agent maintains no expectations at all. Thus it selects every action at random. This serves as a baseline configuration to mark the lower bound of the expectable coordination performance.

For each agent $i \in N$ and every atomic action $a_i \in A_i$, we set the initial Q-values to $Q_i(a_i) = 0$. This leads to a purely explorative behavior in the beginning of the negotiation and in case of repeated refusals. This initialization and randomized action selection avoids a premature over-estimation of potential agreements. Nonetheless, as soon as an agent observes a (partially) successful combination of actions, it utilizes the ε-greedy strategy to exploit its experience. Thus, the agent increasingly tends to stick to those actions which have been beneficial in past iterations.

To terminate the negotiation, the agents employ a time dependent heuristic as specified in Eq. 5. They use an initial acceptance level of $U_{acc,0}$ = 1, a reservation level of U_{res} = 0.0, a Boulware negotiation tactic ($\beta = 3$), and a deadline of t_{max} = 800 iterations. The Boulware tactic increases the impact of their learning as the agents slowly concede to their reservation levels. Each experiment consists of 120 simulation runs.

4.2 Experiment Results and Discussion

Figure 6 depicts the average number of consumer agent teams participating in the negotiation over time for varying learning rates. It shows that the agents' learning efforts significantly reduce the time required for identifying an acceptable negotiation result. While the non-learning agents require more than 700 iterations for most of them to terminate their negotiations, the learning rates of $\lambda = 0.2$ and $\lambda = 0.4$ achieve this in about 500 iterations. The higher learning rates result in durations between those values. These results indicate that the generation of social order has a large impact on the time required for finding an appropriate resource allocation. The team managers learn which resource providers to contact in order to receive advantageous offers. Thus, they tend to repeatedly select those options which

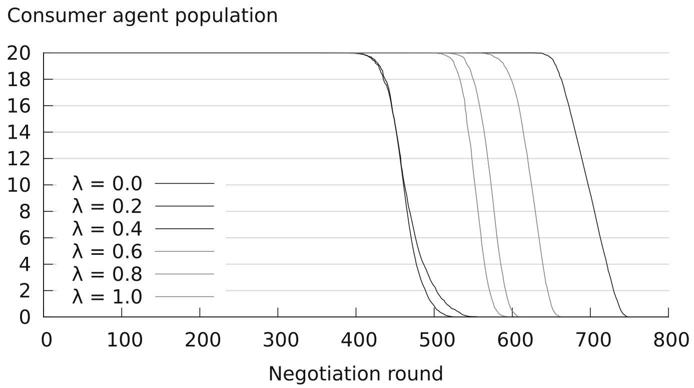

Fig. 6 Number of teams participating in the negotiation over the course of time

provide high payoffs. Although they occasionally explore alternative ones, they only adopt them if these actions provide a significant advantage over the already known activities.

Moreover, maintaining expectations for every single action of individual team members enables the team managers to systematically change their selections for those individual members. Thus, their activities become both increasingly stable and successful for small learning rates which leads to early identifications of acceptable results. By contrast, higher learning rates ($\lambda \geq 0.6$) lead to faster adoptions of alternative activities. This can lead to mutual disturbances between the multiagent teams. Hence, they require more time for their negotiations (while still being superior to a non-learning approach).

Nevertheless, the duration of a negotiation is only loosely connected to the actually achieved result quality. To complement the preceding results from that perspective, Fig. 7 depicts the development of the average team welfare during the negotiation. This confirms the aforementioned effects of the learning rate. The random action selection results in largely constant welfare values at a low level around 0.35.

Contrastingly, the learning approach leads to gradually increasing welfare values over time. This particularly holds for small learning rates. Therefore, the agents adopt successful behaviors and refine them if they manage to find superior options for specific actions. As their activities become increasingly predictable, they learn to anticipate the corresponding outcomes. This is evident in the later iterations where the welfare increases rapidly. In these iterations, the first teams terminate their negotiation processes by permanently allocating the offered resources. Other agents cannot receive any further offers from the corresponding providers. Consequently, the results of those actions become perfectly predictable.

The more teams finish their negotiation, the easier it is for the remaining ones to adapt their behaviors accordingly. While the average welfare for these agents is still suboptimal, its development shows that they are able to establish expectations to successfully anticipate and increase the outcomes of their activities. This enables

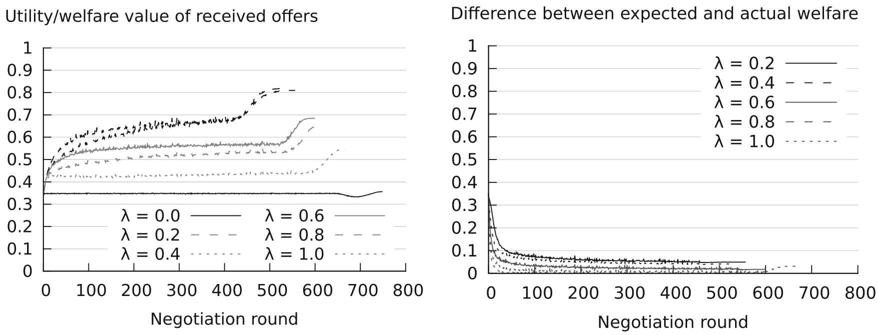

Fig. 7 Development of the received offers' welfare as well as differences between the expected and actually observed outcomes for the teams over time

them to drastically outperform non-anticipating agents. In particular, the anticipative approach improves the final result by up to more than 130 % (final result of 0.818 ± 0.001 for $\lambda = 0.4$ compared to 0.356 ± 0.001 for $\lambda = 0.0$).[3]

Finally, Fig. 7 also presents the differences of the aforementioned observed welfare values and the expected ones for the selected actions. A small difference denotes an accurate anticipation of the results while a large one indicates an agent's failure to expect the actual outcome of its activities. The figure shows that all positive learning rates lead to a convergence of these differences toward zero. As a result, the agents are able to anticipate their negotiation partners' offers. High learning rates lead to even smaller deviations from the real outcomes. This confirms that the agents rapidly adapt their expectations in that case which leads to the discussed tendency to disturb each other. Because they are equally as fast in their reactions to those disturbances, they retain their expectations' accuracy. However, this hampers their ability to generate stable social structures. By contrast, agents with lower learning rates accept slightly larger deviations from their expectations without overreacting to them. This leads to the previously observed higher performance and the successful emergence of social order.

5 Conclusions and Outlook

In this paper we have proposed the application of multiagent reinforcement learning to concurrent iterated negotiations. We have analyzed the standard negotiation mechanism for multiagent coordination. This analysis has shown that the mechanism is unable to ensure successful negotiation outcomes. To overcome its shortcomings, our approach enables negotiating agents to anticipate each other's behaviors and adapt their own activities accordingly. In that context, the agents can group together to cooperate with each other within a team while several of these teams still compete for the best negotiation results.

The anticipation of their activities' effects allows for the agents' distributed approximation of best responses to their counterparts' actions without requiring them to directly observe those actions. Taking inspiration from Luhmann's theory of social systems [15, 17], we enable the learning agents to derive expectations from their received offers. The resulting behaviors are generated in a self-organizing process of anticipation and adaptation. Therefore, they are an emergent effect of the agents' concurrent learning efforts. The agents approximate this result by means of individual decision criteria for the termination of a negotiation process.

For the empirical evaluation of this approach, we have applied it to a multiagent resource allocation scenario. The results show that the learning agents successfully anticipate each other's behaviors. Their performance in terms of negotiation time and achieved payoff depends on their applied learning rates. If these rates are too small,

[3] All deviations are half-widths of the 99 % confidence interval.

they are unable to develop any expectations at all. If they are too large, the agents tend to overreact to their observations. Consequently, they require a balanced parameter setup to facilitate the generation of stable social structures. In that case, their adaptation method enables them to achieve high payoffs in small amounts of time. Nevertheless, all tested parameters lead to (drastic) improvements of the agents' average performance in comparison with a non-anticipative benchmark setting.

To summarize, the contributions and results of this paper are as follows.

- Anticipation enables software agents to select adequate activities in a partially observable negotiation setting.
- Social systems theory provides valuable inspiration for implementing anticipative behaviors in artificial agents. Their mutual anticipation of those behaviors leads to the emergence of social order among multiple agents.
- Anticipative behaviors improve the performance of software agents in negotiations by up to more than 130 % (in the evaluated setting with the tested parameter values).

Nevertheless, there are still questions open for future research. While we have briefly mentioned the possibility to transfer our method to bargaining type negotiations, its actual implementation and evaluation will be subject to future work. Moreover, additional analyses of our existing approach will facilitate a better understanding of its components and their interaction. In particular, to guarantee the convergence of the reinforcement learning part to mutual best responses, an analytical assessment of self-organizing negotiations is necessary. Additionally, further empirical evaluations will focus on different scenarios with heterogeneously parameterized populations to assess the capabilities and limitations of distributed learning for the anticipation of agent behaviors in concurrent iterated negotiations.

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The Ways of Scientific Anticipation: From Guesses to Probabilities and from There to Certainty

Aaro Toomela

Abstract Science of anticipation can be distinguished into three kinds, each relying on a different psychological mechanism. Further, these mechanisms—based on everyday conceptual thinking, thinking in logical concepts and thinking in systemic concepts, respectively—are in hierarchical relationships the first being the least developed and the last the most developed form of (scientific) thought. Each of these three sciences has specific to it understanding of what is scientific explanation and by which methods the explanation can be achieved. It is noteworthy that following from the epistemology and methodology of each of the three kinds of sciences, different forms of scientific anticipation can be achieved. The least developed everyday conceptual science grounds anticipation essentially on chance discoveries of patterns in everyday observations. Logical conceptual thought allows formalization of anticipation, mathematical in the first place. Yet formal anticipation is limited, because it does not contain understanding of why, by which mechanisms, certain events—"causes"—are followed by others–"effects." This limitation can be overcome by structural-systemic science, which grounds anticipation on explicit understanding of the structures and the ways they change.

Keywords Science of anticipation · Psychic mechanisms · Structural-systemic concepts · Everyday concepts · Logical concepts

1 Déjà Vu

In 1925, relatively well-known at that time British-American psychologist William McDougall gave a lecture where he introduced his understanding of psychology as follows:

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> I seem to be in a position analogous to that of an anatomist called upon to defend the proposition that man is a biped, or that of a physiologist required to prove that man breathes air. That is to say I am expected to support by argument a fact familiar to all men through first-hand experience, a fact so familiar and well established that it has become embodied in the very structure of all languages and is recognized and acted upon by all men in all the practical conduct of daily life. This is a strange and embarrassing position for any man of science [1, p. 273].

What was this so obvious idea that for some reason he had to defend as novel? In 1930, he wrote on this subject referring back to a little earlier time—time that today is almost exactly a century ago:

> Fifteen years ago American psychologists displayed almost without exception a complete blindness to the most peculiar, characteristic, and important feature of human and animal activity, namely, *its goal seeking*. ([2], p. 3, my emphasis)

McDougall was indeed talking about his so-called Purposive or Hormic Psychology which essentially proposes that "man's acting and thinking are purposive" [1, p. 273]. If human behavior is purposive—and it is—then obviously it involves anticipation. Purpose is a description of the future state of affairs that is achieved if behavior leads to expected results. Thus purpose can be understood as a prediction of the changes of the environment and organism-environment relationships. So it seems to be rather naïve—if not to say self-obvious—to prove that anticipation is useful. And yet the books, conferences and workshops dedicated to anticipation began slowly to emerge in Anglo-American science during last three decades only.

We are slowly rediscovering the obvious; just a decade ago a conference summary proposed—"it is no overstatement to suggest that humanity's future will be shaped by its capacity to anticipate, prepare for, respond to, and, when possible, even prevent extreme events" [3]. Reading this statement the feeling of *déjà vu* should be strong for anybody with some knowledge of the history of life sciences beyond Anglo-American. Russian neurophysiologist Piotr Anokhin, for example, proved already almost a century ago that anticipation and based on it purposeful action is not just about making life better—there would be no life without anticipation and corresponding result-oriented action. It is so because to be alive means to survive in environments that can change beyond tolerance limits of a living organism at any given moment ([4, 5], see also [6]). Such survival is possible only when an organism is able to anticipate potentially harmful changes of the environment—only then it can act by changing either the environment or itself so that environmental change does not lead to destruction of its integrity.

These thoughts I just expressed are rather deconstructive—what good can come out from the statement that "all this has been here before"? I think understanding the situation where we are at the moment with our science of anticipation is necessary for defining its future. If there seem to be difficulties or problems now, these must be discussed. Furthermore, our whole Study Group—Anticipation Across Disciplines—is defined in a way, which actually supports the conclusions I just arrived at and also shows what constructive can come out of this. One of the three areas of work is dedicated to… Learning from the Past.

Science is usually supposed to be cumulative; later developments are thought to surpass the earlier. Yet it is not always true. There are periods in science history where the opposite turns out to be correct—past is ahead of the most recent. There are all the reasons to suggest that this is exactly where psychology is standing at the very moment: last 60 years of research have not contributed much to better understanding of the (human) mind. In fact, psychology of the first half of the 20th century is ahead of today's mainstream psychology [7–12]. This is the idea I wanted to arrive at with my introduction. The ideas I am going to develop in this chapter are directly rooted in "old" pre-WWII Continental European psychology. I do not see much use of modern mainstream psychology (see for definition of it, [13]) for this direction of thought; path to future seems to lie through going back to past and continuing from where they stopped.

2 Why We Must Have Psychology of Anticipation

Readers of this chapter may feel that my comments on the state of psychology are not related to anticipation research in other fields of science; state of psychology may seem to be irrelevant for them. Yet it is not so. Let us go back to a short quote by McDougall, I brought above: "man's acting and thinking are purposive" [1, p. 273]. All studies in all fields of sciences are cases of purposive acts based on purposive thinking. Let me add here one more idea, a little older. Plato, through the mouth of Socrates, made in his *Phaedrus* an interesting statement:

> I am still unable, as the Delphic inscription orders, to know myself; and it really seems to me ridiculous to look into other things before I have understood that. [14, p. 510, 230a1–3]

I think this statement has more in it than it superficially may seem. If we would like to improve our ways of anticipation in particular or any scientific study in general, it is necessary to know ourselves as mental beings. Why so? The reason is that there is more than one way in which our mind can operate. There are different ways of thinking that can be arranged into a hierarchy of development beginning from the most primitive mechanisms of noticing associations between sensory events to most complex ways of organizing knowledge structural-systemically (see Russian psychologist Lev Vygotsky's grounding works on the hierarchy of thinking mechanisms [15–18] and [6, 19–21] for recent developments of this theory). Developmentally later and more complex ways of thinking are also more efficient in making sense of the world.

Psychology cannot formulate principles of the most advanced form of thinking before it has emerged and is used—psychology can only discover it. But after discovering, psychology can describe this form and, through this, allow to decide rationally, which mechanism of thinking to apply in solving the problems ahead or to discover which form of thinking was used in creating what we already know.

Here lies exactly the potential use and power of psychology—if it can describe the mechanisms of thinking, it brings them under our control and helps to avoid moving inconsistently between more and less developed forms of thought without ever noticing it. I think psychology—especially a non-mainstream branch of it that explicitly grounds itself on past theories skipping the present—is ready to provide that ground.

We do not need all the theory of thought at this point. In the following I am going to describe three developmentally latest forms of thinking. This can be done in different ways. For our purposes—to advance anticipation studies—the best way, I believe, is to take a look at these forms of thought from the perspective of science methodology. Before going further, I think it is necessary to mention that methodology is not sum of scientific methods. Methodology is a theory of scientific methods—it answers the question, why we think [sic!] our methods provide us path to answers we as scientists are looking for. Why, for instance, we think that mathematical data analysis can reveal hidden from direct observation mechanisms that underlie observed phenomena. After asking this question we discover that—it cannot [22–26]. Other similar questions about our scientific methods of study—which include the choice of the things or phenomena we study, tools and tasks we use in our studies, "data" we construct on the basis of our observations, and data interpretation methods—must be asked and answered in the same way.

Methodology is not the most fundamental area of questions for scientists to ask. Methodology is grounded on understanding—explicit or implicit—of what is scientific explanation. Without going into details on this point, I think it is justified to equate scientific explanation with description of causes of studied things and phenomena (see, e.g., [11, 27, 28]).[1] Here it is important to realize that causality can be defined in more than one way. Thus the question about scientific explanation can be also formulated as a question about what "cause" means. Without answering that question we are not able to ground methodologically our decisions about choice of methods. Overall, three qualitatively different definitions of scientific explanation can be distinguished in modern sciences. Research methodology and methods correspond to the views on scientific explanation. Each of the stages of thought development is also related to different ways of (scientific) anticipation. At the same time, these three views correspond to three last stages of thought development. First I introduce very shortly these stages of thought development.

[1]It should be also mentioned that there are many theories of (scientific) explanation as well as of causality. The theory of scientific causal explanation I am describing here is based on a developmental theory of human thought operations. It is beyond the scope of this chapter to discuss why it is feasible to follow this and not some other theory of scientific explanation.

3 Everyday Concepts, Logical Concepts, and Structural-Systemic Concepts

All living organisms have receptors that react to certain set of physical-chemical events in their environment. Developmentally the earliest way to anticipate events in the environment and act accordingly is based on purely biotic mechanisms. Living organisms relate to their environment on the basis of species experiences. Next in phylogenesis, psychic ways of organism-environment relationships emerge. Psyche is based on individual experiences (see for definitions of life and psyche, [6, 29, 30]). Even though more complex ways of representing world on the basis of individual experience develop (cf. [18, 19]), these all are constrained by the senses; nothing beyond sensory-based regularities of the world can be represented. Human world is different. Over the history of human race, knowledge about the world beyond senses has been accumulated. How is it possible to have reliable and valid knowledge about the world we have no sensory contact with? Roots of the answer to this question lie in Vygotsky's theory, according to which humans have developed unique way of thought—thought, in the structure of which a linguistic sign is an essential element (e.g., [15, 17, 18, 31]). I have shown elsewhere, how semiotically mediated thought is the mechanism by which limits of the senses can be overcome [32, 33].

For us it is important that structure of linguistic sign—or 'word' in generalized sense, as Vygotsky used—develops over a hierarchy of stages. Thus there are, according to him, three consecutive stages of word meaning structure development, which correspond to three general stages of cognitive development [15]. Vygotsky called the stages syncrets, complexes or everyday concepts and scientific concepts, respectively. Based on vast amount of knowledge accumulated after his death, it is now possible to distinguish not three but five stages [20]. Last three of them are of particular importance in the context of anticipation science as the two earliest stages of word meaning development—those of syncretic concepts and object concepts—are not differentiated enough to ground organized search for knowledge as the last three stages allow.

So, first, so-called *everyday concepts*. Everyday concepts allow to describe in language all the sensory-based world, it properties, objects, and relationships between objects. Categories, referred to by the words are with fuzzy boundaries. Language, being a medium where symbols can be used differently from their referents [33], allows to construct expressions and narratives, which content refers to the world beyond senses. Fairy-tales, myths, and religions belong to this class of creations. Yet there is no way to distinguish reliable and valid inferences about the world beyond senses from imaginary. Another side of these imaginary worlds is that they all can be "translated" into sensory-based experiences. Angels are just people with wings and a god is an old man sitting on a cloud.

Reliable and valid inferences about the world beyond senses can be achieved relying on *logical concepts* (akin to Vygotsky's "scientific" concepts). At this stage, it becomes possible to evaluate the structure of one's own thought—logical forms of inference are clearly distinguished from those that are not logical. Among other attributes of logical-conceptual thought, the words refer to categories with clear yes-or-no boundaries. Logical clear-cut structure of concepts, in turn, grounds the ability to distinguish imaginary worlds from realistic worlds beyond senses. Science in the modern sense emerged at this stage of thought development. Logical concepts are also limited in their use. The main problem lies in the weakness of all logical inferences—formally correct inferences are also realistically correct if and only if the premises of them are correct. Thought in logical concepts does not ground basis for selecting premises of inferences.

At the final stage of thought development, that of *structural-systemic concepts*, the whole process of sense-making is made conscious. The clear-cut logical structures are contextualized both in terms of the world described by them as well in terms of the thought processes that underlie sense-making of the world. Now not only inferences but also their premises and sources of the latter can be explicitly studied. From scientific activity point of view, I would suggest, the main characteristic of this stage of thought is an ability to distinguish and define all relevant for scientific enterprise ideas from most abstract epistemological and ontological principles to most specific concrete aspects of scientific methods. Knowledge formulated in this way can develop into a coherent whole where each element is clearly positioned in respect of others in the whole of scientific thought.

Next we see, how these different mechanisms of thought are related to views on scientific explanation and corresponding methodology and methods. Each of the stages is also characterized by the specific form of (scientific) anticipation that can be achieved at that stage. In this Chap. I look at the development of thought from the anticipation science perspective. This I have not done before. The overall idea of relationships between word meaning structure development and scientific methodology, nevertheless, has been discussed elsewhere [11, 27, 34, 35].

4 Everyday Concepts and Phenomenological Qualitative Science

4.1 Scientific Explanation

Thinking in everyday concepts is characterized by fuzzy boundaries of categories referred to by words. This way of thinking, thus, does not distinguish clearly and unequivocally neither qualitatively different phenomena one from another nor the researcher and his or her way of thinking from what is studied. One consequence of that kind of limit on thinking is expressed in understanding, what is (scientific) explanation and causality—there is no understanding of it. In an unbounded world everything seems to be constantly changing; therefore instead of studying what things are and in which ways they lawfully change, everyday conceptual science focusses on process, on change.

A reader may feel now that even if that kind of science may have existed in some remote time in the past, it does not exist any more. In fact, this kind of science—which by its essential characteristics is more akin to art than to science [36]—exists today in many areas of social and human sciences (cf. [11, 28, 35]. I am not going to put too much effort into proving that this kind of scienting is increasingly common today; there are too many sources available to prove that (e.g., [37]). So I just provide a quote showing that there is a kind of science, indeed, which is not able to distinguish between who is studying from what is studied:

> We have left the world of naïve realism, knowing now that a text does not mirror the world, it creates the world. Further, there is no external world or final arbiter—lived experience, for example—against which a text can be judged [38, p. xiv]

Others have been even clearer. One quite popular approach in modern qualitative science has formulated several assumptions that underlie their methodology; the first of them states:

> Assumption 1. The external world is a symbolic representation, a "symbolic universe." [39, p. 6]

So it is made clear that the "external" world cannot be distinguished from personal. Further, there is also no clear understanding of what kind of understanding is searched for. It is rather collection of endlessly growing descriptions which basically lead nowhere:

> At some point we [qualitative researchers] ask, 'Did we get the story 'right'?', knowing that there are no 'right' stories, only multiple stories. Perhaps qualitative studies do not have endings, only questions. ([40, pp. 44–45]; see also [41, 42], for similar ideas)

4.2 Research Methods

Everyday conceptual thinking is not able to go beyond directly perceivable facts about the world. Even though many methods are used in this kind of science—interviewing; direct observation; the analysis of artifacts, such as documents, photos, diaries, etc.; the use of personal experiences etc.—all these methods can be reduced to one: description of directly perceived experiences. Without constraining artificially study conditions it is not possible, however, to go beyond appearances, superficial subjective descriptions of personal experiences. The world beyond senses can be understood only by manipulating environment of the studied things, be them physical, living, or psychic. So the research methods of everyday conceptual science reflect the essence of that stage of thought development.

4.3 Scientific Anticipation

It might seem that everyday conceptual science can result in no reliable anticipation. Indeed, science that is explicitly based on confusing the world with the semiotic representation of it and relying on methods that cannot do more than just describe what seemed to the researcher to be interesting at the moment, could end up with nothing more than what they claim the world to be—a personal story with no valid connection to the world. Yet it is not entirely so.

Everyday conceptual qualitative science collects observations and finds regularities in them on inductive-intuitive basis. It is important that there are two possible bases for regularities in such a process of data interpretation. As observations that are analyzed are observations of the world, the regularities that are recognized in the data may reflect regularities of the perceived world. Such regularities can lead to beyond-chance level predictions of some events in the world. But there is also another ground for regularities that cannot be distinguished by everyday conceptual thinker from the first. Namely, observed regularities can be purely subjective, intralinguistic. A researcher may observe certain regularities and find further support for them not because there is some regularity in the world but because he or she just selects observations that correspond to the prediction and rejects others that do not correspond. In that case the criterion for regularity is purely subjective: if it is possible to relate certain observations one to another in a certain way then the researcher just does it. As in semiotic systems every sign can be in principle related to any other sign—because all linguistic signs can in principle be used in ways and contexts that are different from the referents of the sign [33]—the researcher is actually unbounded in "discovering" regular patterns in observations. These patterns, however, would be intrapsychical with no necessary connection to the world observed and described.

As the criterion for deciding whether reliable pattern was discovered—a category of observations, for instance—is subjective, then a researcher may end up with interpreting the collected data as "making sense"—because intuitively it feels in this way. Without clearly distinguishing the way of one's thinking from the world thought about, realistic and subjective patterns of observations cannot be distinguished. Paradoxically there is also no way to demonstrate to everyday conceptual thinker that the "results" of this kind of studies are only accidentally reliable and never valid about the world beyond senses. The reason for this impossibility lies in the fact that for that researcher subjectively all may "make sense"; it may "feel" meaningful. No rational argument can refute that kind of feeling.

5 Logical or "Scientific" Concepts and Cartesian-Humean Science

5.1 Scientific Explanation

Logical conceptual thinking distinguishes process of thought—logic—from what is studied and made sense of with these thought operations. Correspondingly it becomes possible to specify, what is (scientific) explanation as a form of thought about the world. Further, the form of logical concepts is hierarchical; they comprise intralinguistic hierarchies where higher order words refer to a category of lower-order words, which, in turn, refer to sensory-based experiences. A possibility to reflect on thought processes allows at this stage of thought development to explicate the criteria by which categories are composed. This quality of logical concepts allows to distinguish between kinds or categories of the bases of categorization. One specific category—that of scientific laws—can be distinguished among others.

So scientific explanation becomes a description of those laws that are discovered in studies of the world. The concept of law is directly related to Cartesian-Humean view of causality. According to that view, causality is defined as a relationship between two events, cause and effect. Cause is an event that precedes and is necessary for the emergence of another—following to cause—event, the effect. Scientific law in this case is formally and exactly—often mathematically—described cause-effect relationship. It should be noted that there is also a weaker in terms of causality version of a scientific law, where cause and effect are not clearly distinguished. This kind of a law formulates exactly the relationship between two events without a requirement of the cause to bring out the effect. Newton's laws are examples of the latter kind.

5.2 Research Methods

All living organisms have access to the world external to them only through senses. Humans—and scientists among them—are not exceptions. Therefore all knowledge about the world can be based only on observations of sensory-based experiences. It does not follow, however, that all observation-based inferences are in principle the same. There are two sources of fundamental differences between ways of making inferences on the basis of observations. On the one hand, as I have already shown above, there are different psychological mechanisms by which inferences are made. On the other hand, the qualitative difference is introduced by a possibility to manipulate with conditions of observations.

Everyday conceptual science relies on *observations of events in naturally occurring situations*. Such observations are necessary for any kind of science. Yet they are not sufficient for logical conceptual science. The reason is that any event in the world can be described in endlessly many ways. Scientific laws are not really about relationships between specific events. Rather, they are about relationships between categories of events. Depending on in which exact way potential cause-events and effect-events are described, the categories of events that are formed will be different. So a researcher needs in addition to establishing some preliminary hypothetical causal association between events—which can be done on the basis of observations or earlier theory—find out the basis for categorizing the events so that an exact law can be formulated.

Logical conceptual thinking allows to specify exactly the bases of categorizations. Every attribute that is individually necessary for a thing or phenomenon to belong to a certain category is explicitly defined. This allows to choose purposefully for different bases of categorization and discover eventually the best set of attributes that defines the category. A researcher thinking in logical concepts can manipulate with external environment and together with it with the attributes that define the category of events studied. In other words, a researcher can conduct *evocative experiments*—artificially created study-situations where attributes of situations can be explicitly manipulated with the aim to establish, which aspects of a situation are necessary to call or evoke the "effect" into existence. I use the term 'evocative' here to distinguish this kind of experiment from another, what I call *constructive experiment*. The difference is explained in the next section, where structural-systemic science is described.

There is a third class of research methods that is applied in logical-conceptual science. Everyday observations and theory is not always sufficient to formulate a hypothesis about cause-effect relationship that could be tested in experiments. In this case often one step between everyday observations and experiments is introduced—let us call it *constrained observations*. In this case researchers constrain study-situations artificially and search for patterns of relationships between events with no a priori hypothesis about the exact structure of the pattern in the data. If some reliable pattern is discovered, it can be further tested by evocative experiments for establishing a cause-effect relationship.

It is also important, *how the results of evocative experiments are interpreted* in logical conceptual science. Namely there is a problem that needs to be solved—no exact law would emerge from experiments, however well controlled and conducted. The reason is that it is impossible to create closed systems; all experimental situations take place in to some degree unpredictable compositions of the open-systemic study-environments. Therefore necessarily the experimentally observed putative cause-effect relationships will never be mathematically exact. This problem is solved by abstracting the studied relationship from all possible contexts. An *exact mathematical law* is formulated that is supposed to be valid only in theoretical situations where the abstracted cause-effect relationship is isolated from the rest of the world. With this move from real situations to abstract, mathematical formulas brings a new problem to be solved—how to apply the formula in real situations.

This problem has two solutions. Informal solution is to accept the discrepancies between formulas and real-life situations. The cause-effect formula just "works well enough." Another solution is formal: it is possible to calculate the chances the law corresponds to real-life observation. In that case an exact theoretical probability is achieved to predict the chances the established law will or will not be observed. This exact probability, obviously, is abstracted from reality and is valid only in theoretical cases of observations that are supposed to correspond to empirical observations without a "noise".

5.3 Scientific Anticipation and Its Limits

History of science knows many discoveries based on logical conceptual science—Newton's laws are perhaps the best known examples. These laws also demonstrate the weak points of them. The problem was introduced already millennia before Newton. Science is supposed by many to be mainly if not only about measurement—after measuring, the beautiful language of mathematics allows us to make sense of the whole of all the measures we have collected. Measurement, in turn, is, as Plato wrote through the mouth of the Visitor in his *Statesman*, about

> the association of greatness and smallness with each other […] all those sorts of expertise that measure the number, lengths, depths, breadths and speeds of things in relation to what is opposed to them [43, pp. 326, 283d7–8, 328, 284e3–5].

Yet the Visitor would not agree that measurement is only about quantities. He was sure that there is another class of phenomena that also must be measured:

> […] measurement […] let's divide it into two parts […] one part will relate to the association of greatness and smallness with each other, the other to what *coming into being* necessarily is ([43, p. 326, 283d4–9], my emphasis)

I think here lie at least two fundamental limitations of measurement-based formal predictions. Both of them emerge because only first and not the second of the Platonic "measurements" is expressed in formal models. First, establishment of a lawful relationship does not explain, why events are related in this or that particular way. Another—and directly following from the first—problem is that if in real life it is discovered that the exact law did not predict events as expected, there is no understanding, why the prediction failed. Or, in other words, such laws do not contain information about how to get the event we want to happen when the law fails.

Scientific laws discovered in studies and then abstracted from reality and formalized through the thought operations are powerful tools for anticipating future events. This power does not apply in all cases due to the limited epistemology that underlies the logical conceptual thought: efficient causality or the cause → effect relationship between events is detached from the mechanisms by which actual changes of the world take place. The problem is that in efficient causality *events* are related one to another. But event is a change of some observed system with a complex structure. Event is essentially a psychically constructed segment of constantly changing material world. A temporally extended unit, i.e. event of change, cannot force or "cause" something else to happen; change is the process of happening itself. If an event is conceptualized as an entity, as some “cause”, then the actual change is transformed into a fixed unit that does not correspond to the original segment of a process. Event as a fixed unit is abstracted from reality entity of thought, not of external reality that referentially matches the thought.

Events as “causes” cannot reveal the mechanisms of change because there is no constraint on how an event is conceptualized. The very same event can be described and interpreted in endlessly many ways and therefore there is never certainty that only causally necessary attributes of it are chosen. Further, causes as events are also defined negatively by lack of usually unknown qualities—causes are abstracted from reality.

Let us take a simple causal series of events: a moving billiard ball hits the other ball, which begins to move after the hit. We may think that we have scientifically understood the event, when we can formally express the causal relationship between the cause—movement of the first ball, and effect—movement of the second ball. We may know that “the acceleration of an object is directly proportional to the net force acting on it and inversely proportional to its mass.” Usually the second ball moves after caused to move by the first. The formula—within certain limits of error—explains the change of the movement. But if we for some reason encounter a situation where the second ball does not move after being hit, the formula becomes useless. In the formula we have the mass and the velocity of the balls. If the formula does not predict the reality, we would not constrain ourselves only to studying the mass and velocity of the balls. We would also study the table, the stick we used for hitting, the relationship of the balls to the table and perhaps other things. Maybe somebody just magnetized the second ball and then fixed the position of it by the magnet under the table. In that case not only the mass but also the material of the ball becomes relevant, because only some materials can be magnetized. There is no place in the cause-effect formula where the material of the ball is taken into account.

There is also another aspect that is not represented in cause-effect predictions. Namely, there is no information in the exact formulas about how to restore the state of affairs after a cause has had an effect. Formula would perhaps tell us to take the “cause-ball” back at the speed and direction it hit the “effect-ball”. We would discover that it does not restore the situation as it was. This fact reveals from another perspective the same problem of predictive formulas—there is no information in them about what the events and things *are*. So there is probabilistic anticipation but no understanding of what is changing and why—unless “why” is “explained” by essentially empty and circular statement that effect happened *because* there was a cause.

In the previous section I discussed shortly the ways the data are interpreted in logical conceptual science. We saw that formal laws can be formulated only when abstracted from reality. To account for mismatch between the formula and reality it is supposed to reflect, probabilities of the observability of the formal cause-effect or covariative relationship can be estimated. What is not often thought about in such cases is that any way to create a formal formula of probabilities of certain events to be in cause-effect—or any other covariative—relationship suffers from the same problem as the direct formal expression of supposed cause-effect relationships. The formal probabilistic formula is also valid only in theoretical abstract isolated from the real world situations. We would need another probabilistic formula to predict the chances the first formula predicts the probabilities correctly… and another for the second formula, and another for the third, and so on ad infinitum.

Altogether, it can be said that formal prediction can be powerful but yet limited in being necessarily probabilistic. There are two fundamental problems with formal prediction. First lies in the fact that formalization requires abstracting from reality. The second limit of formal prediction stems from the fact that formal models are based on limited efficient causality epistemology, which allows to reveal covariative and asymmetric in time cause-effect relationships between observed events but not the mechanisms of change that underlie the events and their relationships.

6 Structural-Systemic Concepts and Structural-Systemic Qualitative Science

6.1 Scientific Explanation

Structural-systemic thought distinguishes the thought operations from the things and phenomena studied and, at the same time, defines the way the first is related to the second. Among other consequences to this development of thought, the logical-conceptual scientific laws are not considered satisfactory any more. It is recognized that such laws are essentially human-made abstractions that reflect only limited aspects of reality and are not fully suitable for making sense of open systems. Scientific explanation becomes more complex also. To explain something scientifically becomes a question about structure of a studied thing or phenomenon: what are the elements, in which specific relationship and what characterizes the novel whole that emerges in the synthesis of the elements.

This kind of explanation—even though usually not stated as such—is quite common in many branches of modern sciences. We understand atoms as systems of elementary particles; we understand molecules as systems of atoms; we understand genes as systems of certain acids; we understand living cells as systems of organelles and other distinguishable elements; we understand multicellular organisms as systems of organs, etc. It is noteworthy that none of these theories require mathematics[2]; all the elements, their relationships and qualities of the emergent whole can be defined qualitatively (see for definitions of mathematics [26]).

[2]I am not suggesting that mathematics is not involved in building such theories; often use of mathematics is useful or even essential at certain stages of theory-construction. Yet the final theory —the explanation of what the studied thing or phenomenon is—is not mathematical. So it can also be said that mathematics cannot define what a thing or phenomenon is even though it can reflect certain aspects of relationships between things.

6.2 Research Methods

As at previous stage, structural-systemic science uses everyday observations, constrained observations and evocative experiments. Even though superficially similar, the use of these methods is essentially different from previous stages. In addition, a new kind of experiment emerges what I have called *constructive experiment*. Next I characterize briefly each of the methods.

First, *everyday observations* in structural-systemic science can take different forms. First of all, all the observations are explicitly theory-guided as any observation entails selection of aspects that are observed; the only difference is whether the basis of selection is explicit or implicit. Another aspect in structural-systemic observations is that these can be explicitly aimed at searching for situations where either the theory seems to fail or there seems to be no theory to explain subjectively perceived patterns in events. Differently from everyday-conceptual science it is clearly understood that no spontaneous observation without artificially constrained study-situations can lead to scientific explanation but rather only to new questions to be answered. Differently from logical-conceptual science, the observations are used to look for possibilities to falsify existing theories. Logical science is aimed at looking for patterns and treats violations of theoretically predicted patterns as noise or error of observation. In structural-systemic science, theoretically unpredictable situations call for explanation.

Second, *constrained observations* in structural-systemic science have a different aim: the aim is not to look for relationships between events but rather for changes in the ways the studied thing relates to its environment with changes of the context. Another possibility is to look for thing-environment relationships when the context is physically the same but the thing has changed—for example, a human child has developed. Thing-environment relations are changing; thus in such observations also events are studied. But the events are studied as structured wholes—with distinguishing the elements of the events, their relationships and changes in the qualities of the elements of the events. Structural study of observed events allows to develop hypotheses about the structure of the thing studied. Perhaps it is noteworthy that in structural-systemic science it is understood that directly observable structures are usually not in one-to-one correspondence with the structure of the thing that is studied. Sciences, with rare exceptions, aim at understanding the world beyond directly observable. In these cases, as a rule, structure of the observed events where the studied thing is participating is not identical with the structure of the studied thing. Thus, for example, human behavior is not in direct correspondence to psychic structures that underlie the behavior. The structure of the human mind can be revealed only by varying either the context the humans are or the individuals themselves.

Third, *evocative experiments* in structural-systemic science aim explicitly at distinguishing the elements and their relationships in studied structures. In evocative experiments it is attempted to vary either the element or certain relationship between the elements of the whole and observe whether the whole changes in theoretically expected way. In other words—structural-systemic experiments are studies of development. Development, in this context, is defined not as any change but as a hierarchical reorganization of a system. Thus development can take three forms: element is added into a structure, element is taken away from a structure, or relationships between the elements change. In all three cases the whole structure changes qualitatively. In that perspective, structural-systemic experiment requires explicit hypotheses about what qualities of the whole change when certain element or certain relationship is experimentally manipulated. These hypotheses are created on the basis of everyday and constrained observations.

Finally, *constructive experiment* can be conducted. The idea of constructive experiment was born, as far as can tell, for more than a century ago. Friedrich Engels did not agree with many philosophers, according to whom either knowledge of the world is not possible at all or it is possible only about very limited aspects of it. He argued:

> The most telling refutation of this […] is practice, namely, experiment and industry. If we are able to prove the correctness of our understanding of a natural process by making it ourselves, producing it from its preconditions and making it serve our own purposes into the bargain, then it's all over with the Kantian ungraspable "thing-in-itself." The chemical substances produced in the bodies of plants and animals remained such "things-in-themselves" until organic chemistry began to produce them one after another… [44, p. 19].

So, Engels proposes what we can take, I think, as a criterion of truth: if we know how to create a thing we try to understand, we have understood it, we know that our understanding is "true", i.e., it corresponds to reality as it is. We can go further and define, what kind of knowledge in principle is knowledge about how to make a thing or phenomenon—it is knowledge about the structure. If we know, what elements should be put into which kinds of relationships, we know how to make a whole. Thus the ultimate test of a structural theory is *constructive experiment*, where theoretically distinguished elements are synthesized with the aim to create a whole with exactly those qualities, predicted by the theory.

It should be noted here that constructive experiment should be distinguished from logical-conceptual evocative experiment. In the former, the successful result is the creation of the thing or phenomenon with qualities identical to those that characterize the thing studied. In the latter, however, conditions are created, in which the expected event is evoked to take place—but it is not known, how actually the result emerges. I think it is relatively easy to distinguish the two kinds of experiments. The difference becomes especially clear, when experiment fails. In the logical-conceptual evocative experiment, the researcher would try to manipulate with the "cause" of the supposed "effect"; the effect itself, however, would not be studied. When it becomes clear that evocative experiment failed, the researcher returns to everyday and constrained observations for improving the theory about the cause.

In the constructive experiment, on the contrary, the "effect"—the result of the experiment—would be the first to study. It should be made clear, whether indeed all the theoretically necessary elements were synthesized and in which specific relationships they ended up. Also the emergent whole would be studied to reveal, how exactly it is different from the theoretically expected whole. If all the theoretically distinguished elements and their relationships are discovered but the whole came out different from what was expected, then the researcher returns to observations and evocative experiments. These studies would be aimed at understanding, what the "effect" is.

6.3 Scientific Anticipation

Structural-systemic anticipation is the only kind of exact anticipation. If constructive experiments have proved that correct elements and their relationships have been theoretically established, then any time the same elements become into the same kind of relationships, the whole with expected qualities is exactly anticipated. It does not follow, however, that structural anticipations do not fail in reality. They fail, if the elements or their relationships have not been correctly described. Modern industry is an example of structural anticipation: every new car, spaceship, computer, drug, material or whatever produced is anticipated to be with specific qualities. If the result turns out to be unexpected, the product is studied and, as a rule, the ill-defined element or relationship can be revealed. It is noteworthy that despite extreme complexity of many industrial products, the failure rate is remarkably low.

Structural-systemic thinking does not exclude less developed forms of anticipation. These are used, when no structural theory is available yet. When such less developed forms of anticipation are used, the shortcomings of them are explicitly understood—and the possible ways to overcome these shortcomings through structural studies are recognized.

7 Summary and Conclusions

Science of anticipation was born about a century ago. During this century humans have learned more than ever before how to anticipate events in diverse areas of life. Yet the process of anticipation itself—the psychic mechanisms of it—are much less understood. Interestingly, there are all reasons to suggest that the psychology as a whole as well as the psychology of anticipation in particular was far more advanced about six decades ago than it is now. For this reason in this chapter my discussion of psychic processes that underlie anticipation was based on ideas created by continental European psychologists before the WWII.

Science of anticipation can be distinguished into three kinds, each relying on a different psychological mechanism. Further, these mechanisms—based on everyday conceptual thinking, thinking in logical concepts and thinking in systemic concepts, respectively—are in hierarchical relationships the first being the least developed and the last the most developed form of (scientific) thought. Each of these three sciences has specific to it understanding of what is scientific explanation and by which methods the explanation can be achieved. It is noteworthy that following from the epistemology and methodology of each of the three kinds of sciences, different forms of scientific anticipation can be achieved. The least developed everyday conceptual science grounds anticipation essentially on chance discoveries of patterns in everyday observations. Logical conceptual thought allows formalization of anticipation, mathematical in the first place. Yet formal anticipation is limited, because it does not contain understanding of why, by which mechanisms, certain events—"causes"—are followed by others—"effects." This limitation can be overcome by structural-systemic science, which grounds anticipation on explicit understanding of the structures and the ways they change.

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Anticipatory Engineering: Anticipation in Sensory-Motor Systems of Human

Yoshikatsu Hayashi, Jamie Blake and Slawomir J. Nasuto

Abstract In visual tracking experiments, distributions of the relative phase between target and tracer showed positive relative phase indicating that the tracer precedes the target position. We found a mode transition from the reactive to anticipatory mode. The proposed integrated model provides a framework to understand the anticipatory behaviour of human, focusing on the integration of visual and somatosensory information. The time delays in visual processing and somatosensory feedback are explicitly treated in the simultaneous differential equations. The anticipatory behaviour observed in the visual tracking experiments can be explained by the feedforward term of target velocity, internal dynamics, and time delay in somatosensory feedback.

Keywords Anticipatory mode · Delayed differential equations · Somatosensory feedback · Mode transition

1 Introduction

Experimental evidence concerning periodic movements suggests that in order to adapt to changing environment, humans exhibit the mode transition from the reactive to anticipatory mode as the frequency of motion increases. This behaviour is understood as one of the manifestations of the anticipatory nature of the human mind, with the purpose of overcoming the inevitable time-delays in the sensory-motor systems.

In the context of human behaviour, the previous works have reported instances where body motion may occur prior to an external reference signal in hand tracking and finger tapping tasks [1, 2]. Human subjects are also able to generate motion

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preceding a periodic target signal [3]. These phenomena indicate that the human sensory-motor system may operate in an anticipatory mode rather than a reactive mode, when the target motion is relatively fast. Recently, extending single tapping/tracking experiments for mutual interactions, we found that the anticipatory mode leads to synchronised motion between pairs of participants [4, 5].

In fact, the ability to anticipate future input seems to underpin many cognitive processes. A major advantage of such anticipatory brain mechanisms is that they allow cognitive agents to respond adequately to fast input signals. In addition, the assumption that feedback delays are threats to successful control, being regarded as an unfortunate feature of the biological systems, seems to also favour the anticipation hypothesis. Thus, a fundamental question in cognitive neuroscience is what mechanisms might give rise to such signal processing capabilities.

The simplest visual-motor coordination laboratory experiments consist of participants being asked to minimise the positional error between a tracer and a target they are asked to track. The tracer on the display represents the hand motion by being detected by the robotic manipulator.

One of the early models of human visual-motor control was based on the well-known PID feedback control law using the relative positional error between target and tracer. The relative positional difference between target and tracer is an input signal to PID control, and hand motion is generated to minimize the relative positional error. However, this control law amounts to essentially the reactive behaviour mode. The implementation of a feedback loop does not require any modelling of the system in concern.

On the other hand, the feedforward control requires some modelling framework. For example, if the dynamics of the controlled object is known, the inverse model can be calculated to generate the controlling signal directly for desired target trajectory. However, such feedforward control violates the causality in terms of the time derivative, and can be destabilised by unknown factors in the environment.

In order to explain the anticipatory mode found in visual tracking experiments, it was shown that if the feedforward term for target velocity was included, the resulting feedback and feedforward (FB/FF) model showed precedence of tracer with respect to target motion [3]. This simple extension of the conventional feedback control successfully explained the precedence of the tracer driven by anticipatory mechanism of humans. However, although this FB/FF model can be analytically pursued to explain the anticipatory behaviour in visual tracking experiments [3], and a stability analysis identified the conditions for the stable precedence of tracer, it does not explain the synchronised motion of two subjects' dyad engaged in mutual motion interactions, i.e., when a pair of visual motor systems are coupled. This limitation is due to the fact that the FB/FF model is driven by the external dynamics and it lacks of its own internal dynamics [4].

Strong anticipation has been recently proposed as a mechanism of interaction of dynamical systems in such a way that a slave system traces the future trajectory of a master system, exhibiting the constant positive phase as if the slave were anticipating the master evolution [6]. Interestingly, in the original formulation, it is the presence of a delay in the coupling that is a necessary condition to achieve the slave's anticipation of the master's dynamics [7, 8]. Note here that the slave should share identical dynamics with the master system. The positive, productive status of the delayed feedback should be emphasized in contrast to the classical feedback control law, as it may have very important implications for our understanding of how cognitive systems can predict future outcomes during many crucial tasks. We propose a putative mechanism enhancing the precedence of tracer with more stable conditions by incorporating the strong anticipation paradigm which employs internal dynamics and time delay in somatosensory feedback.

In this paper, we discuss the anticipatory mechanism of the control law based on the integration of visual and somatosensory information with focus on the time delay in visual processing and somatosensory feedback.

2 Experimental Method and Analysis

In order to investigate the properties of the anticipation mechanism, we performed single tracking experiments in which participants are asked to minimize the positional error between the tracer and the target. A total of 10 right handed participants performed the task. The tracer displacement on the display is proportionally related to the hand motion detected by the robotic manipulator attached to the participant.

The tracer in display was set to move along a circular trajectory of 13 cm diameter positioned in the plane of a display screen. The phase angle of the tracer was calculated, transmitted to the display computer, and was presented along the guideline circle on the display of the participant. The initial position of target and tracer are the same, and the target started to move along the circumference of the circle in a clockwise direction. The programmed target frequency was fixed in each trial and from trial to trial increased from 0.1 to 2.0 Hz with a step of 0.1 Hz. At each trial, the participant was asked to trace a moving target for 20 s with a 10 s break period. 3 trials were performed at each of the 20 frequencies.

The distribution functions of relative positional errors between target and tracer were calculated at each frequency, and were fitted by the Gaussian distributions to identify the position of the peak of the distributions.

3 Experimental Results

Figure 1 shows the distributions of the relative phase between target and tracer at different frequencies. The positive relative phase indicates that the tracer precedes the target position. At the frequency region of 0.2 Hz, the peak of the Gaussian distribution is located below 0, presumably as a result of the visualmotor system time delay. However, there is a clear gradual shift towards the precedence of tracer over the target as the frequency increases above 0.4 Hz (Fig. 2). The same gradual shift has been observed for other 9 participants [9].

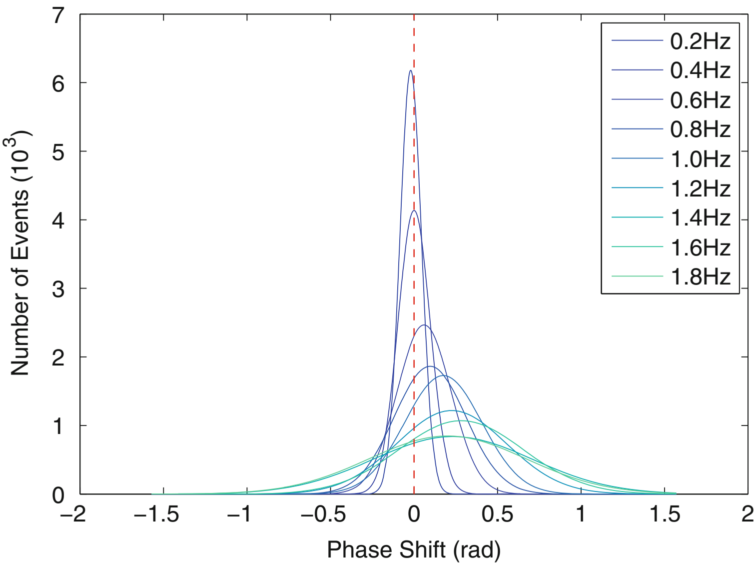

Fig. 1 Distributions of the relative phases between target and tracer across a range of frequencies for a typical subject. The positive phase indicates the precedence of tracer with respect to target

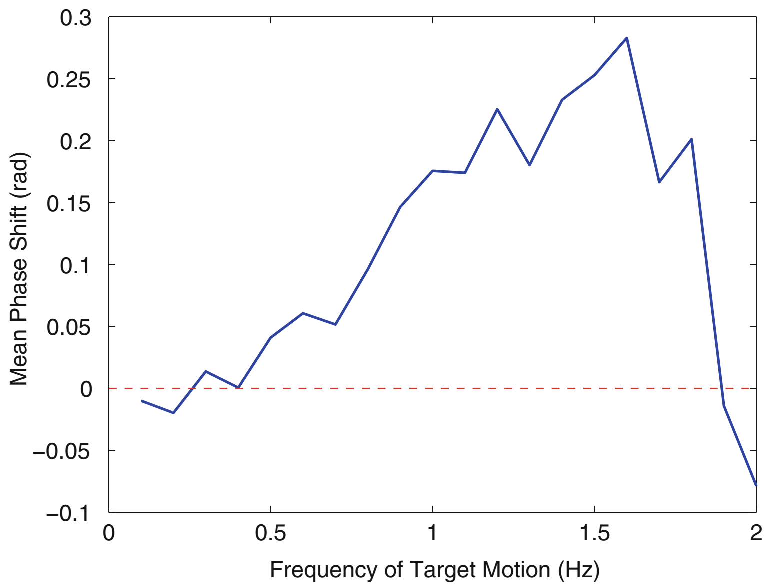

Fig. 2 Mean values of the distributions as a function of frequency for a typical subject. The positive phase indicates the precedence of tracer with respect to target

In short, we also found a mode transition from the reactive to anticipatory mode. Even though the same trend has been found in visual tracking experiments of harmonic oscillators [3], our experimental results showed that humans exhibit the transition towards anticipatory mode even though the target moves at a constant velocity along the circle guide line. This is highly significant as the simplest explanation could be that the anticipatory mode was triggered by the rhythmic component of external stimuli. Rather, we found that rhythmic components of hand motion were generated when the participant showed the anticipatory mode [9].

Additionally, around the frequencies around 1.6 Hz, the distributions tend to move towards the origin as they develop large spreads indicating the subject is unable to follow the target.

4 Theoretical Framework for Anticipatory Behaviour of Visual-Motor Systems

In this section, we would like to discuss a theoretical framework explaining the anticipatory behaviour found in the visual tracking experiments. The aim is to provide a plausible account of a mode transition from the reactive to anticipatory mode with simple delayed differential equations, focusing on time constants and time delays in visual motor system (Fig. 3). The general signal flow in the visual motor system is assumed to comprise visual processing, motor command generation, and body dynamics. The target position $X(t)$ and the tracer position $Y(t)$ are presented on the display in front of the participant. The position of target and tracer, and the velocity of target are considered to be perceived by subjects with a time delay needed to register and to process the visual information.

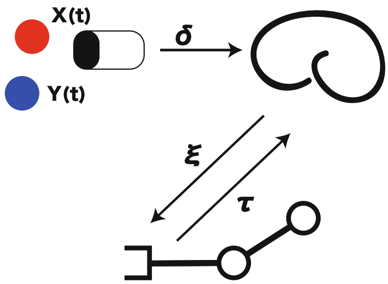

Fig. 3 Schematic picture of visual motor systems with time delays in visual and somatosensory feedback

The motor command $S(t)$ is generated by feedback and feedforward control from the visual information. A dynamics of motor command generation is given by

$$\frac{dS(t)}{dt} = \frac{1}{\tau_{vi}}[X(t-\delta) - Y(t-\delta)] + \gamma\frac{dX(t-\delta)}{dt} \quad (1)$$

Where τ_{vi} is a time constant of visual processing. The first term describes a feedback control for relative positional difference between target and tracer, and the second term describes a feedforward control for the target velocity with a tuning parameter γ [3].

The signal $S(t)$ is transmitted to the hand with the time delay ξ, and the dynamics of hand motion $Y(t)$ is driven by a feedback control between the brain and feedback signal. Note that $S(t)$ is generated by visual information and hence is driven solely by input signals, and will fade away when visual information is no longer available.

In contrast, we assume that the dynamics of hand motion $Y(t)$ has a corresponding representation in the brain, $g(Y)$. This means that the brain has a representation of the hand dynamics which is able to generate the actual hand motion in the work space even without external inputs. This autonomous dynamics should be modulated by the brain signal representing the visual information with respect to the hand position $Y(t)$. To account for integration of sensory information, we suggest that somatosensory feedback is used to identify the hand position. This somatosensory feedback would have a time delay τ which is larger than the time delay in visual processing ($\tau > \delta$).

Thus, the considerations above imply the hand dynamics described by

$$\frac{dY(t)}{dt} = g(Y) + \frac{1}{\tau_{mo}}[S(t-\xi) - Y(t-\tau)] \quad (2)$$

where τ_{mo} is another time constant to process a proportional control between the brain signal and the feedback signal, and ξ is the time delay to transmit the signal to hand.

In short, simultaneous equations of the visual processing and hand dynamics utilise a mechanism of adapting hand dynamics to trace target motion by integrating the visual and somatosensory feedback.

5 Discussion

The average relative phase between the target and the tracer, the peak location of the Gaussian distribution clearly showed the transition to the precedence of the tracer as the target frequency increased (Fig. 2). The mode transition from the reactive to anticipatory mode was found in the visual tracking experiments in which the target moves at a constant velocity.

The integrated model here provides a framework to understand the anticipatory behaviour of human movement, focusing on the integration of visual and somatosensory information. The time delays in visual processing and somatosensory feedback are explicitly treated in the simultaneous differential equations. Although, the anticipatory behaviour observed in the visual tracking experiments can be explained by the feedforward term of target velocity [3], FB/FF equations alone will not explain the anticipatory synchronisation between pair of participants since this model is driven by external input only.

To include the internal dynamics in hand motion, we proposed an integrated model incorporating the internal dynamics of the hand motion and the time delay in the somatosensory feedback.

Even though systematic numerical calculation of the integrated model and comparison with behavioural data is necessary to determine the constants of time delays and time constants, in the asymptotic limit of time constants of τ_{vi} and τ_{mo}, the proposed model indicated a robust stability in the precedence of the tracer. Intuitively, the brain signal $S(t)$ can be considered as a virtual target in brain generated by visual processing to which a hand motion dynamics is coupled, and, the internal dynamics of hand motion represented in brain and the time delay in somatosensory feedback will further enhance the precedence of tracer with respect to the target trajectory, since the virtual target itself already shows the precedence of tracer by the feedforward term.

The stability of the FB/FF model is attributed to the Hopf bifurcation, whereas the stability of the internal dynamics model is attributed to the asymptotic relaxation to the fixed point [7]. Therefore, the proposed integrated model enhances the anticipatory horizon of precedence of own motion with respect to the target motion in visual tracking.

The model suggested here is empirical and uses the simultaneous differential equations with relevant time delays in the sensory motor system. The degrees of freedom considered in these equations are limited to a few parameters. The next question is to relate these empirical equations to brain dynamics.

From the microscopic point of view, the brain consists of billions of neurons. The neuronal networks are not static and passive systems simply responding to the external stimulation or the sensory input, but rather, spontaneous activity of individual neurons and their connectivity make it possible to generate a variety of cohesive patterns for imposed sensory-motor coupling to select a certain phase from a series of transitions of the intrinsic attractors. Consistent with this synergetics view [10], the temporal dynamics should be extracted with a few set of order parameters. Therefore, we expect that the delayed differential equations here can be validated with order parameters extracted from measurement of brain activity.

In the future study we will perform systematic numerical calculations of the integrated model to define stability conditions for the time constants and time delays leading to the stable anticipatory mode comparable with behavioural data. A model proposed in this paper.

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Anticipation and Computation: Is Anticipatory Computing Possible?

Mihai Nadin

Abstract Anticipation, a definitory characteristic of the living, is expressed in action. It implies awareness of past, present, and future, i.e., of time. Anticipatory processes pertain to the world's dynamics. Anticipation also implies an observation capability, the acquired function of processing what is observed, and the ability to effect change. Computation means processing quantitative distinctions of physical entities and of those that inform the condition and behavior of the living. Autonomic processing is the prerequisite for anticipatory expression. In the physical, processing is reactive; in the living it is autonomic. Automated calculations, inspired by human "computers," are different in nature from those involved in living dynamics. To distinguish between anticipatory and predictive computation is to account for the role of the possible future in dealing with change.

Keywords Algorithmic · Anticipation · Computer · Forecast · Prediction · Non-algorithmic · Turing

1 Theoretical Considerations

1.1 Preliminaries

The context is clear: it was asserted (Mitchell [1]) that the world to which we belong is the outcome of computation (of quantum nature, in particular, according to Deutsch [2]). Consequently, to understand computation is a prerequisite for evaluating the message of concern regarding the long-term consequences of the

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increasing dependence on a particular machine, i.e., the computer, that humankind is experiencing. The broad view recalled above does not assuage the worry some express. But even if the hypothesis were to prove wrong, the dependence would not go away. In particular, artificial intelligence, together with the associated science of robotics, has prompted messages of doom: "The development of full artificial intelligence (AI) could spell the end of the human race" (Hawking [3]). Such messages are comparable, I hasten to add, to those euphoric forecasts (Kurzweil [4]) announcing an age in which machines will outsmart even those who conceived them. Shannon [5] went as far as to say that "I visualize a time when we will be to robots what dogs are to humans, and I'm rooting for the machines." (As respectful as I am of Shannon, I am not willing to accept the leash.)

Of particular interest in this respect are achievements in the area of predictive computation and, related to it, in neural networks-based deep reinforcement learning competing with human-level control. The most common embodiment of these developments is mobile computing. What used to be wireless telephony became the hybrid platform of algorithmic computation, integrated with a variety of non-algorithmic processes, supported by a vast array of sensors. Machine learning affords the connection of data and meaning (e.g., position, activity, possible purpose, in other words: what, where, why). It produces information pertinent to the situation (e.g., a sales chart for a marketing meeting, a simulation for a class in Big Data visualization). Other "feats" make for spectacular headlines: the algorithm for playing video games that plays better than the living player for whom the games were conceived; and the algorithm for understanding language. These transcend Big Blue, a high-performance machine programmed to play chess, and which eventually became a successful contestant on the game show *Jeopardy*, and then a digital doctor. For this purpose, huge resources were made available to be thrown at the problem of beating a world champion (through brute force computation). The more recent claims are for game competence across the gamut of games, regardless of experience; and for understanding questions posed in everyday language, that is, the ability to answer them. High-dimensional sensory inputs (representations of the environment) drive deep network agents able to outperform humans. (In language understanding, deep reinforcement learning is the chosen path.) The video game playing "intelligent" machine knows nothing about the Atari games (of the early "romantic" age of video games). It was tested on 49 of them (Minh et al. [6]). It makes inferences from pixels from the game images and from game scores, that is, how others played. Of course, the game's algorithmic nature itself is congruent with that of the artificial agent driven by high-dimensional sensory inputs.

In reference to understanding language (Weston et al. [7]), proxy tasks are set out in order to facilitate the evaluation of reading comprehension via the mechanism of answering questions. By no coincidence, a particular kind of games (text adventure connected to interactive fiction, Monfort [8]) provides a medium for categorizing various types of questions. Far from being only examples of successful programming and clever methods, these define a new frontier in computation. Implicit in the challenge is the question of whether human performance, anticipatory in nature, can be matched, or even outdone, by algorithmic forms of computation. Of course, the goal has to be defined as clearly as possible. To understand the significance of all this breakthrough research, we shall first define the underlying concepts involved.

1.2 What Is and What Is not Anticipation—A Question that Does not Go Away

Let us return to the issue of the human being's progressive dependence on computers. Being part of a reality within which everything associated with human existence is, in one way or another, dependent on computers undermines the effort of a neutral evaluation. For example, this present text originates in a word-processing program. In the writing, the author used speech recognition and image processing, and benefited from machine learning-based search for references. The text will, along the academic path of publication (editing, peer review, additional feedback, layout, etc.) be made available—on paper, using digital printing, and in e-formats—to a readership shaped by the experience of computation to the extent that dependencies are established. References will be cross-linked, keywords highlighted; the text will become an easy-to-explore hypertext, all set to be further indexed and eventually fed into a complex network visualization. If the means of expression (language, formulae, images, etc.), communication (sharing), and signification (evaluation of originality, impact, usefulness over time, etc.) were passive, it would not make any difference that this text is not the outcome of orality, or of handwriting on parchment or paper, or of lead-based typography, or of the Gutenberg printing press. But the media involved are *never* neutral. Tools are not passive partakers in the activity. Being used within a culture, they "make" a new content, a new user, a new public—and thus contribute to the change of culture itself.

This is all the more important as we realize the ubiquity and diversity of computation. We understand that a new human condition is ascertained in the ever-expanding use of digital technology. Humankind might project itself into a way more exciting future than ever. Alternatively, it might wipe itself out (or at least place itself on a degenerative path), and thus eliminate humans from the dynamics of evolution, or at least diminish their influence. Computers that perform better in chess or programs that outperform the human in Atari games (or any other machine-based game), and computers capable of understanding and answering questions, are only indicative of the breadth of the process. What counts in the perspective of time is the depth of the process: how the mind and body change, how human pragmatics is redefined.

1.2.1 Winning, or Changing the Game

Having taken this broader view in order to establish a context, it is time to focus on the terms that frame the question we are trying to answer: anticipation and computation. Mitchell (or for that matter Wolfram [9] or Zuse [10]) claims that somehow the universe is being deterministically computed on some sort of giant but discrete computer (literally). If indeed all there is is an outcome of deterministic computation, then what is the rationale behind the fact that, in the world as we know it, some entities are alive and some not? Computation, itself grounded in rationality, ought to have an explanation for this, if indeed we are only its outcome (whether as stones, micro-organisms, or individuals who conceived computation). Living entities (from bacteria to the human being) come into existence at some moment in time, unfold in a dynamic driven by survival—including reproduction—and eventually die. As they do so, they join the non-living (water, chemical elements, dissipated energy, etc.), characterized by a dynamic driven by the forces at work on Earth and in the cosmic space Earth occupies (according to descriptions in astrophysics). Of course, sun and wind, humidity, a variety of particles and radiations, as well as interaction (local or galactic), affect stones and rivers, the air, and decomposition of dead organic matter as much as they affect the living. Experimental evidence shows that the dynamics of the living is, moreover, characterized by adaptivity. The non-living does not exhibit adaptivity—at least not at the timescale of those who observe them. What most radically distinguishes life from not-life is the sense of future, i.e., the vector of change. It is goal-driven change that explains why there is life, more so than the rather unsubstantiated, and therefore dubious, affirmation of a universal computation of almost deistic nature.

Between the living and the physical—which is subject to descriptions constituting a body of knowledge known as physics—there is a definite systemic distinction: the living is complex; the physical is complicated. To reproduce here the arguments upon which this epistemological model is based would probably invite attention to a subject different from that pursued herein. Suffice it to say, the criterion used is derived from Gödel's [11] notion of the undecidable: entities of complex nature, or processes characterized as complex, cannot be fully and consistently described. The living is undecidable. This means that interactions implicit in the dynamics of the living cannot be fully and consistently described. As a consequence, no part of a living entity is less complex than the whole to which it belongs—unless it is reduced to a merely physical entity. The famous decerabrated frog experiment (described in almost all physiology books) is illustrative of this thought. The physical is decidable. A fragment of a stone is as much representative for the whole stone as the laws of physics are for the universe. Of course, Gödel referred to descriptions of reality (a nominalist view), to statements about it, to the logic guiding such statements, and, further, to operations upon them. We take the view (resulting in the definition of G-complexity, Nadin [12]), that the decidable/undecidable, as a gnoseological construct, defines states of complementary nature (physics vs. living). Anticipation is associated with the undecidable nature of the living. In the decidable realm, action-reaction entails change.

The most recent attempt to explain the emergence of life (England [13]) returns to the obsessive model of physics inspired by the laws of thermodynamics. If indeed capturing energy from the environment and dissipating that energy as heat were conducive to the restructuring of matter (carbon atoms, in particular), leading in turn to increased dissipation, the process would not have ended, and more such restructuring would take place. It does not take place on Terra, (i.e., our Earth) and nobody has yet documented it on other planets or cosmic bodies. That physics is fundamentally inadequate for explaining the emergence of life and, further, for explaining it, is a realization that physicists swore to ignore. Anticipation does not contradict the predicaments of physics, but complements them with an understanding of causality that integrates the future. The increased entropy (cf. the Second Law of Thermodynamics) of physical systems explains, to a certain extent, how they change over time. Physical information degrades. Reaction is the only remedy. In the living, we are faced with the evidence of long-term stability of species. Biological information (DNA is an example) is maintained as a condition of life. Entropy does not increase. Anticipation is the expression of the never-ending search for equilibrium in the living, and therefore its definitory characteristic.

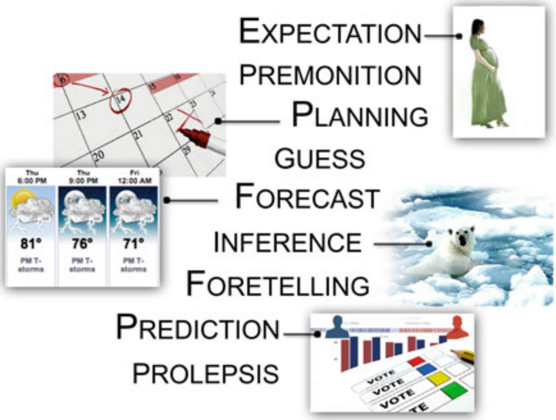
It is easier to postulate (such as in the above text) and navigate a clean conceptual universe in which words mean exactly what we want them to mean (cf. Humpty Dumpty in Carroll [14]). To deal with the messy reality of complementarity—the living and the non-living—in which concepts are ill defined, implies awareness beyond the views that shaped civilization after Descartes. In respect to anticipation, such clarity—not only of semantic nature—is essential since the terminology permeates the pragmatic level, in particular in the language domain associated with computation.

When machine performance (of the computer or of any other device) is juxtaposed to that of the human—machines outperforming world champions in chess or game fanatics in 49 Atari games—one has to define the criteria. The same applies for understanding language. On account of anticipation, humans answer questions even before they are posed. Indeed, the knowledge used in such performance is as important as understanding the difference between repetitive tasks and creativity. Algorithms that integrate better prediction models in data-processing characteristic of playing games (or any other form of algorithmic expression) or understanding questions, together with high-speed processing, will outperform the human being to the extent that the "self-driving" car will outperform the human-driven car. But the real problem is "Will they generate new games, or new instances of competitive dynamics? Will they generate, as human do, new language, within which new ideas are seeded?" This is where anticipation comes into the picture. Winning and changing the game are two sides of a coin about to be flipped. Making way for new language is part of the continuous remaking of the individual.

1.2.2 Reaction and Anticipation

Anticipation pertains to change, i.e., to a sense of the future. The image (Fig. 1) is suggestive.

Fig. 1 Ways of considering the future



To comment on the particular words would only result in anecdotal evidence. First, let us clarify some of the terms. Foremost in importance is the understanding that the physical is defined through interactions driven exclusively by reaction. The physics of action-reaction, as formulated in Newton's Third Law [15] provides a decidable model:

Lex III: Actioni contrariam semper et æqualem esse reactionem: sive corporum duorum actiones in se mutuo semper esse æquales et in partes contrarias dirigi.

(Translated to English, this reads: Law III: To every action there is always opposed an equal reaction: or the mutual actions of two bodies upon each other are always equal, and directed to contrary parts.)

If body $\boldsymbol{A}$ exerts a force $\mathbf{F}$ on body $\boldsymbol{B}$, then body $\boldsymbol{B}$ exerts an equal and opposite force $-\mathbf{F}$ back on body $\boldsymbol{A}$.

$$\mathbf{F}_{AB} = -\mathbf{F}_{BA} \tag{1}$$

The subscript $\boldsymbol{AB}$ indicates that $\boldsymbol{A}$ exerts a force on $\boldsymbol{B}$, and $\boldsymbol{BA}$ indicates that $\boldsymbol{B}$ exerts a force on $\boldsymbol{A}$. The minus sign indicates that the forces are in opposite directions. Often $\mathbf{F}_{AB}$ and $\mathbf{F}_{BA}$ are referred to as the *action force* and the *reaction force*; however, the choice of which is which is completely arbitrary. Elementary particles, as much as physical entities (at the scale of our immediate reality or at cosmic scale), behave as though they follow the law. Within the living, this is no longer the case. Cells, in their infinite diversity, have a dynamics for which the description in Newton's laws are no longer applicable.

Descriptions of entities and processes restricted to the dynamics originating in action-reaction can be fully and non-contradictorily described. As stated above, this applies across the reality of physics—from the micro-universe to cosmic space.

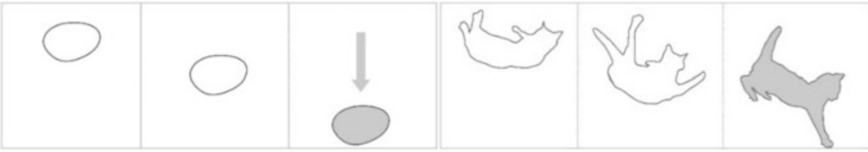


Fig. 2 Not all falls are the same, but all are subject to gravity

1.2.3 The Undecidable “Falling of the Cat”

The living, like the physical, is embodied in matter; hence, the reactive dynamics is unavoidable. However, the physical dynamics—i.e., how change of matter takes place—of what is alive is complemented by the anticipatory dynamics—how the living changes ahead of what might cause its future condition. Newton’s laws, like all laws anchored in the deterministic cause-and-effect sequence (past→present→future), preempt the goal-driven changes ahead of material causes. Awareness of change, pertaining to the living, is reactive. The living reacts (to changes in temperature, to stimuli, to other people, etc.), but at the same time, it is also anticipatory (preparedness, as well as foresight, for instance). Adaptivity over shorter or longer intervals is the specific expression of this interplay. It also explains the long-term stability of the living. From a physics perspective, the following would appear as unavoidable: A stone and a cat of equal weight fall (Fig. 2), regardless of the moment in time, and even regardless of the measuring process, acceding to Newton’s law of gravity. But the stone falls “passively”—along the path of the gravitational force. The cat’s fall is suggestive of anticipation. It is expressed in action; and it is meant to preserve life (the cat usually avoids getting hurt).

The equation of the “change”—coordinates (falling from height h) in this case—is straightforward:

$$\mathrm{h} = 1/2\mathrm{gt}^2 \tag{2}$$

in which **h** is the falling height, **g** the acceleration due to gravity, and **t** the falling time. If, for example, the height is given by h = 10 m and g = 9.81 m/s^2, the predicted falling time is obtained by inserting these values in (2) and solving for **t**. Introducing the variable **T** for the falling time and the function $\mathbf{A_t}$ for the prediction procedure yields the following predicted event, which consists of one element only:

$$\mathrm{A_t}(\{10, 9.81\}) = \{1.4278431220270645\} \tag{3}$$

This description omits some variables related to air resistance (object’s shape, air density, effect of temperature and humidity, etc.).

The cat falls “actively.” The cat’s response to falling (even if the fall is accidental, i.e., not caused within an experiment) is at least a change in geometry: actively turning (by triggering the motoric) increases the surface, and thus air resistance. The equation pertinent to the fall of the stone still applies, but in a rather approximate way (more approximate than considering friction). The living “fights” gravity. (The metaphor is a mere translation of the fact that nobody likes to fall.) The past (cat’s position at the start of the fall), but also the possible future (how and where to land) affect the outcome.

1.2.4 The Living Can Observe the Physical

The fall of the same stone, repeated, from the same position, is captured in the physical law description: air resistance can be precisely accounted for and, even under experimental conditions, maintained. The gravitational field strength (9.8 N upon every 1 kilogram) is a characteristic of the location within the Earth’s field of gravity, not a property of the falling stone or cat. The nomothetic (Windelband [16]) corresponds to a description of a phenomenon (or phenomena) characterized as law. The fact that mathematicians extend the nomothetic description to the falling cat is testimony to their incomplete knowledge. It does not include anticipatory dynamics. Indeed, the cat, as opposed to the stone, will not fall the same way twice. Mathematicians, like many others, scientists or not, observed the fact mentioned above.

But since the cat’s falling became a mathematical problem, let’s take a closer look at what is described. The purpose is simple: that we understand why the “recipe” for calculating the parameters of physical phenomena cannot be extended to predictions of living processes. Prestigious scientists (such as George Gabriel Stokes [1819–1903], James Clark Maxwell [1831–1879], and Etienne Jules Marey [1830–1904]) were tempted to explain the falling of cats, more precisely, how they turn in the air.

For them and their followers, the falling cat problem consists of explaining the physics underlying the common observation of the “cat-righting reflex.” To discover how a free-falling cat can turn itself right side up as it falls—no matter which way up it was initially, without violating the law of conservation of angular momentum—is a challenge. There is one limitation: all that counts is that the cat fall on its legs. As a leading mathematician in the falling cat problem puts it:

> Although somewhat amusing, and trivial to pose, the solution of the problem is not as straightforward as its statement would suggest, leading towards surprisingly deep mathematical topics, including control theory for nonholonomic systems, optimal motion planning, Lagrangian reductions, differential geometry, and the gauge theory of Yang-Mills fields [17].

Within this study, we will not go into the details of all of the above. In broad strokes: applied differential geometry allows for the approximate description of an object flipping itself right side up, even though its angular momentum is zero.

In order to accomplish that, it changes shape (no stone changes shape in the air). In terms of gauge theory, the shape-space of a principal SO(3)-bundle, and the statement, "Angular momentum equals zero," defines a connection on this bundle. The particular movement of paws and tail conserves the zero angular momentum. The final upright state has the same value. This is the "geometric phase effect," or *monodrony*.

The idea is simple: Let a cat fall; and derive the pertinent knowledge from the experiment. (In 1882, Marey used a chronophotographic gun for this purpose; in our days, motion capture equipment is used.) But this is no longer a reproducible event. It is not the passive fall of a stone—reproducible, of course—but the active fall embodying anticipation. The outcome varies a great deal, not the least from one hour to another, or if the landing topology changes. The stone will never get tired, annoyed, or excited by the exercise. And it will never learn. We shall explain this, in reference to the cat's fall, using images (Figs. 3 and 4).

The cat's shape is given by two angles: (Θ) (ψ).

ψ is the angle between the two halves of the cat's body.

Θ describes the direction of the cat's legs ($\Theta = 0$ when the front and back legs are closest to each other).

A change in Θ corresponds to a rotation of the cat's body around the \spinal axis. Heisenberg's uncertainty relation [20] suggests that, although such descriptions are particularly accurate, we are, in observing the falling of a cat, not isolated viewers, but co-producers of the event. To observe entails influencing the result. The falling of human beings, of consequence as we advance in age, makes it clear that "to know how to fall" (as the cat obviously does) is more than a problem in physics or a mathematical exercise. (No kitten should be subject to such an experiment.)

Just as an aside: inspired by the cat's fall, Apple, Inc. patented a method for controlling the accidental fall of the iPhone on its precious screen. The iPhone's vibration motor (Fig. 5) is programmed to change the angle of the fall in mid-air. This change is based on data from the device's positioning sensors. The patent is, in its own way, an example of engineering inspired by the expression of anticipation in the living. It is based on knowledge from physics (coordinates and center of gravity) and takes predictions based on Newton's laws in order to activate the

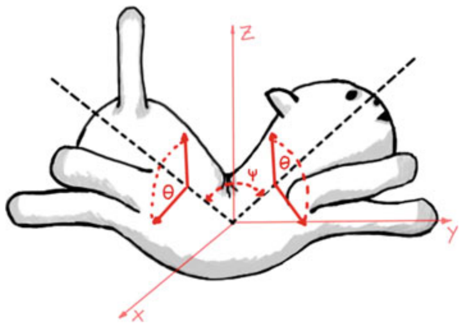


Fig. 3 Representation of a falling cat (Drawing by. E. Kuehne, in Mehta [18, p. 5])

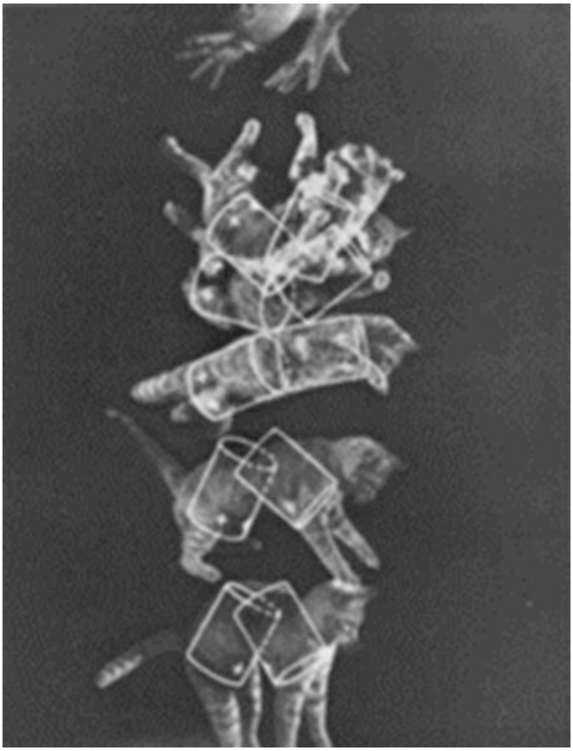


Fig. 4 This image is representative of the Kane-Scher solution [19] to why cats fall on their feet. (Reproduced from [18])

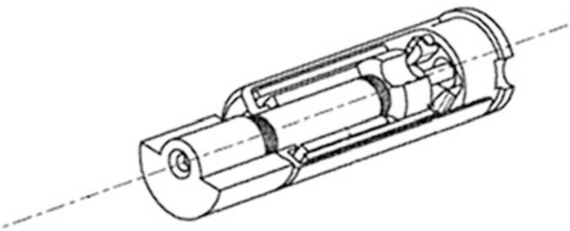


Fig. 5 The vibration motor. Statistical analysis of the fall, by comparing gathered data against other information stored in device memory, serves as trigger to activate the spin and change the phone's center of gravity (cf. patent application)

vibration motor so that the device is turned in the air—pretty much like a cat made out of stone or wood.

With this device, we are in the reaction domain, taking advantage of a good understanding of physical laws.

The unity reaction-anticipation—characteristic of the living—corresponds to a different condition of matter and its change over time. The measurement process, i.e., the observation of the change (the falling cat), influences the outcome. Our watching how the smartphone falls does not affect the process.

Thesis 1: The living can observe the physical.

Actually, as it evolves, it continuously does—because the process is affected by the context. The physical does not have an observation capability. It is rather a stage on which the living performs (while it also reshapes the stage). Perception is nothing more than the process through which awareness of here and now is established.

Thesis 2: Awareness of immediate space and time is the outcome of perception processes.

1.3 Expectation, Guessing, Prediction

We become aware of anticipation when it is successful: falling the “right way,” avoiding danger, rewarding creative activities, competence in competition, understanding language, images, and textures, for example. From such activities, we can generalize to processes in which anticipation is sometimes involved, and also to other forms of dealing with the future. From guessing and expectation to prediction and planning as human endeavors, we infer that reaction and anticipation are not reciprocally exclusive, but rather intertwined. Acknowledged in language (and in experiments) are various forms of what is called premonition (of danger, usually), foretelling (mostly associated with the dubious commerce of “seeing into the future”), not to mention curses and blessings, and voodoo. There is no reason to go into these; although for those fixed on the notion of algorithm—description of actions through which a goal is attained—they can be given as examples of processed information to which misinterpretation also belongs. Each of the above-mentioned aspects (including the slippery practices) is a combination of reaction and anticipation. Just as an innocent illustration: The fortuneteller reacts to someone’s need for reassurance or comfort, creating the illusion of a successful (or unsuccessful) anticipation, “You will not be awarded the Nobel Prize, but your love life will improve.”

1.3.1 Guessing

To *guess* is to select from what might happen—a sequence of clearly defined options—on account of various experiences: one’s own; of others; or based on unrelated patterns (the so-called “lucky throw” of a coin or dice, for example).

Guess → selection from a well-defined set of choices

$$(P_{os}(p_i)), p_i \geq N \quad (C(c_i)), c_i \geq N \tag{4}$$

If you have to guess a number from one to one hundred, the first thing is to reduce the space of choices.

The reaction component ("I know that the person asking the question likes the queen of hearts!") is based on real or construed prior knowledge. For an anticipatory dimension, one would have to combine a wager: "Guess what number I chose" (or what card, or what word) "and you win!" (See Fig. 6). A generalization can be made: when reaction and anticipation are suggested, the outcome will show that some people are better at guessing than others because of heightened perception of cues of all kind.

Reactions are based on the evaluation of the information pertinent to the situation—different when one visits a fortuneteller or a casino from when one guesses the correct answer in a multiple-choice test. In the multiple-choice situation, one infers from the known to the unknown. When patterns emerge, there is learning in guessing: the next attempt integrates the observation of related or unrelated information. This associative action is the cognitive ingredient most connected to guessing and, at the same time, to learning. (We retain patterns and recall them when faced with choices.) The rest is often statistics at work, combined with *ad hoc* associative schemes pertinent to what is possible. (That's where premonition, mentioned above, comes into play.) Let us acknowledge that guessing (as well as learning) is reduced to nil in predictable situations. The anticipation component of guessing is related to the state of the self. From all possible games in the casino, some are more "favorable" at a certain time, something like: "Guess who's knocking at the door," after grandma's voice was heard. Only surprise justifies the effort, even when the result is negative. Recent research of responses of the human frontal cortex to surprising events (Fletcher et al. [21]) points to the relation to learning mentioned above. The dorsolateral prefrontal cortex contributes to the adjustment of inferential learning. Associative relationships (Fig. 7) that lead to learning (also qualified as associative) are based on the action of discriminating the

Fig. 6 Two examples of guessing

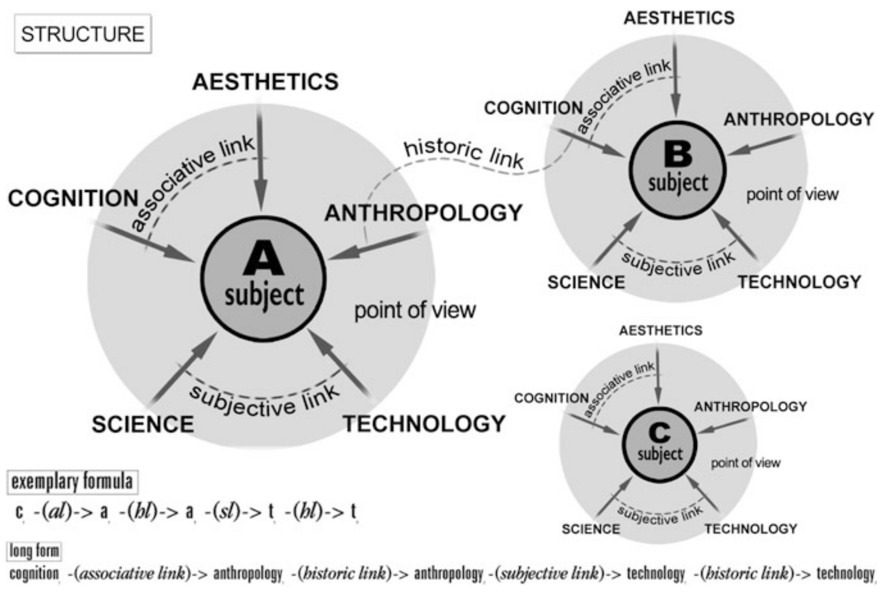


Fig. 7 Examples of associative relationships (Associative Encyclopedia, Nadin [22])

degree (strength) of interrelation. Of course, fuzzy sets are the appropriate mathematical perspective for describing such interrelations.

Empirical data (statistics, actually) document "better days," i.e., above-average guessing performance. This corresponds to a variety of circumstances: additional information about the process (acquired consciously or, most of the time, through processes "under the radar"), a state of cognitive or sensorial alertness (for whatever reason), or simply a statistical distribution ("lucky"), to name only a few. There is no magic in the exceptional (a "good" day, "bad luck"), but there is quite a bit to consider in terms of the large number of variables involved in the outcome of human actions. The manner in which anticipatory action is intertwined with the reactive is difficult to describe exactly because of the multiplicity of factors involved. If anything, anticipation actually undermines success in guessing, given its non-deterministic nature; it integrates the subjective, the emotional, the spontaneous. A guessing machine—computer or any other type of machine—can automate the guessing knowledge specific to well-defined selection and thus outperform the guessing living (not only human beings are involved in guessing as they face change). Machine learning provides a good basis for such applications. The algorithm for successfully playing computer games is based on data acquired through what is called *deep reinforcement learning*. The algorithm for understanding questions formulated in natural language is based on a *multilinear map* subjected to processing in Memory Networks (MN).

1.3.2 Expectation

In comparison to guessing, expectation does not entail choosing ("Heads or tails?"), but rather an evaluation of the outcome of some open-ended process. An example: A child's expression is informative of what might happen when the child will "hang out" with friends. The parents' evaluation might be difficult, if at all possible, to describe (e.g., "I know what you guys plan to do"), that is, to formalize. In the act of forming an expectation (such as in carrying out experiments), the focus on the reaction component changes from the probable (which number from the set defined?) to the inferred. Several sources of information pertinent to forming an expectation are weighed against each other. What appears most probable out of all that is possible gets the highest evaluation, especially if its outcome is desirable (for instance, pleasant weather preferred over the expectation of rain). Expectations associated with experiments are usually in the area of confirming a hypothesis or someone else's results. If the outcome is judged to be negative, then avoiding it is the basis for action. Again, anticipation—reflected in what is perceived as possible—meets reaction, and information is associated with probable cause. Weather is often expected—inferred from opinion, observation, data—not guessed. So are the outcomes of activities that weather might influence. Agriculture practiced prior to the integration of digital information in agricultural production was often in the realm of the expected. A cornfield is not equally fertile in every spot. Learning how to increase production by extracting data (through GPS-based measurements) pertinent to fertility and applying fertilizers or planting more seeds in certain spots grounds expectation in knowledge—and thus makes it look like an algorithm (a set of rules which, if respected, can yield a result). Based on the evaluation of the outcome, new expectations are generated. Events with a certain regularity prompt patterns of expectation: a wife awaits her husband, a child awaits a parent, a dog awaits its owner, who usually returns from work at a certain time. Such regular events are encountered on many occasions and in many activities.

Expectation → evaluation of outcome based on incomplete knowledge (from a limited set of probabilities)

$$P(p_1, p_2, \ldots p_n) \tag{5}$$

An expectation machine is actually a learning procedure that attaches weights (some subjective) to choices from the limited set of possibilities. The reactive component dominates the anticipatory. False expectations (of personal or group significance) are the outcome of skewed evaluations. Expectation and superstition are examples of such evaluations. They are driven more by desire or wishful thinking that tends to falsify the premise (adding self-generated data to the factual incomplete knowledge).

Among the cognitive illusions (Kahneman and Tversky [23] existing in culture are those formed by gamblers (Delfabbro [24], as well as by a professional acting in a state of over confidence. Physicians making inferences based on limited medical tests (Gigerenzer and Gray [25], Sedlmeier and Gigerenzer [26]); coaches captive to the "hot-hand" model (Tversky and Gilovich [27], Miller and Sanjurjo [28]; economists absorbed in data patterns more relevant to the past than applicable to future developments (Hertwig and Ortmann [29]) can be given as examples. These have in common the perception of random and non-random events. Statistically significant deviations from the expected (e.g., the average scoring performance of a gambler in a casino, of a basketball player, of the stock market, etc.) lead to beliefs that translate into actions (a gambler can be refused entry, the basketball player believed to have a "hot-hand" day faces a stronger defense, hot stock market days mean more trades, i.e., more speculation, etc.). Physicians interpret deviations in respect to expected values (blood glucose, cholesterol, vitamin D, creatinine), and automatic procedures (comparison with average values) trigger warnings. What we get after a blood test, for example, is an expectation map. Guessing and expectation, each in its own way, are meant to inform choices or result in decisions. Positive and negative factors weigh in with every option. The integration of biases in making the choice leads to the surprising observation that what some call instinct (choose among options in the absence of identifiable previous knowledge, in common parlance, "gut feeling") can explain successful guesses or actions driven by expectation [30]—such as which direction to take at a fork in the road.

1.3.3 Prediction

Connecting cause and effect, i.e., associating data generalized from statistical observations describing their connection, is the easiest way to characterize prediction. Causality, as the primary, but not exclusive, source of predictive power is rarely explicit. Prediction—explicit or implicit—expresses the degree of ignorance: what is not known about change. Uncertainty is the shadow projected by each prediction (Bernoulli [31]). Therefore, it is representative of the limits of understanding whatever is predicted. In some cases, the prediction is fed back into what we want to predict: how a certain political decision will affect society; how an economic mechanism will affect the market; how technological innovation (let's say multimedia) will affect education. As a result, a self-referential loop is created. The outcome is nothing more than what is inputted as prediction. Those who predict are not always fully aware of the circularity inherent in the process. The impossibility of disconnecting the observer (the subject, in learning) from the observed (the object of learning) is an inherent condition of learning, whether human or machine learning. The constructivist perspective demonstrated the point quite convincingly (von Glasersfeld [32]).

Prediction → inference based on probability

$$\mathcal{P}\,(\text{frequency, ignorance, belief}) \tag{6}$$

$$\begin{aligned}&\mathrm{F} : \mathcal{D} \rightarrow \mathrm{X}(\mathcal{D})\\&\text{from an initial state } (\mathcal{D}) \text{ to state } (\mathrm{x})\end{aligned} \tag{7}$$

Prediction machines of all kind are deployed in situations in which the outcome is associated with reward/punishment (loss). In particular, Bayes-inspired prediction is driven by a hypothesis: You "know" the answer, or at least part of it (your best guess). Predictions of election results, of weather patterns, of sports competitions are based on such assumptions. Prediction as a process that describes the outcome of action-reaction dynamics can be usefully affected by experiential evaluations.

1.3.4 Future States and the Probability Space

But there are also predictions driven, to an extent larger than the Bayesian state of belief, by anticipatory processes, involving the probability space also. Falling in love at first sight—which is neither guessing nor expectation—is a prediction difficult to make explicit. (It combines rationality and consistency with a subjective perspective such as the above-mentioned "gut feeling.") There is no explicit cause-and-effect connection to uncover, and no frequencies to account for. The future state (the romantic ideal of a great love, or the calculated outcome of an arranged marriage) affects current states as these succeed each other in a sequence of a time often described as "out of this world." We could add the dopamine release during anticipation of a musical experience (Salimpoor et al. [33]). Peak emotional responses to music are different from the experience of winning a computer game, or answering a question. Therefore, it would be inadequate to even consider an algorithm for returning the value of musical experience based on statistical data. Machine-based performance (such as winning games, or understanding questions) corresponds to different domains of computation.

Facial expression as a predictor is yet another example of Bayesian probability-based inferences. In very sophisticated studies (Ekman and Rosenberg [34], Ekman [35]), it was shown that the "language" of facial expression speaks of facts to happen before they are even initiated—which is anticipation in pure form. The Facial Action Coding System (FACS), which is a taxonomy of facial expression (and the associated emotional semantics), inspired Rana El Kalioubi in her work on computationally interpreting the language of faces. For those who "read" the face's expression, i.e., for those who learned the language of facial expression, the emotion predictions based on their own anticipation guides their action. Gladwell [36] describes the case of a Los Angeles policeman who reads on the face of the criminal holding a gun on him that he will not shoot, leading the officer to avoid shooting the criminal. The expectation—criminal pulls out gun and points it at the policeman pursuing him—and the prediction—this person with the particular facial expression, as studied by the interpreter, will not shoot—collide. So do the probability of being shot and the prediction informed by knowledge otherwise not accounted for.

Descriptions of the relation between expectation and prediction are informative in respect to the mechanisms on which both are based. The various levels at which learning—different in expectation-driven from prediction-based decisions—takes place are not independent of each other. Expectations pertain to more patterned situations: e.g., "I expect to be paid for my work based on our agreement." (The intitial state d, to be hired; the future state x, to be paid for work, depends on initial state d.) The prediction, "Based on the record of your employer, you will be paid," conjures different data. An acceptable description is that the learner extracts regularities or uses innate knowledge. They are often an expression of what in ordinary language is described as stereotype or, in some cases, wishful thinking. However, when the individuals become involved in the activity of predicting (literally, "to say beforehand," i.e., before something happens), they expect the prediction to actually take place. It is no longer a wish, but rather the human desire, expressed in some action, to succeed.

Many activities, from policing the streets to conceiving political reform, urban development, military strategy, educational plans (to name a few areas of practical activity with features with little or nothing in common) are informed by the very competitive "industry" of predictions. Generalizing from the past can take many forms. Sensor-based acquisition of data provides in algorithmic computation the simuli of learning through experience. Evidently, the focus is on relationships as a substratum for deriving instructions pertinent to the present and of relevance to the future. Ignorance, which is what probabilities describe, is fought with plenty of data. The typology of predictions (linear, non-linear, statistical inference, stochastic, etc.) corresponds to the different perspectives from which change and its outcome are considered. At the processing level, extraction of knowledge from data makes available criteria for choices (such as those in spatial navigation, playing games, choosing among options, etc.).

Change means evolution, variability over time. Predictive efforts are focused on understanding sequences: how one step in time is followed by another. However, these efforts focus on what, ultimately, anticipatory processes are: a modeling of the entity for which they are an agency, and the execution of the model in faster than real time speed. The limited deterministic perspective, mechanic in nature, repetitive—i.e., what cause leads to which ensuing effect—affects the understanding of anticipation through a description of predictive mechanisms. Predictions made following known methods (such as time series analysis and linear predictors theory) capture the reaction component of human action (Arsham [37]). The anticipatory component is left out most of the time, as a matter of definition and convenience. Complexity is difficult to recognize, and even more difficult to handle because it corresponds to open-ended systems. Once a predictive hypothesis—let's say every minute the clock mechanism engages the minute hand—is adopted, it defines the cognitive frame of reference. On a digital display, the predictive hypothesis will be different. Should the predicted behavior of the mechanism somehow not take place, expectation is tested. However, mechanisms, as embodiments of determinism, rarely fail. And when they do, it is always for reasons independent of the mechanism's structure.

1.3.5 Learning and Expectation

Predictions concerning the living are less obliging since interactions are practically infinite. Structure matters, interdependencies are fundamental. It happens at all levels of the living that predictions—what will happen next (immediate or less immediate future)—are either partially correct or not at all. In studying learning and selective attention, Dayan et al. [38] refer to reward mechanisms in the Kalman filter model (more experience leads to higher certainty). For any process in progress—e.g., moving a vehicle, recalling a detail in an image, thinking something out—there are, from the perspective of the Kalman filter, two distinct phases: 1) predict; 2) update. The filter is a recursive operation that estimates the state of a linear dynamic system. In physical entities, the space of observable parameters is smaller than that of describing the degrees of freedom defining the internal state. In the living, the situation is reversed. Learning, for instance, triggers expectations that turn out to be a measure of how much the deterministic instinct (culture, if you prefer) takes over the more complex model that accounts for both reaction and anticipation in the dynamics of the living.

Predictors reflect the desire to understand how change takes place. They express the practical need to deal with change. However, they omit change from the equation of those predicting or subject to prediction. Actions from thoughts, as Nicolelis [39] calls them, account for the self-awareness of change. What is learned supports inferences (statistical or possibilistic); uncertainty results as the competitive resources engaged in the inference are overwritten by unrelated factors. Predictions also capture the interconnectedness of all elements involved in the dynamics of the observed. Learning involves predictions. In this sense, they open access to ways to emulate (or imitate) change.

Expectations have no direct learning component. One cannot learn explicitly how to expect, even accepting that there might be structure in the learning process after an expectation is validated, and in the representation associated with the expectation. Expectations only occasionally produce knowledge: a series of expectations with a certain pattern of success, or failure for that matter. Predictions, even when only marginally successful, support activities such as forecasting—for short or less than short sequences of change—of modeling, and of inference to the characteristics of the observed dynamic entities.

For learning (prerequisite to prediction and to anticipation) to come about, representations of the dynamic process have to be generated. Some will correspond to the immediateness of the evolving phenomena—what the next state will be, how the phenomena will evolve over time—others involve deeper levels of understanding. Whether in medicine, the economy, politics, military actions, urban policy, or education, etc., predictions or anticipations emerge on account of considerations regarding cascading amounts of data. Just to genralize, we can consider the ever-increasing amount of sensors deployed as the source of this data. Integrated sensors generate high-level, multi-dimensional representations. Their interpretation, by individuals or intelligent agents, emulates the machine model of neuronal activity. As a consequence, we end up with algorithmic computation, extremely efficient in terms of generalizing from past to present. The so-called deep Q-network agent, which has as output "human-level control" performance (in playing games, but applicable as well to other choice-making situations), is the embodiment of prediction based on reinforcement learning [6].

1.3.6 Interconnectedness

Without the intention of deriving full-fledged conclusions, an example could suggest the interrelated nature of expectation, guessing, and prediction. The painful revelation of the practice of torture associated with the "war on terror" (a very misleading formula) prompted discussions that ranged from the moral, aesthetic, medical, to political, and ultimately focused on how successful torture is in extracting useful information. Data of all kind, from anecdote to statistics (perversely kept by those regimes that for centuries have practiced torture, some methodically, some as circumstances deemed necessary) document both the efficiency of brutal treatment of prisoners and the possibility of collecting misinformation. The process is non-deterministic. Moreover, principles of conduct—some by tacit agreement (what is hateful to you, don't do to others), others codified by the community of nations—associated with extreme treatment of the adversary, set moral borderlines (some less clear than they should be). Still, contrary to this foundation on data and rules, the practice continues. (Those on whose behalf torture is employed tend to find justification for it, since they form the notion that it has served them well.)

Prediction-data show that torture occasionally begets information. A torture information production machine—i.e., a computer, or better yet, a robot, with the applicable moral constraints built in—would decide on a cost-benefit analysis model whether torture should be applied or not. In retrospect, it is evident that guessing would be a weak description of the future: it has the highest margin of error. Expectation would not be much better: a machine does not output expectations since their variability escapes algorithmic descriptions. Predictions, especially in the Bayesian sense, are more effective. According to the Report of the Senate Intelligence Committee on the CIA Counter-Terrorism Program, some cases of torture were doomed from the outset.

Of course, the above description pertains to the macro-level. The interrogator and the interrogated are actually in an anticipatory situation: winning or losing drives their actions. Guessing, expectation, and prediction meld as they do in hide-and-go-seek, in playing tennis, in poker. In view of this observation, the understanding of prediction (implicit in guessing and expectation) takes on new meaning.

Predictions regarding the living, although inappropriate for systematically capturing their anticipatory dimension, are a good indicator of what is lacking when anticipation is ignored. An example: in focusing only on human beings, predictions based on physiological data remain at a primitive stage at best, despite the spectacular progress in technology and in the scientific theory of prediction. Streams of data (from a multitude of sensors) in association with some analytical tool (data-mining, usually) could, of course, help identify where and how the physical component of life is affected by change (aging, environment, medical care, hygiene, alimentation, driving, etc.). The reactive component of what is called "health" is of extreme importance. Clogged arteries, degradation of hearing or of the eyes can be identified with the help of real-time monitoring of blood pressure, hearing, or the macula. But they remain partial indicators. In evaluating change in the condition of the living, of the human being, in particular, what counts are not only the parts under observation, but their interconnectedness, especially of the whole.

Reaction is reductive. Anticipation is a holistic expression. Albeit, if we could improve such predictions by accounting for the role of anticipation—the possible future state influencing, if not determining, the current state—we would be in a better position to deal with life-threatening occurrences (strokes, sudden cardiac death, diabetic shock, epileptic seizure, etc. (Nicolelis and Lebedev [40]). Learning (i.e., deep reinforcement learning) about such occurrences in ways transcending their appearance and probability is one possible avenue. Things are not different in the many and varied attempts undertaken in predictions concerning the environment—the well-known climate change issue, for example—education, market functioning. It is easier, when addressing a given concern, to deal with "recipes" (e.g., reduction of CO2 emissions as a solution to climate change, with its reductionist focus, to the detriment or exclusion of other variables, either ignored or opportunistically downplayed), than to articulate an anticipatory perspective, holistic by definition.

Unless and until anticipation is acknowledged and appropriate forms of accounting for it are established, the situation will not change drastically. Neither will medical care, environmental policies, political matters, or education change, no matter how consequential their change (if appropriate) could be. Physical processes have well-defined outcomes; living processes have multiple outcomes (some reciprocally antagonistic.) This aspect becomes even clearer when we look at the very important experiences of forecasting and planning. Policies, i.e., social awareness and political action, depend on forecasts and involve responsible planning, liberated from the influence of opportunistic interests.

1.3.7 Forecasting and Planning

Predictions, explicit or implicit, are a prerequisite of forecasting. The etymology points to a pragmatics, one that involves randomness—as in casting. Under certain circumstances, predictions can refer to the past (more precisely, to their validation after the fact). Take a sequence in time—let's say the San Francisco earthquake of 1906—and try to describe the event (after the fact). In order to do so, the data, as registered by many devices (some local, some remote) and the theory are subjected to interpretations. The so-called Heat-Flow Paradox is a good example. If tectonic plates grind against one another, there should be friction and consequently heat. This is the result of learning from physical phenomena involving friction. Along the well-known San Andreas Fault, geologists (and others) have measured (and keep measuring) every conceivable phenomenon. No heat has been detected. The generalization from knowledge regarding friction alone proved doubtful. Accordingly, in order to maintain the heat dissipation hypothesis as a basis for forecasting, scientists started to consider the composition of the fault. This new learning—extraction of regularities other than those pertaining to friction and heat dissipation—was focused on an aspect of friction initially ignored. A strong fault and a weak fault behave differently under stress, and therefore release different quantities of heat. This is a case in which data is fitted to a hypothesis—heat release resulting from friction. To adapt what was learned to a different context is frequently used in forecasting.

In other cases, as researchers eventually learned, what was measured as "noise" was treated as data. Learning noise patterns is a subject rarely approached. Procedures for effectively distinguishing between noise and data are slow in coming, and usually involve elements that cannot be easily identified. In medicine, where the qualifiers "symptomatic" vs. "non-symptomatic" are applied in order to distinguish between data and noise, this occurs to the detriment of predictive performance. The lawsuit industry has exploited the situation to the extent that medicine is becoming defensive at a prohibitive cost (or overly aggressive, through the variety of surgical interventions, for instance, at an even higher price).

In general, theories are advanced and tested against the description given in the form of data. Regardless, predictions pertinent to previous change (i.e., descriptions of the change) are not unlike descriptions geared to future change. In regard to the past, one can continue to improve the description (fitting the data to a theory) until some pattern is eventually discerned and false knowledge discarded. (Successive diet plans exemplify how data were frequently fitted to accommodate the pharmaceutical industry's agenda, sometimes to the detriment of patient health.)

To ascertain that something will happen in advance of the actual occurrence—prediction (the weather will change, it will rain)—and to cast in advance—forecast—(tomorrow it will rain) might at first glance seem more similar than they are. A computer program for predicting weather could process historic data: weather patterns over a long time period. It could associate them with the most recent sequence. And in the end, it could come up with an acceptable global prediction for a season, year, or decade. In contrast, a forecasting model would be local and specific. The prediction based on "measuring" the "physical state" of a person (how the "pump," i.e., heart, and "pipes," i.e., blood vessels, are doing, the state of tissue and bone) can be well expressed in such terms as "clean bill of health" or "worrisome heart symptoms." But it can almost never become a forecast: "You will have a heart attack 351 days from now;" or "In one year and seven hours, you will fall and break your jaw." Or even: "This will be a historic storm" (the prediction, so much off target, of the "Nor'easter" of January 2015).

Forecast → infer from past data-based predictions to the future under involvement of self-generated data

$$\mathcal{F}(\text{predictions, self-generated data}) \tag{8}$$

Forecasts are not reducible to the algorithmic machine structure. They involve data we can harvest outside our own system (the sensorial, in the broadest sense). The major difference is that they involve also data that human beings themselves generate (informed by incomplete knowledge or simplified models). The interplay of initial conditions (internal and external dynamics, linearity and non-linearity, to name a few factors), that is, the interplay of reaction and anticipation, is what makes or breaks a forecast.

To summarize: forecasting implies an estimation of what, from among few possibilities, might happen. The process of estimation can be based on "common knowledge" ("Winds from the west never bring rain"); on time series; on data from cross-sectional observation (the differences among those in a sample); or on longitudinal data (same subject observed over a long time). Evidently, forecasting is domain specific. Meteorology practices forecasting as a public service; commerce needs it for adapting to customer variability of demand. Urban planners rely on forecasting in order to optimize municipal dynamics (housing, utilities, traffic, etc.). The latter example suggests a relation between forecasting and planning. How change might affect reality in comparison to how change should affect reality distinguishes forecasts from predictions.

Predictions are based on the explanatory models (explicit or not) adopted. Forecasts, even when delivered without explanation, are interpretive. They contain an answer to the question behind the forecasted phenomenon. "The price of oil will change due to…." You can fill in the blank as the situation prompts: cold winter, pipeline failure, war. "Tomorrow at 11:30 AM it will rain…." because of whatever brings on rain. "There will be a change in government…." "Your baby will be born in the next two hours." A good predictive model can be turned into a machine—something we do quite often, turning into a device the physics or chemistry behind a good prediction: "If you don't watch the heat under the frying pan, the oil in it will catch fire."

Our own existence is one of never-ending change. Implicit in this dynamic condition of the living are:

(a) the impossibility of accurate forecasting, and
(b) the possibility of improving the prediction of physical phenomena, to the extent that we can separate the physical from the living.

Our guesses, expectations, predictions, and forecasts—in other words, our learning in a broad sense—co-affect human actions and affect pragmatics. Each of them, in a different way, partakes in shaping actions. Their interplay makes up a very difficult array of factors impossible to escape, but even more difficult to account for in detail. Mutually reinforcing guesses, expectations, predictions, and forecasts, corresponding to a course of events for which there are effective descriptions, allow, but do not guarantee successful actions. Occasionally, they appear to cancel each other out, and thus undermine the action, or negatively affect its outcome. Learning and unlearning (which is different from forgetting) probably need to be approached together. Indeterminacy can be experienced as well. It corresponds to descriptions of events for which we have insufficient information and experience, or lack of knowledge. They can also correspond to events that by their nature seem to be ill defined. The living, in all its varied embodiments, reacts *and* anticipates. Of course, this applies to every other living form. The reaction-anticipation conjunction defines how effective the living is in dealing with change.

1.4 Self-awareness, Intentionality, and Planning

The human being has a distinct condition in the extraordinarily large realm of the living. It doesn't only play games (the example chosen in advanced research of high levels of control), but also conceives them. It not only understands questions in a given language, but also changes the language according to the human's changing pragmatic condition. Moreover, the human depends on a variety of other forms of living (billions of bacteria, for instance, inhabit the body), but in the larger scheme of things, it acquired a dominant position (not yet challenged by the technology created). In our world, human activity (although often enhanced through science and technology) is, for all practical purposes, the dominant force of change. Humans "are what we do" (the pragmatic foundation of identity, [41, pp. 258ff], [42]). The only identifier of human actions (and of other living entities) is their outcome. This is an instantiation of identity at the same time. The question, "What do you do?" cannot be answered with "I anticipate," followed, or not, by an object, such as "I anticipate that an object will fall," or "I anticipate my wife's arrival," or "I anticipate smelling something that I never experienced before."

Anticipation is a characteristic of the living, but not a specific action or activity. Humans do not undertake anticipation. The dopamine release in anticipation of high emotional anticipation (associated with sex, eating, music, scientific discovery, for example) is autonomic. Humans are in anticipation. Anticipation is not a specific task. It is the result of a variety of processes. As an outcome, anticipation is expressed through consequences: increased performance (an anticipated tennis serve is returned); danger (such as a speeding car) is avoided; an opportunity (in the stock market, for instance) is used to advantage. Anticipatory processes are autonomic. Implicit in the functioning of the living, such processes result in the proactive dimension of life. This is where identity originates. Anticipatory processes are defined in contrast to reaction, although they often imply reaction as well. Playing a computer game—with the game "canned on the machine," or competing with someone via the medium of the game or a MMORPG (massively multiplayer online role-playing game)—over the internet can be reactive (with a predictive component) or anticipatory. It can also be random. Characteristic of the deterministic sequence of action-reaction defined in physics, reaction is the expression of the living's physical nature. Identity is expressed in the unity of the reactive and proactive dimensions of the human being. It appears as a stable expression, but actually defines change. It is the difference between what we seem to be and what we are becoming as our existence unfolds over time. Identity is affected by, but is not the outcome of, learning.

No matter what humans do, the doing itself—to which explicit and implicit learning belongs—is what defines the unfolding identity. The outcome is the expression of physical and intellectual abilities. It also reflects knowledge and experience. The expression of goals, whether they are specifically spelled out or implicitly assumed, affects the outcome of actions as well. The process through which existence is preserved at the lowest level—as with the phototropic mono-cell and progressing all the way up to the human being—is anticipatory. But at a certain level of life organization and complexity, the preservation drive assumes new forms through which it is realized. Anticipation is the common denominator. However, the concrete aspect of how it is eventually expressed—i.e., through self-awareness, intentionality, or in the activity called "planning"—changes as the interdependence of the processes through which the living unfolds increases.

Anticipation at the level of preserving existence is unreflected. Facial expression in anticipation of an action is a good example here, too. It seems that facial expression is not defined on a cultural level but is species wide (Ekman [35], Gladwell [36]). It is not a learned expression. Individuals can control their facial expression to an extent. However, there is always that one second or less in which control is out of the question. Intentionality is always entangled with awareness—one cannot intend something without awareness, even in vague forms. But this awareness does not automatically make human expressions carry anticipations more than the expression of the rest of the living does. We sweat "sensing" danger even before we are aware of it. The difference is evident on a different level. Humans reach self-awareness; the mind is the subject of knowledge of the mind itself. As such, we eventually recognize that our faces "speak" before we act (or before perspiration starts). They are our forecasts, the majority of them involuntary. Those intent on deciphering facial expression obtain access to some intriguing anticipatory mechanisms, or at least to their expression.

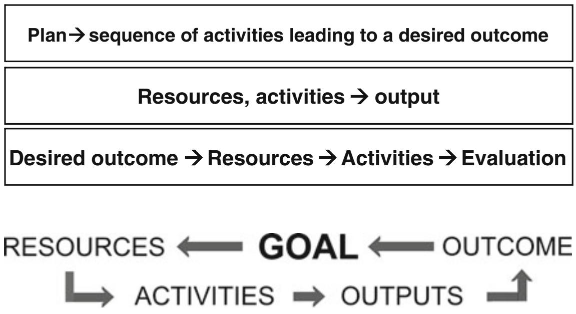


Fig. 8 Goal-driven means: future informed

Planning (Fig. 8) is more than calculation. A planning machine for integrated activities carried out in an open system over a longer period of time would require real-time adaptive capabilities.

The planning dimension is based on learning capabilities: what road to choose at which time; how long it takes to find the daughter and prepare for the gym; how long will parent and daughter spend at the gym; which is the best way home, assuming that some other activity might be spontaneously chosen. It also implies flexibility, as a form of adapting to new circumstances (the daughter has a lot of homework, for example). "Take me from the University to my daughter's school. After she joins me, take us to the gym. After that, we go home." To prepare for a worst-case situation, one would have to generate possible breakdown timelines and provide contingency measures for each. Various reactive components (which correspond to reactive planning, i.e., how to react) can be effectively described in computational terms. For instance, process planning maps from design (which is an expression of anticipation) to instructions and procedures, some computer-aided (e.g., 3D printing), for effectively making things, or changing things. Operations (deterministic), operation sequences, tooling, and fabrication procedures are described in computer process planning and serve as input for automated activities.

Planning, expressed through policymaking, management, prevention, logistics, and even design, implies the *ante* element—giving advance thought, directing towards something, looking forward, engaging resources (including the self). Moreover, it implies understanding, which resonates with the initial form of the word denoting anticipation: *antecapere*. As such, the activity through which human beings identify themselves as authors of the blueprint of their actions takes place no longer at the object level, but on a meta-level. It is an activity of abstracting future actions from their object. It is also their definition in a cognitive domain not directly associated with sensory input, but rather with understanding, with knowledge. Plans synthesize predictive abilities, forecasting, and modeling (Fig. 9).

A plan is the expression of understanding actions in relation to their consequences. It is what is expressed in goals, in means to attain these goals, as well as in the time sequence for achieving them. A plan is a timeline; it is a script for interactions indexed to the timeline. To what we call understanding belong goals, the means, the underlying structure of the endeavor (tasks assumed by one person,

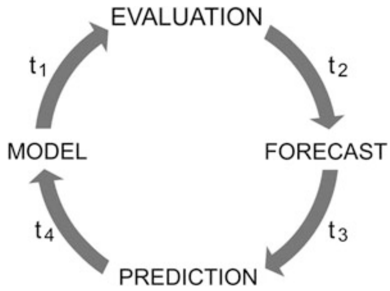


Fig. 9 Integrated Planning Process (IIP) as part of the understanding process

by several, the nature of their relation, etc.), a sense of progression in time, awareness of consequences, i.e., a sense of value. As such, they report upon the physical determination of everything people do, and of the anticipatory framework. In every plan, from the most primitive to the utmost complex, the goal is associated with the reality for which the plan provides a description (a theory), which is called *configuration space*. If it is a scientific plan, such as the exploration of the moon or the genome project, the plan describes where the "science" actually resides, where those equations we call descriptions are "located." If it is a political plan, or an education plan, the configuration space is made up of the people that the plan intends to engage, and of the means and methods to make it work. Our own description of the people, like the mathematical equations of science, is relative. Such description of the configuration space, and, within that space, of the interactions through which people learn from each other are subject to adjustments.

The plan also has to describe the time-space in which the goal pursued will eventually be embodied. This is a manifold, towards which the dynamics of actions and interactions (social context) will move those involved. In science, this is the landing on the moon, or the map of the human gene; it can as well be a new educational strategy or, in politics, the outcome of equal opportunity policies. The plan associated with the self-driving automobile taking its user to the daughter's school, to the gym, etc., is of a different scale, but not fundamentally dissimilar. All the goals are anticipations projected against the background of understanding change in the world as an expression of the unity between the dynamics of the physical and the living. Plans spell out variables to be affected through actions, and the nature of the interrelationships established in pursuing the plans. Quite often, plans infer from the past (the reactive component) to the future (proactive component). They also project how the future will eventually affect the sequence of ensuing current states. Planning and self-regulation are related. The inner dynamics of phenomena and their attractors—the goals to be attained—reflect this interconnectedness. These attractors are the states into which the system will settle—at least for a while. They are the descriptions of self-organizing processes, their eventual destination, if we can understand it as a dynamic entity, not the statement of a static finality. Planning sets the limits within which adaptive processes are allowed. Each plan is in effect an expression of learning in action, and of the need to adapt to circumstances far from remaining the same.

Processes with anticipatory, predictive, and forecasting characteristics are described through

Control → function of (past state, current state, future state) system
Adaptivity → circumstances related to goals

Knowledge of future states is a matter of possibilistic distributions:

$$r : \cup \rightarrow [0,1] \tag{9}$$

in which ∪ defines the large space of values a variable can take. The function $\mathcal{R}$ is actually a fuzzy restriction associated with the variable **X**:

$$\mathcal{R}(\mathrm{X}) = \mathrm{F} \tag{10}$$

It is associated with a possibility distribution $\Pi_{\mathbf{x}}$ (Nadin [43]). Nothing is probable unless it is possible. Not every possible value becomes probable.

The anticipated performance (von Glasersfeld [32]) and the actual performance are usually related. The difference between the pursued goal and the concrete output of the process, together with the reward mechanism, guides the learning component.

Functioning under continuously changing conditions means that control mechanisms will have to reflect the dynamics of the activity (Fig. 10). This is not possible without learning. If we finally combine the automated part (everything involving the change of the physical can be automated) and human performance (expressed in behavior features), we arrive at an architecture that reflects the hybrid nature of plan-driven human activities that feed values into the sensors. Based on these values, the system is reconfigured under the control of the dynamic model continuously refreshed in accordance with the behavior of the world. Learning results in the process of successive refreshment of data. Effectors act upon the world as a control procedure. If we compare this architecture to that of the Google Deep Mind Group, we notice that the difference is operational. Convolutional neural

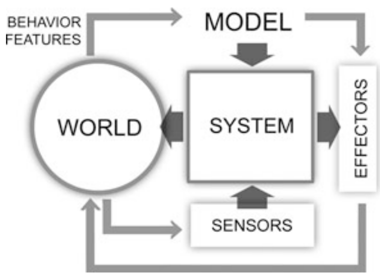


Fig. 10 Generic diagram of a hybrid control mechanism endowed with learning (Nadin [44])

networks are used to appropriate the parameters that guide the action. The Q-network agent is nothing other than a reduction of anticipation to prediction.

Indexed behavior features (of students in a class, patients, vehicle drivers, airplane pilots, politicians in a power position, computer game choices, etc.) and the methods for extracting regularities characteristic of their behavior are connected. Learning ensues from adapting to new circumstances (i.e., change). The "learning"—classroom, physician's office, car, airplane, management system guiding a prime minister or a secretary of state, successfully playing a game, understanding a question and answering it, etc.—is thus one that combines its own dynamic (modified, evolving knowledge) and that of the persons involved (anticipation included). The suggestion here is that conceiving intelligent classrooms, intelligent schools, intelligent cars and airplanes, intelligent "assistants" for those in power, or intelligent game players is characteristic of an anticipatory perspective. However, the perspective does not automatically translate into proactive activity. Most of the time the system remains reactive. Embodied intelligence and the intelligence of challenged users could augment the perception of time, and thus help mitigate consequences of change for which society is rarely (if ever) prepared. If the generic diagram of the hybrid control mechanisms endowed with learning conjures associations with the smartphones of our time (i.e., mobile computing), it is not by accident (as we shall see in the second part of this study).

2 Practical Considerations

Pursuing the enticing goal of making everything behave like a machine—and paying the price for it—stands in sharp contrast to a vision of acknowledging the living and its definitory anticipation. One writer put it in quite expressive terms: "Think of the economy as being more like a cat than a washing machine," (Taleb [45]). Evidently, becoming servants to robots, as Shannon cavalierly conceded, goes in the opposite direction. With this note, we are back to the preliminaries to the broader question of whether anticipatory computing is possible.

2.1 The "Why?" Question

Actually, "Why anticipatory computing?" would be a better question than simply questioning its feasibility. The reason for entertaining the question is straightforward: computation, of any nature, is nothing other than counting or measuring. The digital computer, as opposed to the person whose work was to calculate, i.e., to be a "living computer" provides automated calculation. (The first documented use of the word computer dates to 1613; it refers to persons performing calculations, to which we shall return.) It is not surprising that the human associates with calculation certain desired capabilities: the ability to make distinctions (large, small, wide, narrow), to compare, to proceed in a logical manner, to guide one's activity. From the stones (*calculae*) used yesteryear to describe property, effort, and sequences of all kind to the alphabet of zeroes and ones (or Yes and No) of the new electronic abacus, the change was merely in scale, scope, speed, and variety of calculations, but not in its nature. The reason for calculations, and, implicitly, for measurement, remains the same: to cope with change, to account for it, to impact change.

Considering computer industry claims (e.g., Cigna CompassSM™, the MindMeld™ iPad app, among others), the question of whether anticipatory computing is possible appears to be meaningless. The public and the major users of computation (banks, the military, healthcare, education, the justice system, etc.) are enticed by gadgets supposedly able to perform anticipations. Leaving aside the marketing gags—"We know where you will be on February 2, 2017 and with whom" states the Nostradamus bot—what remains, as we shall see, are computations with predictive features. As respectable as one or the other is, their performance does not have identifiable anticipation features. It is still hard to believe that the computer community, of presumed smart individuals, simply falls prey to the seductive misrepresentation methods characteristic of marketing. This is an example of lack of knowledge, of incompetence. Setting goals (to anticipate) not connected to what is actually offered—to extract information from patterns of behavior with the aim of predicting—does not qualify as competence. To define human-level control in terms of computer game proficiency is as misleading (regardless of the unreserved blessing of being published in *Nature* [6]).

The reason for this extended study of whether anticipatory computing is possible is to set the record straight and inform future work that reflects the understanding of anticipatory processes.

2.1.1 Counting

Stones, or knots on a rope (Fig. 11), are a form of record keeping: so many sheep, so many slaves, so many arrows, whatever; but also number of days, of bricks, of containers (for water, oil, wine, etc.), of anything that is traded. Such measurements translate as the basis for transactions: those entitled to a portion of the exchange (yes, change of ownership, currency of reference related to the days and weeks it took to hunt, process, make, preserve, etc.) will exercise their rights. To know ahead of time what and how things will change always afforded an edge in the economy of survival (as in any subsequent economy, including the transaction economy characteristic of our time). Ahead of time (*ante* is Latin for "before") is ahead of others. Actions ahead of time are anticipatory. They are conducive to higher performance.

Therefore, anticipation as the "sense of the ever-changing context" is co-substantial with the preoccupation of describing change, either in words or in numbers, or, more generally, in any form of representation. Hence: representing change, as image (in the prehistoric cave paintings, for instance), as words trying to describe it, as numbers, equations, visualization, etc. is indicative of anticipation—the never-ending wager against change.

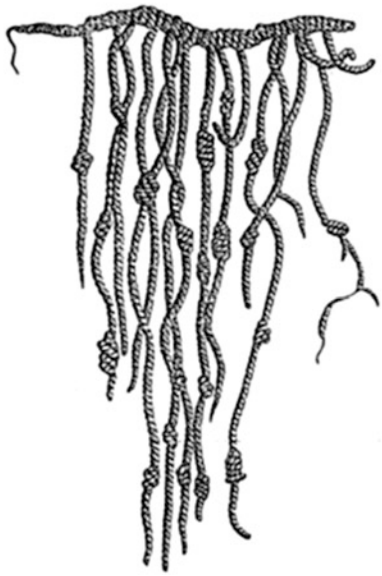


Fig. 11 The Incan *quipu*

The fact that some descriptions (i.e., representations) are more adequate than others for certain activities is a realization of the nature of observations leading to learning. Where quantitative distinctions are more effective, numbers become more important than images, sounds, or words. With numbers—very much derived from the geometry of the human body (single head; pair of eyes, nostrils, ears; set of fingers and toes; myriad strands of hair)—comes the expectation of capturing change in operations easy to understand and reproduce. Counting emerges as a fundamental cognitive activity. Leibniz went so far as to state that music is the pleasure that the human mind experiences from counting without being aware that it is counting. (Poetry would easily qualify for the same view, so would dance.) This statement can be generalized, although temporal aspects (music unfolding over time/duration/interval, as expression of rhythm) and spatial aspects are rather complementary. Still, counting involves the most basic forms of perception: the visual and the aural. To count implies the abstraction of the number, but also the abstraction of point, line, surface, and volume. A straight line is a set of adjacent points that can be counted (and the result is the length of the line); a surface is the collection of all lines making it up; and volume is represented by all the elements needed to arrive at it.

Just for illustration purposes: a more than 500-year-old woodcut (*The Allegory of Arithmetic*, Gregor Reisch, 1504). This image is part of the *Margarita Philosophica* describing the mapping from a counting board (for some reason, Pythagoras was chosen as a model) to the emergent written calculation (in which, for some even more obscure reason, Boethius is depicted). In this image, Hindu representation of numbers is used in what emerges as the art and science of mathematics.

Fig. 12 *The Allegory of Arithmetic*. The *abacist* uses the abacus; the *algorist* is involved in formulae

Indeed, the calculating table (counting board) is a machine—conceptual at that stage—and so are the abacus and all the contraptions that make counting, especially of numbers of a different scale than that of the immediate reality, easier, faster, cheaper. In the image (Pythagoras competing with Boethius), an *abacist* (one who knows how to count using an abacus) and an *algorist* (one who calculates using formulae) are apparently competing (Fig. 12). The abacist is a computer, that is, a person who calculates for a living. It is appropriate to point out that there are many other forms of computing, such as counting the elements that make up a volume of liquid, or a mass (of stone, wood). Under these circumstances, counting becomes an analog measurement. With the abacus, after moving the appropriate beads, you only have to align the result, and it will fall in place. This holds even more with the attempt to measure, i.e., to introduce a unit of reference (describing volumes, or weights).

2.2 Measuring

The act of measuring most certainly implies numbers. It also implies the conventions of measuring units, i.e., a shared understanding of what the numbers represent, based on the science behind their definition. Indeed, the numbers as such are data, their meaning results from associating the numbers to the measuring process, such as "under the influence of gravity" (Fig. 13).

Fig. 13 Measurement as pouring medicine into beaker (The pharmacist "computes" the quantities prescribed)

Quantitative distinctions are associated with numbers. Qualitative distinctions are associated with words, or any other means for representing them (e.g., sounds, colors, shapes). In the final analysis, there are many relations between quantitative and qualitative distinctions. Of course, numbers can be represented through words as well, or visually, or through sounds.

It should be clear at this time that counting numbers (or associating qualities, such as small, round, soft, smelly, etc.) is a discrete process, while "falling in place" (measuring, actually) is based on analogies and is a continuous process. This distinction pretty much defines the numbering procedure—one in which representations are processed sequentially, according to some rules that correspond to the mapping from the questions to be answered to what it takes to answer it. Example: If you have 50 sticks of different length, how does one order them from shortest to longest? Of course, you can "count" the length of each (using a measuring stick that contains the "counted" points corresponding to the units of measurement) and painstakingly arrange them in the order requested. Or you can use a "recipe," a set of instructions, for doing the same, regardless of how many there are and how long each one.

2.2.1 The Early Meaning of Algorithm

Let us recall the calculating table from *Margarita Philosophica* allegory of arithmetic: to the right, the human "computer," checking each stick, keeping a record of the length of each, comparing them, etc.; to the left the *algorism* (no spelling error here)—a person using a counting method by writing numbers in a place-value form and applying memorized rules to these numbers. Before that, once the scale changed (say, from tens to hundreds to thousands and tens of thousands), the representations used, i.e., the symbols, such as Roman numerals, changed. LVI means 56. A native of Kharazuni (a locality in what today is Uzbekistan) gave his name (Al-Khwarizuni arrived in Latin as *Algorituni*) to a treatise on the number system of the Indians (*Algorituni de Numero Indorum*). Actually, he provided the decimal number system for counting.[1] The fact that the notion of the algorithm, which has characterized the dominant view of computation since Turing, is associated with his name is rather indicative of the search for simple rules in counting. Those implicit in the decimal number system and in the place value form are only an example. Algorithm (on the model of the word logarithm, in French) maintains the connection to *arithmos*, ancient Greek for *number*. Numbers are easier to use in describing purposeful operations, in particular, means and methods for measuring. Such means and methods replace guessing, the raw estimate that experienced traders knew how to make, and which were accepted by all parties involved. The ruler and the scale are "counting" devices; instructions for using them are algorithms.

Historic accounts are always incomplete. Examples related to the need and desire to make counting, and thus measurement, more like machine operations are usually indicative of the dominant knowledge metaphor of the time (the clock, the pneumatic pump, the steam engine, etc.). The machines of those past times embody algorithms. Leibniz used the label *machine* in describing the rules of differential calculus, which he translated into the mechanical parts (gears) of his machine. Machines such as clocks, water wheels, and even the simple balancing scale (embodying the physics of the lever) were used for various purposes. The balancing scale was used to estimate weight, or the outcome of applying force in order to move things (the most elementary form of change, i.e., in position), or change their appearance. Recalling the various contributions to computation—Blaise Pascal and his Pascaline device; Leibniz and his computer; Schickard and the calculating clock associated with his name; Babbage's analytical engine inspired by the loom, etc.—means to recall the broader view of nature they embody. It also suggests that calculations and measurements can be performed basically in either an analog manner or a digital manner (Fig. 14).

2.2.2 Why Machines for Calculations?

To this question Leibniz provided a short answer: "…it is unworthy of excellent men to lose hours like slaves in the labor of calculation which could be safely relegated to anyone else if machines were used." This was written 12 years after he built (in 1673) a hand-cranked machine that could perform arithmetic operations.

[1]He also wrote the famous *Istikhvay Tarikh al-Yahud* (Extraction of the Jewish Era), a lunar cycle-based calendar for the Jewish holidays. This elaborate calendar, still in use, is a suggestion of his possible Jewish roots. (At the time of his activity, he was a Muslim scholar of the early stages of the creed, after he gave up his Zoroastrian identity). Inspired by the Hebrew *Mishnat ha Middot* (Treatise on Measures), he suggested elements of geometry well aligned with those of Euclid. That was a world of practiced diversity, including diversity of ideas.

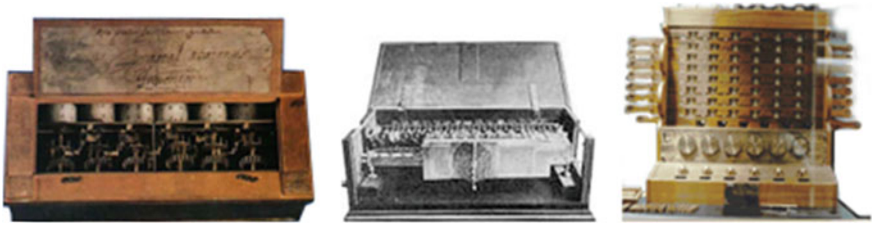


Fig. 14 The Pascaline, Leibniz's machine, Schickard's calculating clock

What he wrote is of more than documentary relevance. Astronomy, and applications related to it, required lots of calculations in his time. Today, mathematics is automated, and thus every form of activity with a mathematical foundation, or which can be mathematically described, benefits from high-efficiency data processing. Excellent men and women (to paraphrase Leibniz) program machines that process more data and faster, because almost every form of human activity involves calculations. Still, the question of why machines for calculation does not go away, especially in view of realizations that have to do with a widely accepted epistemological premise: mathematics is the way to acquire knowledge. The reasonable (or unreasonable) effectiveness of mathematics in physics justifies the assumption. But there is no proof for it. Can this hypothesis be "falsified"?

It is at this juncture that our understanding of what computation is and the many forms it takes becomes interesting. Eugen Wigner's article of 1960 [46] contrasts the "miracle of the appropriateness of the language of mathematics for the formulation of the laws of physics" to the "more difficult" task of establishing a "theory of the phenomena of consciousness, or of biology." Less than shy about the subject, Gelfand and Tsetlin [47] went so far as to state, "There is only one thing which is more unreasonable than the unreasonable effectiveness of mathematics in physics, and this the unreasonable ineffectiveness of mathematics in biology." Leibniz would have seconded this formulation. Vellupillai [48] uses the same formulation in respect to economics.

2.3 Analog and Digital: Algorithmic and Non-algorithmic

The analog corresponds to the continuity of phenomena in nature. Pouring water or milk into a measuring cup in order to determine the volume, and thus, indirectly, the weight, is indicative of what analog calculations are. It is counting more than one molecule at a time, obviously. Similarity defines the domain. The lever on a scale automates the counting. It functions in the analog domain: add two or three more ounces until the scale is level, and that is the outcome of the calculation. Of course, to model simple phenomena and scale them is easy. But to reconfigure the analog—from calculating the volume of a liquid to that of a gas or solid—is more difficult.

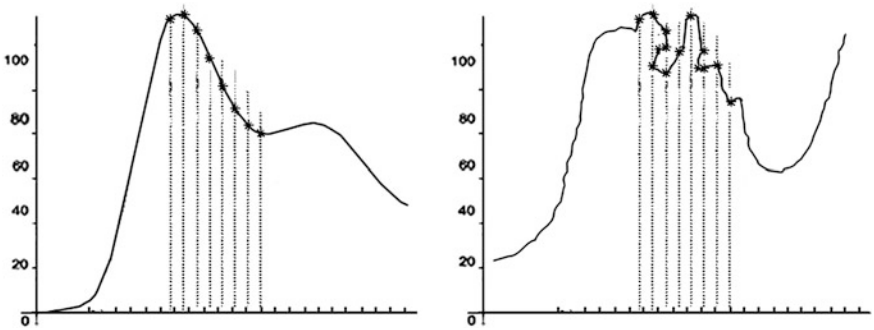


Fig. 15 Sampling: comparisons of rate and data retention in sampling

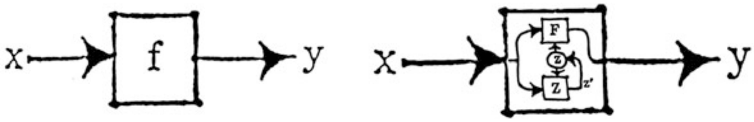


Fig. 16 Heinz von Foerster: trivial and non-trivial machines (his own drawings)

Moreover, it is hard to distinguish between what is actually processed and the noise that interferes with the data. By way of counter-example, when you count beans in a bag, by hand, you can easily notice the stone among them.

The digital is focused on sampling, on making the continuous discrete. At low rates of sampling, much relevant data is lost. The higher the rate, the better the approximation. But there is a cost involved in higher rates, and there are physical limitations to how fast a sampling machine can go (Fig. 15).

In the context of interest in machines of all kind (for conducting wars, for successful wagers, for calculating the position of stars, for navigation, for making things, etc.), the theoretic machine called *automaton* was the most promising. For a while, what happened in the box (how the gears moved in Leibniz's machine, for example) and what rules were applied—which is the same as saying which algorithm was used—was not subject to questioning. Heinz von Foerster took the time to distinguish between trivial and non-trivial machines (Fig. 16).

His distinction proved to be more consequential than initially assumed, once the model of the neuron (more precisely, its deterministic reduction was adopted (Fig. 17).

It is important to understand that input values are no longer a given, and that in the calculation scheme of neuronal networks, the machine is "taught" (through training) what it has to do. This applies from the simplest initial applications of the idea (McCulloch and Pitts, 1943) to the most recent deep Q-network (DQN) that combines reinforcement learning in association with deep neural networks (in the case of mimicking feed-forward processing in early visual cortex (Hubel and Wiesel [49]).

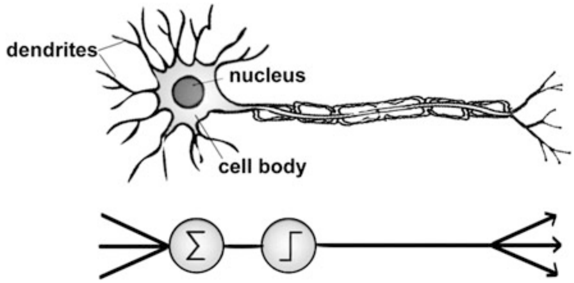


Fig. 17 The neuron machine

Evidently, the subject of interest remains the distinction between reaction-based processes—the theoretic machine has input, a number of inner states, and an output that is the outcome of the calculation—and predictive performance. There is no anticipatory dimension to account for. The "non-trivial machine" (von Foerster and Poerksen [50]) is essentially reactive: part of the calculation implies a dynamic dimension of the inner state connections. It is conceivable that along this line of an autonomic function associated with the inner state, anticipation could be defined as the result of the self-organization of such a machine. The DQN, like the professional human game testers, acquires a good understanding of the game algorithm, outperforming other reinforcement learning methods (including the training of living gamers).

2.3.1 The *a-Machine*

With the Turing machine, the real beginning of automated calculation was reached. Interestingly enough, behind his theoretic machine lies the same problem of automatic operations, in this case, the making and testing of mathematical statements. Hilbert was convinced that calculations were the basis for them. The meta-level of the enterprise is very relevant:

(a) objects in the reality of existence → representations → acts upon representations → new knowledge inferred from representations
(b) objects → numbers → counting → measurement → ideas about objects → ideas about ideas

The Turing saga was written so many times (and filmed with increased frequency) that it is hardly conceivable that the most important about it was not yet made public. Still, to understand the type of computation associated with his name—moreover, whether it is a possible path to anticipatory computing—a closer look is called for. Hilbert's conjecture that mathematical theories from propositional calculus could be decided—*Entscheidung* is the German for decision, as in proven true-or-false—by logical methods performed automatically was rejected. Indeed, Turing (after Gödel and Alonzo Church) disappoints Hilbert, the mathematician who challenged the community with quite a number of hard problems (some not yet elucidated).

First and foremost: Turing provided the mathematical proof that machines cannot do what mathematicians perform as a matter of routine: developing mathematical statements and validating them. This is the most important, and most neglected, contribution. Nevertheless, the insight into what machines can do, which we gain from Turing's analysis, is extremely important. Wittgenstein [51], recalling a conversation with Turing (in 1947) wrote: " 'Turing's machines': these machines are humans who calculate. And one might express what he says also in the form of games." Indeed, the idea behind digital computers is machines intended to execute any operation that could be done by a human computer. (Remember: initially, as of 1613, "computer" applies to a person employed to calculate, what Gregor Riesch meant by an algorist.) Turing [52] himself wrote, "A man provided with paper and pencil and rubber, and subject to strict discipline, is in effect a universal machine." At a different juncture, he added: "disciplined but unintelligent" [53]. Gödel would add, "mind, in its use, is not static, but constantly developing" [54]. "Strict discipline" means "following instructions." Instructions are what by consensus became the algorithm. Intelligence at work often means shortcuts, new ways for performing an operation, even a possible wrong decision. Therefore, non-algorithmic means not subject to pre-defined rules, but rather discovered as the process advances. For those who fail to take notice of Turing's own realization that not every computation is algorithmic, non-algorithmic computation does not exist.

Automatic machines (*a-machines* as Turing labeled them) can carry out any computation that is based on complete instructions; that is, they are algorithmic. One, and only one, problem remains: the machine's ability to recognize the end of the calculation, or that there is no end. This means that the halting problem turned out to be undecidable. This characterization comes from Gödel's work, where the undecidable names an entity that cannot be described completely and consistently. Turing's *a-machine* consists of an infinite tape on which symbols can be stored, a read/write tape head that can move left or right (along the tape), retrieve (read) symbols from the tape or store (write) to the tape. The machine has a transition tape and a control mechanism. The initial state (one from among many on the transition tape) is followed by what the control mechanism (checking on the transition tape) causes the machine to do. This machine takes the input values, obviously defined in advance; it operates on a finite amount of memory (from the infinite tape) during a limited interval. The machine's behavior is pre-determined; it also depends on the time context. Examining the design and functioning rules of the a-machine, one can conclude the following: whatever can be fully described as a function of something else with a limited amount of representations (numbers, words, symbols, etc.) can be "measured," i.e., completed on an algorithmic machine. The algorithm is the description.

With the *a-machine*, a new science is established: the knowledge domain of decidable descriptions of problems. In some sense, the *a-machine* is no more than the embodiment of a physics-based view of all there is. This view ascertains that there are no fundamental differences between physical and living entities. This is a drastic epistemological reduction. It ascertains that there is a machine that can effectively measure all processes—physical or biological, reactive or anticipatory—as long as they are represented through a computational function.

2.3.2 Choice, Oracle, and Interactive Machines

Turing knew better than his followers. (Albeit, there is no benefit in making him the omniscient scientist that many proclaim him to be, reading into incidental notes ideas of a depth never reached.) In the same paper [53], Turing suggested different kinds of computation (without developing them). Choice machines, i.e., *c-machines*, involve the action of an external operator. The *a-machines* were his mathematical proof for the Hilbert challenge. Therefore, they are described in detail. The *c-machine* is rather a parenthesis. Even less defined is the *o-machine* (the oracle machine advanced in 1939), which is endowed with the ability to query an external entity while executing its operations. The *c-machine* entrusts the human being with the ability to interact on-the-fly with a computation process. The *o-machine* is rather something like a knowledge base, a set subject to queries, and thus used to validate the computation in progress. Turing insisted that the oracle is not a machine; therefore the oracle's dynamics is associated with sets. Through the *c-machine* and the *o-machine*, the reductionist *a-machine* is opened up. Interactions are made possible—some interactions with a living agent, others with a knowledge representation limited to its semantic dimension. Predictive computation is attained; anticipation becomes possible.

The story continues. Actually, the theoretic construct known as the Turing machine—in it's *a-*, *c-*, and *o-* embodiments—will eventually become a machine proper within the ambitious Automatic Computing Engine (ACE) project. (In the USA, the EDVAC at the University of Pennsylvania and the IAS at Princeton University are its equivalents.) "When any particular problem has to be handled, appropriate instructions…are stored in the memory…and the machine is 'set up' for carrying out the computation," (Turing [55]). Furthermore, Turing diversifies the family of his machines with the *n-machine*, (unorganized machine of two different types), leading to what is known today as neural networks computation (the B-type *n-machines* having a finite number of neurons), which is different in nature from the algorithmic machine.

Von Neumann (who contributed not only to the architecture of the Turing machine-based computer, but also to the neural networks processing of data) asserted that, "…everything that can be described with a finite number of words, could be represented using a neural network" (Siegelmann and Sontag [56]). This is part of the longer subject of the Turing completeness or recurrent neural nets. Its relevance to the issue of anticipatory computing is indirect, via all processes pertinent to learning.

One more detail regarding Turing's attempt to define a test for making the distinction between computation-based intelligence and human intelligence possible: human intelligence corresponds to the anticipatory nature of the living. Therefore, to distinguish between machine and human intelligence (the famous

"Turing test") is quite instructive for our understanding of anticipation. It is well established by now that imitation, which was Turing's preferred game, is by no means indicative of intelligence.

Machines were programmed to answer questions in a manner that would make them indistinguishable from humans doing the same. This became the standard for winning in competitions meant to showcase progress in artificial intelligence (AI). To state that some entity—machine, person, simulation, or whatever else—can think is of low relevance, unless the thinking is about change, i.e., that it involves awareness of the future. The number of words necessary for describing such awareness is not finite; the number increases with each new self-realization of awareness. Creativity, in its broadest sense—to originate something (a thought, a melody, a theorem, a device, etc.)—is, of course, better suited to qualify as the outcome of thinking. However, at this level of the challenge, it should be clear that thinking alone is a necessary but not sufficient condition for creativity. Anticipation is the aggregate expression, in action, of all that makes up the living. Turing was not aware of this definitory condition of anticipation. It is difficult to speculate the extent to which he would have subscribed to it.

Not to be outdone by Google DeepMind, Facebook's AI research focused on understanding language (conversing with a human [6]. Learning algorithms in this domain are as efficient as those in playing games—provided that the activity is itself algorithmic. Unfortunately, the lack of understanding anticipation undermines the effort to the extent that the automated grammar deployed and the memory networks become subjects in themselves. The circularity of the perspective is its main weakness. One more observation: Imagine that you were to count the number of matchsticks dropped from a matchbox (large or small). It is a sequential effort: one stick after another. There are persons who know at once what the total number is. The label *savant syndrome* (from the French *idiot savant*, which would mean "learned idiot") is used to categorize those who are able to perform such counting (or other applications, such as multiplication in their head, remembering an entire telephone directory). Machines programmed to perform at this level are not necessarily different in both ability and degree of "autism"—impaired interaction, limited developmental dynamics.

But let us not lose sight of interactivity, of which he was aware, since on the one hand Turing computation is captive to the reductionist-deterministic premises within which only the reaction component of interactivity is expressed, and, on the other, since interaction computing (Eberbach et al. [57]) is not reducible to algorithmic computation. The most recent developments in the area of quantum computation, evolutionary computation, and even more so in terms of computational ubiquity, in mobile computing associated with sensory capabilities, represent a grounding for the numerous interrogations compressed in the question: Is anticipatory computation possible? Moreover, the "Internet of Everything" (IoE) clearly points to a stage in computation that integrates reactive and anticipatory dimensions.

2.4 What Are the Necessary Conditions for Anticipatory Computing?

For a computation to qualify as anticipatory, it would have to be couched in the complexity corresponding to the domain of the living. Elsewhere [12], I argued that description of objects and phenomena, natural or artificial, that correspond to the intractable, make up the realm of G-complexity. Anything else corresponds to the physical.

2.4.1 Beyond Determinism

Anticipation comes to expression within G-complexity entities. Quantum processes transcend the predictable; they are non-deterministic. Consequently, their descriptions entail the stochastic (the aim), which is one possible way to describe non-deterministic processes. To the extent that such quantum-based computers are embodied in machines (I am personally aware only of the functioning of D-Wave, and there is some question whether it is a real quantum machine), one cannot expect them to output the same result all the time (Fig. 18).

Rather, such a computer has no registers or memory locations, and therefore to execute an instruction means to generate samples from a distribution. There is a collection of qubit values—a qubit being a variable defined over the interval {0,1}. A certain minimum value has to be reached. The art of programming is to affect weights and strengths that influence the process analyzed. Instructions are not deterministic; the results have a probabilistic nature. One case: Is the object in the frame analyzed a moving car? The answer is more like "It could be!" than "It is!" or "It's not!"

Predictive calculations are in some form or another inferences from data pertinent to a time of reference (t_0) to data of the same phenomenon (or phenomena) at a later time ($t_1 > t_0$). Phenomena characteristic of the physical can be precisely described. Therefore, even if non-linearity is considered (a great deal of what happens in physical reality is described through non-linear dependencies), the

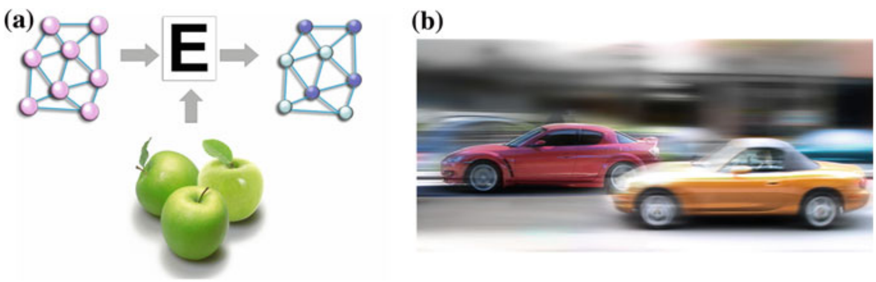


Fig. 18 (**a**) Quantum computation used in image recognition: apples, (**b**) a moving car

inference is never of a higher order of complication than that of the process of change itself. In quantum phenomena, the luxury of assuming that precise measurements are possible is no longer available. Even the attempt to predict a future state affects the dynamics, i.e., the outcome. It is important to understand not only how sensitive the process is to initial conditions, but also how the attempt to describe the path of change is affected in the process. (For more details, the reader should consult Elsasser's Theory of Quantum Mechanical Description [58]. One more observation: the living is at least as sensitive to observation (representation, measurement) without necessarily qualifying as having a quantum nature.

Although very few scientists pursue this thought, it is significant to understand that Feynman argued for quantum computation in order to facilitate a better understanding of quantum mechanics, not for treating what are called "intractable problems." Factoring numbers, which are a frequent example of what quantum computation could provide, is important (for cryptography, for instance). However, it is much more relevant to better understand quantum phenomena. Paul Benioff and Richard Feynman (independently, in 1982) suggested that a quantum system can perform computations. Their focus was not on how long it takes to factor a 130-digit number (the subject of Shor's algorithm), not even the relation between time and the size of the input (the well-known P≠NP problem of computer science).

In computations inspired by theories of evolution or genetics, the situation is somehow different. Without exception, such theories have been shaped by the determinism of physics. Therefore, they can only reproduce the epistemological premise. But the "computations" we experience in reality—the life of bacteria, plants, animals, etc.—are not congruent with those of the incomplete models of physics upon which they are based. Just one example: the motoric expression (underlying the movement of humans and animals) might be regarded as an outcome of computation. Consider the classic example of touching the nose with the tip of the index finger (or any other finger, for that matter [59]). The physics of the movement (3 coordinates for the position of the nose) and kinematic redundancy (a wealth of choices given the 7 axes of joint rotation, 3 axes of shoulder rotation, elbow, joint, wrist rotation, etc.) lead to a situation in which we have three equations and seven unknowns. Of course, the outcome is indeterminate. The central nervous system, of extreme plasticity, can handle the richness of choices, since its own configuration changes as the action advances. However, those who perform computations in artificial muscles do not have the luxury of a computer endowed with plasticity. They usually describe the finite, and at most predict the way in which the physics of the artificial muscle works. There are, of course, many attempts to overcome such limitations. But similar to computer science, where computation is always Turing computation (i.e., embodied in an *a-machine*), biology-based computation, as practiced in our days, is more anchored in physics, despite the vocabulary. In reality, if we want to get closer to understanding the living, we need to generate a new language (Gelfand and Tsetlin [47, pp. 1–22]). Anticipation is probably the first word in this language.

2.4.2 An Unexpected Alternative

Mobile computing, which actually is the outgrowth of cellular telephony—i.e., not at all a computing discipline in virtue of its intrinsic hybrid nature of human-machine—offers an interesting alternative. From the initial computer-telephone integration (CTI) to its many current embodiments (tablets, note- and netbooks, smartphones, etc.), mobile computing evolved into a new form of computation. First and foremost, it is interactive: somehow between the *c-machine* and *o-machine* envisaged by Turing. Things get even more interesting as soon as we realize that the computer sine qua non telephone is also the locus of sensor interactions. In other words, we have a computer that is a telephone in the first place, but actually a video scanner with quite number of functions in addition to communication. Before focusing on the ubiquity of mobile computation, it is worth defining, in reference to the first part of this study, various forms of computation that make possible forecasting, prediction, planning, and even some anticipatory processes.

Regardless of the medium in which probability-based computing is attempted—any physical substratum (such as the artificial muscle mentioned above) can be used for computational purposes—what defines this kind of calculation is the processing of probabilities. Probability values can be inputted to a large array and processed according to a functional description. A probability distribution describes past events and takes the form of a statistical set of data. In this data domain, inductions (from some sample to a larger class), or deductions (from some principle to concrete instantiations), or both, serve as operations based upon which we infer from the given to the future. The predictive path can lead to anticipation. From regularities associated with larger classes of observed phenomena, the process leads to singularities, the inference is based on abduction (or, to be faithful to Peirce's terminology, *retroduction*), which is history dependent. Indeed, new ideas associated with hypotheses (yet another name for reduction) are not predictions, but an expression of anticipation (Fig. 19).

Alternatively, we can consider the interplay of probability and possibility. This is relevant in view of the fact that information—i.e., data associated with meaning that results from being referenced to the knowledge it affords or is based upon—can be associated with probability distributions (of limited scope within the [0,1] interval), or with the infinite space of possibilities corresponding to the nature of open-ended systems. Zadeh, [60] takes note of the fact that in Shannon's data-transmission theory (misleadingly called "information" theory), information is equated with a reduction in entropy—and not with form (not morphology). He understands this reduction to be the source of associating information with probability. But he also calls attention to possibilistic information, orthogonal to the probabilistic: one cannot be derived from the other. In his view (widely adopted in the scientific community), possibility refers to the distribution of meaning associated with a membership function. In more illustrative terms (suggested by Chin-Liang Chang), possibility corresponds to the answers to the question, "Can it happen?" (in respect to an event). Probability (here limited to frequency, which, as we have seen, is one

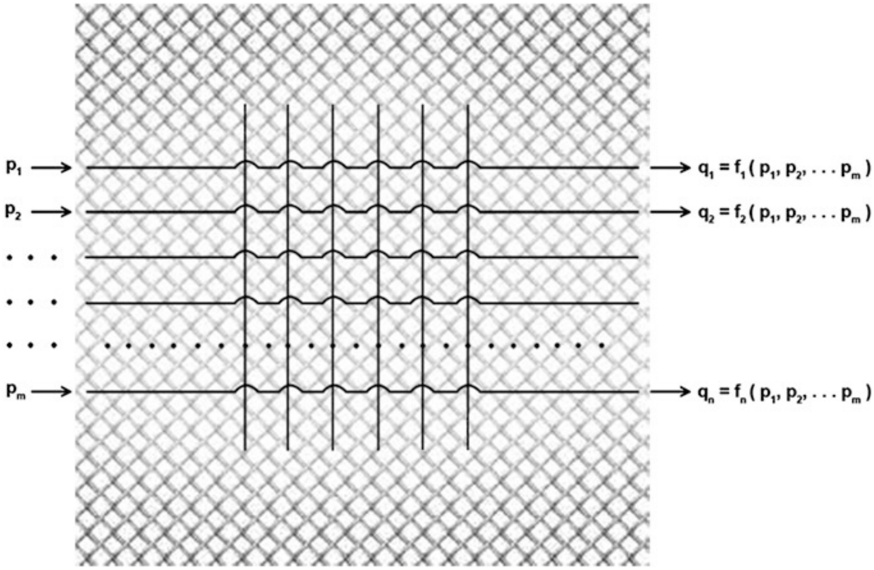


Fig. 19 Probability computer: the input values are probabilities of events. The integration of many probability streams makes possible dynamic modeling

view of it) would be the answer to, "How often?" (Clearly, frequency, underlying probability, and the conceivable, as the expression of possibility, are not interdependent) (Fig. 20).

One particular form of anticipative evaluation can be computing *perceptions* (Zadeh [61]). Anticipation from a psychological viewpoint is the result of processing perceptions, most of the time not in a sequential, but in a configurational manner (in parallel). For instance, facial expression is, as we suggested, an expression of anticipation (like/dislike, etc. expressed autonomously) based on perception. Soundscapes are yet another example (often of interest to virtual reality applications).

2.4.3 Integrated Computing Environment

In the area of mobile computation, the meeting of many computational processes, some digital, some analog (more precisely, some manner of signal processing), is the most significant aspect. Signal processing, neural network computation, telemetry, and algorithmic computation are seamlessly integrated. The aspect pertinent to anticipation is specifically this integration, including integration of the human as a part of the interactive process.

In this sense we need to distinguish between actions initiated purposely by the person (let's say, taking a photo or capturing a video sequence) and actions triggered automatically by the behavior of the person carrying the device (sensing of

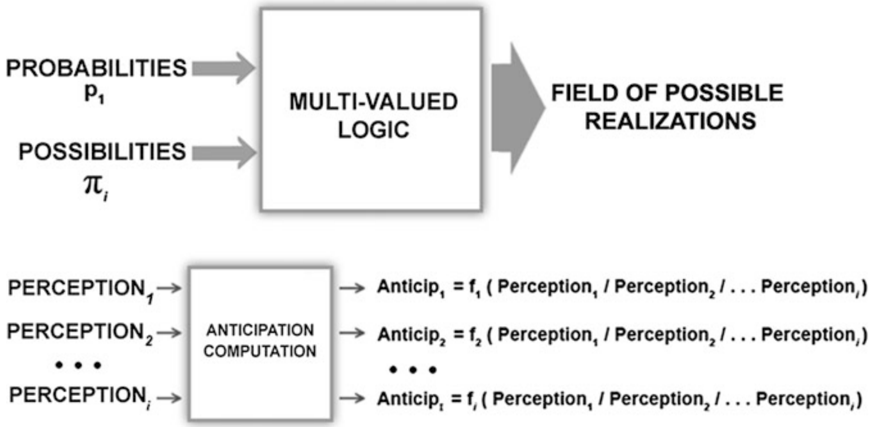


Fig. 20 Computing with probabilities and possibilities, computing with perceptions

emotional state, evaluating proximity, issuing orientation cues pertinent to navigation). It is not only the "*a-machine*" on board (the computer integrated in the "smartphone"), but the mobile sensing connected to various forms of machine learning based on neuronal networks and the richness of interactions facilitated, which make up more than an algorithmic machine. The execution of mobile applications using cloud resources qualifies this as an encompassing information processing environment. Taken independently, what is made available is a ubiquitous calculation environment. The various sensors and the data they generate are of little, if any, significance to anticipation. If they could afford a holistic description, that would be conducive to anticipation (Nadin [62]). In this ever-expanding calculation environment, we encounter context sensing, which neither the desktop machine nor any other computer provides, or considers relevant for their performance. Motion tracking, object recognition, interpretation of data, and the attempt to extract meaning—all part of the calculation environment—are conducive to a variety of inferences. What emerge are characteristics reminiscent of cognitive processes traditionally associated with thinking. This is an embodied interactive medium, not a black box for calculations transcending the immediate. The model of the future, still rudimentarily limited to predictable events, reflects an "awareness" of location, of weather, of some environmental conditions, of a person's posture or position. A pragmatic dimension can be associated with the interpreted *c*- and *o*- machines: "What does the user want to do?"—find a theater, take a train, reserve a ticket, dictate a text, initiate a video conference, etc. Inferring usage (not far from guessing the user's intentions) might still be rudimentary. Associated with learning and distribution of data over the cloud, inference allows for better guessing, forecast, prediction, and becomes a component of the *sui generis* continuous planning process. The interconnectedness between the human and the device is extended to the interconnectedness over the network, i.e., cloud.

These are Internet devices that share data, knowledge, experiences. In traffic, for instance, this sharing results in collision avoidance.

From a technological perspective, what counts in this environment is the goal of reaching close-to-real-time requirements. For this, a number of methods are used: sampling (instead of reaching a holistic view, focus on what might be more important in the context), load-shedding (do less without compromising performance), sketching, aggregation, and the like. A new category of algorithms, dedicated to producing approximations and choosing granularity based on significance, is developed for facilitating the highest interaction at the lowest cost (in terms of computation).

It is quite possible that newer generations of such integrated devices will avoid the centralized model in favor of a distributed block chain process. Once issues of trust (of extreme interest in a context of vulnerability) are redefined among those who make up a network of reciprocal interest, anticipation and resilience will bind. The main reason to expend effort in dealing with a few aspects of this new level of computation is that it embodies the possibility of anticipatory computing. This is not to say that it is the only way to achieve anticipation performance.

In the evolution from portable wireless phones to what today is called a "smartphone," these interactive mobile computing devices "learned" how to distinguish commuting, resting, driving, jogging, or sleeping, and even how to differentiate between the enthusiasm of scoring in a game and the angry reaction (game-related or not). A short list (incomplete, alas!) for suggesting the level of technological performance will help in further seeing how integration of capabilities scales to levels comparable to those of anticipatory performance. From GPS connection (and thus access to various dynamic knowledge bases), to sensors (accelerometers, gyroscope, etc.), communication protocols (facilitating WiFi, Bluetooth, near-field communication), everything is in place to locate the user, the device, the interconnected subjects, the actions meaningful within the context. Multi-core processors, large memories (not the infinite Turing machine tape, but by extension to the cloud close to it), and high performance input and output devices (cameras, microphones, touch screen, temperature sensitive surfaces) work in concert in order to support the generation of a user profile that captures stable as well as changing aspects (identity and dynamic profile). Models connect raw sensed data in order to interface (the ambient interface) the subject in the world and the mobile station. Information harvested by a variety of sensors (multimodal level of sensing) is subject to disambiguitization. It is exactly in respect to this procedure of reducing ambiguity that the mobile device distinguishes between the motorics of running, walking, climbing stairs, or doing something else (still within a limited scope). Example: The attempts to deploy physical therapy based on the mobile device rely on this level. The habit component compounds "historical" data—useful when the power supply has to be protected from exhaustion. Actions performed on a routine basis do not have to be re-computed. Other such strategies are used in the use of the GPS facility (path tracking, but only as the device moves, i.e., the user is on a bike, on a car, train, etc.). Over all, the focus is on the minima (approximate representations). Instead of geo-location proper, infer location from data (as in the person's calendar: restaurant, doctor, meeting, etc.). In some ways, the mobile device becomes an extension of the perception dimension of the living.

Although there is nothing that this kind of aggregated computation has in common with quantum computation, the focus on minima is relevant. As we have seen, there is no need for excessive precision in the performance of most of the mobiles. (This is why sampling, load-shedding, aggregations, etc. are used.) Nevertheless, the user taking advantage of the on-the-fly translation of a phone/video conversation easily makes up the missing details (where sketching is important), or corrects the sentence. Images are also subject to such corrections. The metaphors of quantum computation, in particular the non-locality aspect, quite appropriately describe interactive processes, which no close algorithmic computation could perform. It is at this level where the once-upon-a-time classic texts of Bennett [63, 64], Bennett and Landauer [65], and others make evident the limits of an understanding of computation within the Turing machine model embodied in physical devices. Truth be told, no one has come up with a reassessment of the new context for open forms of computation.

I am inclined to doubt a statement such as "A computation, whether it is performed by electronic machinery, on an abacus, or in a biological systems such as the brain, is a physical process" [65, p. 58]. My position is that meaning is more important in the living than the outcome of any calculation is (should any take place). If there is computation within the living, chances are that it takes place differently from that on the abacus or in silicon. Moreover, I have doubts that the question "How much energy must be expended to perform a particular computation?" is very meaningful in respect to interactive computations. In an information processing environment, energy is not only that of the battery powering the device, but also of the interactions. Interactions in the living, as Niels Bohr suggested, continuously change the system. The neat distinctions of physics (often applied to living processes despite the fact that they are only partially relevant when it comes to life) are simply inadequate. Anticipation expressed in action has a specific energy condition corresponding to the fact that entropy decreases as a result of activity (Elsasser [58]).

Shannon's data transmission theory (improperly called "information theory") describes the cumulative effect of noise upon data. If a word or an image is transmitted over a channel, its initial order is subject to change, that is, it loses its integrity; or, in Shannon's view, its entropy increases. The Second Law of Thermodynamics (Bolzmann) contains a formalism (i.e., a mathematical description) similar to that of Shannon's law. But having the same description does not make the two the same, neither does it establish a causal relation. If we consider the genetic code, we'd better acknowledge that genetic messages do not deteriorate. The Laws of Thermodynamics apply, but not Shannon's law of data transmission. Information stability in processes of heredity, as Elsasser points out, makes the notion of information generation within the living necessary. This generated information guides predictive, as well as anticipatory, action.

2.4.4 No Awareness of the Future

Together with the statement that computation can be performed in any physical system comes the understanding that computers are, in the final analysis, subject to the laws of physics. This applies to energy aspects—how much energy it takes to perform a computation—as well as to computer dynamics. Stepney [66, p. 674] delivers a description of how machines "iteratively compute from the inputs to determine the outputs." Newton's physics and Lagrange's mathematics of the "principle of least action" are invoked and the outcome of the analysis is relatively straightforward: imperative languages (in Watt's sense [67], i.e., "based on commands that update variables held in storage") support Newton-based computations; logic languages (implementing relations) are Lagrangian. As such, the distinction does not really lead to significant knowledge from which computer science could benefit. But there is in the argument one aspect of relevance to anticipation: the time aspect. The underlying physical embodiment is, of course, described through physical laws. This applies to conventional computation as well as to quantum computation. To achieve even stationary condition, the computer would require awareness of the future (at least in terms of recognizing the end of execution time, if not the halting problem). Of course, no program is atemporal. For that matter, algorithms also introduce a time sequence (obviously different from that of programs).

When Turing modeled a calculation with pencil on paper on his abstract machine, his intention could not have been to ascertain a reductionist view. Rather, he focused on what it would take to transfer a limited human form of calculation—based on algorithms—to a machine. But outside that limited form remains a very large space of possibilities. Analog computation corresponds to another subset of calculations, with *ad hoc* rules reflecting a different heuristics. Neural networks, cellular automata, microfluidic processors, "wet computing," optical computing, etc. cover other aspects, and sometimes suggest calculations that might take place in the living (membrane computing, for instance) without being subject to self-control, or even being reflected in one's awareness. For all we know, neural networks dynamics, partially reflected in neural network computation, might even explain awareness and consciousness, but are not subject to introspective inquiry.

With all this in mind, we can, again making reference to our understanding of the difference between expectation, prediction, forecasting, etc., address the relation between computation in a physical substratum and that in a living substratum. A computer can predict its own outcome, or it can even forecast it. Everything driven by probability, i.e., generalizing from the past to the future, is physically computable. A physical machine can predict the functioning of another machine; it can simulate it, too. As a physical entity, such a machine is subject to the laws of physics (descriptions of how things change over time). A machine cannot anticipate the outcome of its functioning. If it could, it would choose the future state according to a dynamics characteristic of the living (evolution), not to that of physical phenomena (the *minima* principle). A machine, as opposed to a living medium of calculations, is infinitely reducible to its parts (the structure of matter down to its finest details, some of which are not yet fully described). Nothing living is reducible to parts without giving up exactly the definitory characteristic: self-dynamics. Each part of a living entity is of a complexity similar to that of the entity from which it was reduced. Within the living, there is no identity as we know it from physics. All electrons are the same, but no two cells are the same.

The Law of Non-Identity: The living is free of identity.

The living describes the world and itself in awareness of the act of describing. The living continuously remakes itself.

2.4.5 The Mobile Paradigm and Anticipatory Computing

But let's continue with more details of the mobile paradigm and the latter's relevance to anticipatory computing. The first aspect to consider is the integration of a variety of sensors from which data supporting rich interactions originate (Fig. 21).

Distinct levels of processing are dedicated to logical inferences (while driving, one is far from the desktop; or, while jogging, is not in the office, unless walking on a treadmill) with the purpose of minimizing processing. Technical details—the physics, so to say—are important, although for our concerns the embodied nature of interaction between user and device are much more relevant. Anticipation is expressed in action pertinent to change (adapt or avoid are specific actions that everyone is aware of). It seems trivial that under stress anticipation is affected. It is less trivial to detect the degree and the level of stress from motoric expression (abrupt moves, for instance) or from speech data. Still, a utility, such as StressSense, delivers useful information, which is further associated with blood pressure, heart rhythm, possibly EMG, and what results can assist the individual in mitigating danger. The spelling of specific procedures—such as the Gaussian Mixture Models (GMM) for distinguishing between stressed and neutral pitch—is probably of interest to those technically versed, but less so for the idea we discuss.

El Kalioubi (whose work was mentioned previously) developed a similar facility for reading facial expression. In doing so, she facilitates the anticipatory dimension of emotions to a degree that this facility makes available information on attention—the most coveted currency in the world of computer-supported interactions. During a conversation we had (at SIGGRAPH 2010, Boston, when she was just starting her activity at MIT), she realized that MindReader—her program at the time—was merely making predictions under the guidance of a Bayesian model of probability

Fig. 21 Sensor integration with the purpose of facilitating rich interactions

inferences. Since that time, at Affidex, her focus is more and more on associating emotional states and future choices. It is easy to see her system integrated in mobile devices. Important is the realization that the description of physical processes (cause-and-effect sequence), and of the living process, with its anticipatory characteristics, fuse into one effective model. This is a dynamic model, subject to further change as learning takes place and adaptive features come into play.

In the physical realm, data determines the process (Landauer [68]). For instance, in machine learning, the structure of classifiers—simple, layered, complicated—is partially relevant. What counts is the training data, because once it is identified as information pertinent to a certain action, it will guide the performance. However, the curse of dimensionality does not spare mobile computing. Data sets scale exponentially with the expectation of more features. Many models excel in the number of features exactly because their designers never understood that the living, as opposed to the physical, is rather represented by sparse, not big, data. This is the result of the fact that living processes are holistic (Chaitin [69]).

At this time in the evolution of computation, the focus is changing from data processing to proving the thesis that all behavior, of physical entities and of organisms (the living) is either the outcome of calculations or can be described through calculations. This is no longer the age of human computers or of computers calculating the position of stars, or helping the military to hit targets with their missiles. Routine computation (ledger, databases, and the like) is complemented by intelligent control procedures. Self-driving cars or boats or airplanes come after the smart rockets (and everything else that the military commissioned to scientists). It is easy to imagine that the deep-Q network will soon give place to even higher performing means and methods that outperform not only the algorithms of games, but also of the spectacular intelligent weapons.

The Law of Outperforming Algorithms: For each algorithm, there is an alternative that will outperform it.

All it takes is more data, higher computer performance, and improved methods for extracting knowledge from data.

Thesis 3: Anticipatory computation implies the realization of necessary data (the *minima* principle).

Working only on necessary data (and no more) gives anticipatory computation an edge. It does not depend on technology (e.g., more memory, faster cycles) as does algorithmic computation.

Corollary: Predictive computation, as a hybrid of algorithmic and anticipatory computation, entails the integration of computation and learning.

Human level control is achieved not by outperforming humans playing algorithmic games, but by competing with humans in conceiving games driven by anticipation. Human-like understanding of questions in natural language is relevant to language at a certain moment in time (synchronic perspective) but lacks language dynamics (diachronic perspective).

2.4.6 Community Similarity Networks: How Does the Block Chain Model Scale up?

Without the intention of exhausting the subject, I will discuss a few issues pertinent to directions that pertain to the anticipation potential of interactive mobile devices. The tendency is to scale from individuals to communities. Autonomous Decentralized Peer-to-Peer Telemetry (the ADEPT concept that IBM devised in partnership with Samsung) integrates proof-of-work (related to functioning) and proof-of-stake (related to reciprocal trust) in order to secure transactions. At this level, mobile computation (the smartphone in its many possible embodiments) becomes part of the ecology of billions of devices, some endowed with processing capabilities, others destined to help in the acquisition of significant data. Each device—phone, objects in the world, individuals, animals, etc.—can autonomously maintain itself. Devices signal operational problems to each other and retrieve software updates as these become available, or order some as needed. There is also a barter level for data (each party might want to know ahead of time "What's behind the wall?"), or for energy ("Can I use some of your power?"). There is no central authority; therefore one of the major vulnerabilities of digital networks supporting algorithmic computation is eliminated. Contracts are issued as necessary: deliver supplies (e.g., for house cleaning, or for a 3D print job). The smartphone can automatically post the bid ("Who has the better price?"), but so could any other device on the Internet-of-Everything. Peer-to-Peer in this universe allows for establishment of dynamic communities: they come into existence as necessary and cease to be when their reason for being no longer exists.

So-called community similarity networks (CSN) associate users—individuals or anything else—who share in similar behavior. A large user base (such as the Turing *o-machine* would suggest) constitutes over time an ecosystem of devices. Fitbit™ (a digital armband) already generates data associated with physical activities (e.g., exercise, rest, diet). A variety of similar contraptions (a chip in the shoe, a heart monitor, hearing- or seeing-aid devices) also generates data. The Apple Watch™, or any other integrating artifact, scales way further, as a health monitoring station. To quote a very descriptive idea from one of the scholars I invited to the upcoming conference on Anticipation and Medicine (Delmenhorst, Germany, September 2015):

> Real time physiological monitoring with reliable, long-term memory storage, via sophisticated "physiodiagnostics" devices could result in a future where diseases are diagnosed and treated before they even present detectable symptoms (McVittie and Katz [70]).

The sentence could be rewritten to apply to economic processes and transactions, to political life, to art, to education. The emphasis is on before, characterizing anticipation. Of course, understanding language would be a prerequisite. (As already mentioned, the AI group at Facebook [6] is trying to achieve exactly this goal.)

On this note I would argue with Pejovic and Musolesi [71] that neither MindMeld™ (enhancing online video conferencing), nor GoogleNow™, or

Microsoft's Cortana™ (providing functionality without the user asking for it) justifies qualifier anticipatory. Nevertheless, I am pretty encouraged by their project (anticipatory mobile dBCI, i.e., behavior change interventions), not because my dialog with them is reflected in the concept, but rather because they address current needs from an anticipatory perspective. Indeed, behavior change, informed by a "smart" device, is action, and anticipation is always expressed in action.

Just as a simple example: few realize that posture (affecting health in many ways) depends a lot on respiration. Upon inspiration (breathing in), the torso is deflected backward, and the pelvis forward. It is the other way around during expiration (breathing out). Anticipation is at work in maintaining proper posture as an integrative process. Behavior change interventions could become effective if this understanding is shared with the individual assisted by integrated mobile device facilities—not another app (there are too many already), but rather a dialog facility.

I would hope that similar projects could be started for the domains mentioned above (economy, social and political life, education, art, etc.). Indeed, instead of reactive algorithmic remedies to crises (stock market crash, bursting of economic bubbles, inadequate educational policies, ill-advised social policies, etc.), we could test anticipatory ideas embodied in new forms of computation, such as those described so far. The progress in predictive computation (confusingly branded as anticipatory) is a promising start.

2.4.7 Robots Embody Predictive Computation (and Even Anticipatory Features)

Anticipatory computation conjures the realm of science fiction. However, neither prediction nor anticipation invites prescience or psychic understandings. The premise of predictive or anticipatory performance is the perception of reality. Data about it, acquired through sensors, as well as generated within the subject, drive the predictive effort or inform anticipatory action couched in complexity. Specifically: complexity corresponds to variety and intensity of forms of interaction, not to material or structural characteristics of the system. The interaction of the mono-cell (the simplest form of the living) with the environment by far exceeds that of any kind of machine. This interactive potential explains the characteristics of the living.

Spectacular progress in the field of robotics comes close to what we can imagine when approaching the issue of anticipatory computation. If the origin of a word has any practical significance to our understanding of how it is used, then *robot* tells the story of *machines supposed to work* (*robota* is the Russian word that inspired the Czech Karel Čapek to coin the term). Therefore, like the human being, they ought to have predictive capabilities: when you hit a nail with a hammer, your arm seems to know what will happen. From the many subjects of robotics, only predictive and anticipatory aspects, as they relate to computation, will interest us here.

The predictive abilities of robots pose major computational challenges. In the living, the world, in its incessant change, appears as relatively stable. For the robot to adapt to a changing world, it needs a dynamic refresh of the environment in which it operates. Motor control relies on rich sensor feedback and feed-forward processes. Guiding a robot (towards a target) is not trivial, given the fact of ambiguity: How far is the target? How fast is it moving? In which direction? What is relevant data and what is noise? Extremely varied sensory feedback—as a requirement similar to that of the living—is a prerequisite, but not a sufficient, condition. The living does not passively receive data; it also contributes predictive assessments—feed forward—ahead of sensor feedback. This is why robot designers provide a forward model together with feedback. The forward (prediction of how the robot moves) and inverse (how to achieve the desired speed) kinematics are connected to path planning. The uncertainty of the real world has to be addressed predictively: advancing on a flat surface is different from moving while avoiding obstacles (Fig. 22).

Intelligent decisions require data from the environment also. Therefore, sensors of all kinds are deployed (to adaptively control the movement but also to make choices). To make sense of the data, the need for sensor fusion becomes critical. The multitude of sensory channels and the variety of data formats suggested the need for effective fusion procedures. As was pointed out (Makin, Holmes & Ehrsson [72], Nadin [73]), the position of arms, legs, fingers, etc. corresponds to sensory information from skin, joints, muscles, tendons, eyes, ears, nostrils, tongue. Redundancy, which in other fields is considered a shortcoming (costly in terms of performance) helps eliminate errors due to inconsistencies or to sensor data loss,

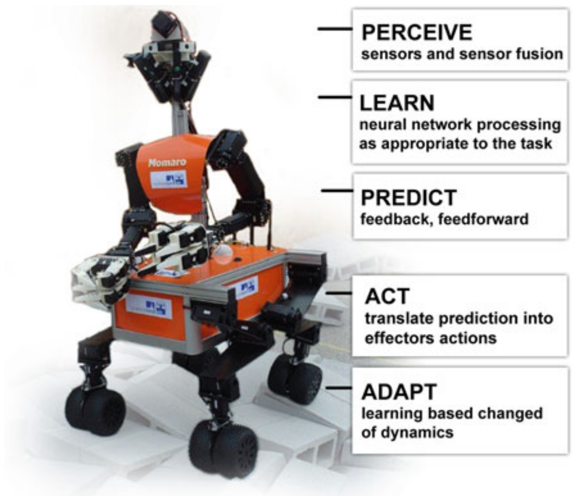


Fig. 22 Interaction is the main characteristic of robots. The robot displayed serves only as an illustration. It is a mobile manipulation robot, Momaro, designed to meet the requirements of the DARPA Robotics Challenge. It consists of an anthropomorphic upper body on a flexible hybrid mobile base. It was an entry from the Bonn University team NimbRo Rescue, qualified to participate in the DARPA Robotics Challenge taking place from June 5–6, 2015 at Fairplex, in Pomona, California

and to compensation of variances. The technology embodied in neuro-robots endowed with predictive and partial anticipatory properties (e.g., "Don't perform an action if the outcome will be harmful") integrates recurrent neural networks (RNN), multilayered networks, Kalman filters (for sensor fusion), and, most recently, deep learning architectures for distinguishing among images, sounds, etc., and for context awareness (Schilling and Cruse [74]). Robots require awareness of their state and of the surroundings in order to behave in a predictive manner. (The same holds for wearable computers.) Of course, robots can be integrated in the computational ecology of networks and thus made part of the Internet-of-Everything (IoE).

2.5 Computation as Utility

Based on the foundations of anticipatory systems, the following are necessary, but not sufficient, conditions for anticipatory computation.

- Self-organization (variable configurations)
- Multiplicity of outcome
- Learning: performance depends on the historic record
- Abductive logic
- Internal states that can affect themselves through recursive loops
- Generation of information corresponding to history, context, goal
- Operation in the non-deterministic realm
- Open-endedness

In practical terms, anticipatory computing would have to be embodied (in effective agents, robots, artifacts, etc.) in order to be expressed in action. A possible configuration would have to integrate adaptive properties, an efficient expression of experience, and, most important, unlimited interaction modalities (integrating language, image, sound, and all possible means of representations of somato-sensory relevance) (Fig. 23).

In view of newly acquired awareness of decentralized interaction structures—i.e., pragmatic dimensions of computation—it can be expected that computation as a utility, not as an application (the ever-expanding domain of apps is rather telling of their limitations), would be part of the complex process of forming, expressing, and acting in anticipation. Achieving an adaptive open system is most important. Outperforming humans in playing closed-system games is not a performance to be scorned. But it is only a first step. The same can be said of conceiving and implementing a so-called "intelligent dialog agent" as a prerequisite for understanding natural language. It is not the language that is alive, but those who constitute themselves in language (Nadin [41]). Memory Networks might deliver within a closed discourse universe, but not in an open pragmatic context. Understanding what anticipation is could spare us wasted energy and talent, as well as the embarrassment of claims that are more indicative of advancing deeper into a

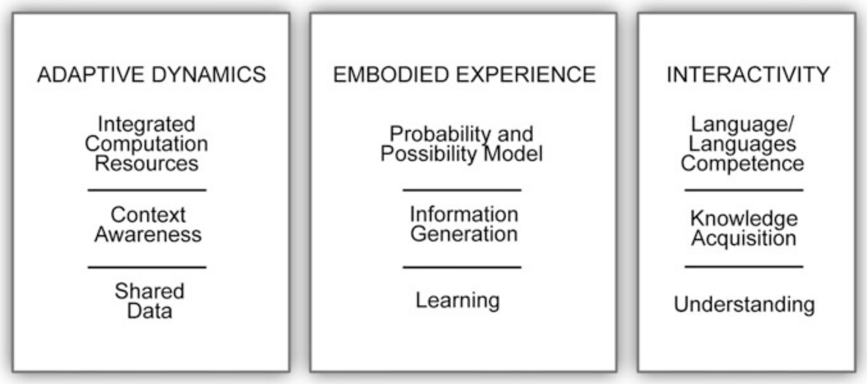


Fig. 23 Adaptive dynamics, embodied experience, and rich interactivity are premises for anticipatory performance

one-way street of false assumptions. Instead, we could make real progress in understanding where the journey should take us.

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MindMeld™ is a trademark of Expert Labs
Fitbit™ is a trademark of Fitbit, Inc.
AppleWatch™ is a trademark of Apple, Inc.

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Part V
Anticipation, Culture, and Society

On the Role of Anticipation in Teaching

Lea Valentine Lavrik and Meir Vladimir Shunyakov

Abstract Successful learning is much dependent on memory and attention concentration processes. In this paper we introduce a method allowing to maintain high levels of learners' attention based on anticipation. Practically, it is difficult to reach high levels of concentration. However, using the selective approach it is possible: when new material is covered, each student experiences attention climax at the most relevant moments and attention decay when irrelevant material is being explained. This approach was called "selective mobilization" of attention and has been successfully used in physics lessons in two colleges in Jerusalem and in the Hebrew University junior high school. The method induces strong emotional response and elevated motivation and activity levels in students. Moreover, anticipation has significant influence on memory processes, which has been demonstrated in our experiments.

Keywords Activity level · Anticipation · Intuitive knowledge · Probabilistic prognosis · Selective mobilization of attention

1 Introduction

Anticipation is an inherent property of living systems. It manifests itself at various levels, from simple organisms to complex social groups. The study of anticipation is a multifaceted interdisciplinary problem.

he problems associated with the concept of anticipation are studied independently in several fields: the physiology of activity [1], the study of neural networks [2],

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the construction of mathematical models of anticipation [3], the cybernetic aspects of anticipation [4, 5], artistic manifestations of anticipation [6], politics, and education.

Our work is dedicated to the application of the concept of anticipation in science teaching. Since our anticipations are not 100 % successful, but only with a certain probability, we call the anticipation-producing mechanism "probabilistic prognosis" [7]. In this paper, we often use the term of "probabilistic prognosis" instead of "anticipation", referring to this understanding.

High technologies development causes changes in requirements applied to future specialists in all areas, be it medicine, economy, transport, construction, art, or education. These requirements include the lifelong need to acquire new knowledge and the ability to make non-standard decisions in unpredictable situations [8].

The traditional educational system has been developing for ages and has attained undeniable achievements, however, it is unable to meet current fast-changing goals. How should professional training of teaching methods change without damaging the valuable accomplishments of traditional educational practice?

Note that improving the system and the teaching quality should not be limited to making changes in study programs, such as adding new material, eliminating some traditional questions, etc., as it is often assumed. In our opinion, it is most essential to change the role of students in the learning process: from passive learners to active creators of their own knowledge dedicated to an existing goal [9]. With this approach, students not only acquire new knowledge, but also become more involved, more motivated, more self-critical, independently controlling and correcting their own learning process.

The purpose of this paper is to find ways to boost motivation and encourage the active role of the learner in the study process, based on consideration and effective utilization of anticipation. On the basis of research results, we have developed a teaching method that emphasizes the important role of anticipation in education and allows creating a specific method for boosting emotional and goal-oriented involvement of the learners. The current paper describes the application of the above method of selective mobilization of attention in science education on the example of physics and mathematics.

2 Selective Mobilization of Attention Method Principles

Selective mobilization of attention method principles lies at the intersection of various psychological and educational approaches. One of them was initially developed by Piaget [10] and Vygotsky [11]. The second approach is connected to the concept of anticipation and prognosis developed by Bernstein [12, 13], Rosen [3], Nadin [5, 14], Feigenberg [15, 16], and other researchers.

Piaget and Vygotsky studied the process of scientific concepts formation and its interaction with everyday concepts. Throughout the last half-century, significant progress has been made in the understanding of the learning process as a process of concept formation and change, based on the ideas of constructivism [17, 18].

One of the important discoveries was that emotional influence on this process can enhance learning [19].

Although understanding memory as passive information storage mechanism is outdated and people deny having such point of view, it is sometimes used implicitly. Phrases like "I explained this so many times, how come they still don't remember it!" or "How can you forget such simple things? I explained them on the previous lesson!" are common.

Such an understanding of memory pops up in everyday instruction routine, which implies covering a huge amount of information within a short period of time, and in study books and learning programs. Sometimes teachers presume that student memory is like a video camera and demand exact reproduction of their words.

According to Bernstein [12], throughout evolution, our memory has acquired the ability to create a model of a future situation, "image of the required future".

The main source of the model of the future situation is based on past experience: which probabilistic structure is stored in memory. It allows one to adjust to approaching events and plan his/her actions, which provides an essential advantage in critical life situations. In the works of Feigenberg, this memory mechanism was named *probabilistic prognosis.* The concept is being constantly developed by his followers [15, 16].

3 Interaction Between Everyday Intuitive and Analytical Scientific Concept

One of the approaches we use in our work is related to cognitive psychology. A student who starts learning a subject, such as sciences, already holds a developed system of intuitive understanding of the surrounding world. This conceptual system has different names in academic bibliography, such as: heuristics or previous knowledge, intuitive naive knowledge, mental models, alternative conceptions, common-sense patterns of reasoning [18–22].

This system is based on the person's participation in particular situations and his/her life experience. Sometimes the system of intuitive knowledge, basis of human common sense, conflicts with scientific concepts that constitute the logical foundation of scientific knowledge.

Let us analyze two related examples. Learners imagine the familiar concept of "shadow" of an object as a silhouette on a flat surface, whose contour depends on the relative disposition of the object and the light source. However, from the point of view of physics, shadow is a part of a three-dimensional space where light penetration is difficult since the object is opaque, and therefore it either reflects or absorbs the light that falls on it. In this respect the concept of "night" is nothing but a shadow formed by the Earth when the Sun is the light source. Clearly, the naïve understanding of "night" associates with specific emotions which are very far from the scientific concept.

In this context it becomes clear that as long as students' actual knowledge level tests remain an inseparable part of the standard educational system, students can find themselves in a very complicated situation. Correct, but impersonal knowledge may constitute a concept system formed by logical connections, however detached from the students' everyday experience.

The students face the dilemma of whether to learn the required "right concepts" for a test (and get high grades) or to reply using their inner "common sense" (and likely get lower grades!). Common are situations when both knowledge systems coexist: one is used to answer the teacher's questions and the other one in everyday life.

Vygotsky demonstrated the development of the above systems necessary for the learning process as movement of objects directed towards each other: abstract scientific concepts should be enriched with specific material from the new experience at the time of learning, while intuitive concepts should be analytically reconsidered, generalized and raised to the level of abstract scientific concepts [11]. Clearly, this complicated and continuous process demands active participation of both the students and the teacher.

Therefore, the teaching approach, which ignores personal experience of the learners and is not able to integrate scientific and everyday concepts into a complete system adequately describing the surrounding reality, cannot be efficient.

Hence, the following questions arise: How can we initiate and control the above processes? What should we know in order to control the relevant cognitive processes? What learner's memory mechanisms are supposed to be involved in this process? By considering probabilistic prognosis and the process of everyday and scientific concepts development, we may find answers to these questions.

4 How Selective Mobilization of Attention Method Works

Is it acceptable to start a lesson with a quick test about the material which is about to be studied? It is usually considered that we cannot require a student to know anything about the material before it has been covered. We also came across an opinion that tests are to check the covered material; therefore the beginning of a lesson is a good time to give a test on the material from the previous lesson.

However, this unusual lesson start is justified in the following situations:

1. lesson topic is familiar to the students from their previous experience;
2. questions are multiple-choice;
3. suggested answers presented along with the correct answer represent common misconceptions of the students in the subject area (This is a significant condition).

From our experience, students don't find these questions difficult, because the situations described in the questions are familiar to them. However, if the suggested topic is so unfamiliar to the students that they don't have any prior knowledge about it, this kind of test does not make sense.

In order to create such a test, the teacher should collect information about intuitive knowledge of the students. Creative teachers can reach this information by independent observation of their own students or from literature [20, 22–24]. By conducting a quick (3–4 min-long) test at the beginning of the lesson, we allow our students to formulate their intuitive knowledge based on probabilistic prognosis, which sometimes they are not even aware of. Let us consider the example of an optical atmosphere phenomenon: appearance of a rainbow after rain on a sunny day. We suggest a test to our students at the beginning of the lesson [25, 26].

Along with the correct picture B, the answers contain the incorrect picture A, which represents a wrong intuitive image (Fig. 1).This image contains both the rainbow and the Sun (which is the light source) within the field of view.

Students are given an opportunity to express their intuitive mental models, as well as some time to discuss their answers with their neighbors and prove their point of view. All students are required to write down each other's opinions before and after the discussion (the test blank contains a special section for this purpose, see Fig. 1). Usually, students' opinions vary and they become curious about which of them is right. From our experience, the right answer given by the teacher immediately after the test causes a very strong emotional reaction (some of those

Here are two elements of the picture of a rainbow taken from the painting of a medieval artist. Which of the following pictures is correct?
Choose and mark:
A B
Discuss the options with other students and circle your answer
A B

Prove your answer:

_ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _

Which answer (given by the teacher) is right?
A B
Do you consider the teacher's answer logical or strange?

_ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _

Why?

_ _ _ _ _ _ _ _ _ _ _ _ _ _ _

What feelings did you experience when the teacher revealed the correct answer?

_ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _

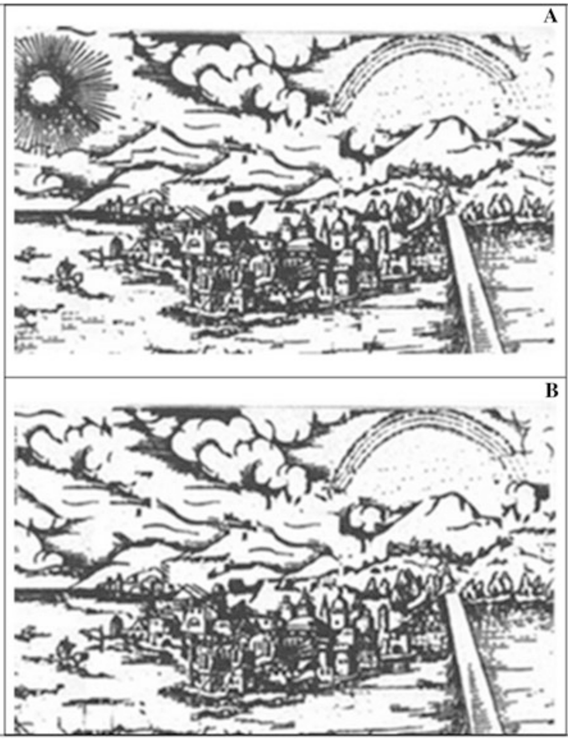

Fig. 1 Initial test according to the method of selective mobilization of attention

lessons were videotaped) [25, 27, 28]. The reaction is especially strong when there is a mismatch between the probabilistic prognosis of the student and the right answer. A student might experience disappointment and annoyance: "Why? What was my mistake? This is very strange." Students whose prognosis was correct cannot help but show their excitement: "I was right! I'm proud of myself."

We believe that this part of the lesson is a very significant step in the process of attention concentration, because starting this very moment the audience turns from a group of indifferent and passive listeners, preoccupied with their personal issues, into active and interested participants. Each of the participants has his/her own focus: those who suggested a correct prognosis are interested in comparing their explanation with the scientific one. Those who made a wrong prognosis are interested in correcting the mistake and understanding the meaning of the task. According to the studies of Nobel laureate D. Kahneman, and his colleagues, "loss aversion" is a very strong emotion, much stronger than "pleasure of gain" [29]. Thus, attention concentration of each participant is different: if the information is relevant to the student, he/she will demonstrate a high level of attention concentration, whereas if the student is satisfied with his correct prognosis, he will be at ease. Therefore, we call our method "selective mobilization of attention."

From the moment the students turn into involved listeners, the teacher starts presenting the new material. Let us consider the application of this technique to the example of a lesson about rainbow formation. During the lesson students get a detailed explanation of light beam refraction in a drop of rain, consistent with physics textbooks [30].

At the end of the lesson there is a final test based on the new material. The test gives the students a new chance to apply prognosis, but this time integrating their new knowledge. The test is based on the same principle as the first one, but adjusted to the new material, allowing the students to understand it better. According to Bernstein [1, 9], the final test represents a "repetition without repetition."

Obviously, the image used in the test allows determining Sun location, considering the shadow direction of the object placed in front of the rainbow. This way the teacher can check to what extent each student understands the geometrical basis of rainbow formation. It is interesting that this geometry aspect was first defined by René Descartes in 1637: the Sun must be situated behind the observer in a way that the sunbeams reach the eye of the observer after their refraction and dispersion.

After accomplishing the final test (which usually doesn't take more than 2–4 min), the right answer is announced. It causes a strong emotional reaction in the students, especially those who understand their past mistake. They experience happiness and self-satisfaction. When we wanted to skip the final test or postponed the announcement of the correct answers, the students demanded the test and were eager to know the correct answers. As the feedback questionnaires demonstrated, student interest was due to personal involvement in the lesson material. They found it important to check whether they understood it correctly.

To examine the effectiveness of our method, we selected four groups of students aged 13–15 years. In two of them (N = 67), we used the method of selective mobilization (experimental groups), and in the other two (control groups) (N = 52) we conducted a regular lesson. All groups studied the same material (rainbow formation). Students in all groups were asked the same questions, namely those that appeared in the initial and final tests (Figs. 1 and 2). However, for the "traditional" lesson, both tests were given after the explanation of the new material, and the correct answers were not revealed to the students. Thus, they were unable to juxtapose their probabilistic prognosis with the correct answers to the test questions.

In the groups that studied using the method of selective mobilization of attention, the amount of correct answers in the initial and in the final tests differed significantly: 42 % versus 92 %, respectively. In the control groups that were taught using the "traditional" method, the initial test result was 47 %, while the final test result was 67 %. Students showed low involvement level during the lesson and didn't express strong emotional reactions at all.

To compare the effectiveness of lessons with and without the use of selective mobilization method, we can use the ratio between the difference between the successful answers in the initial and the final tests, and the amount of wrong answers to the initial test [31]

$$g = \frac{N_f - N_i}{N_o - N_i} \quad (1)$$

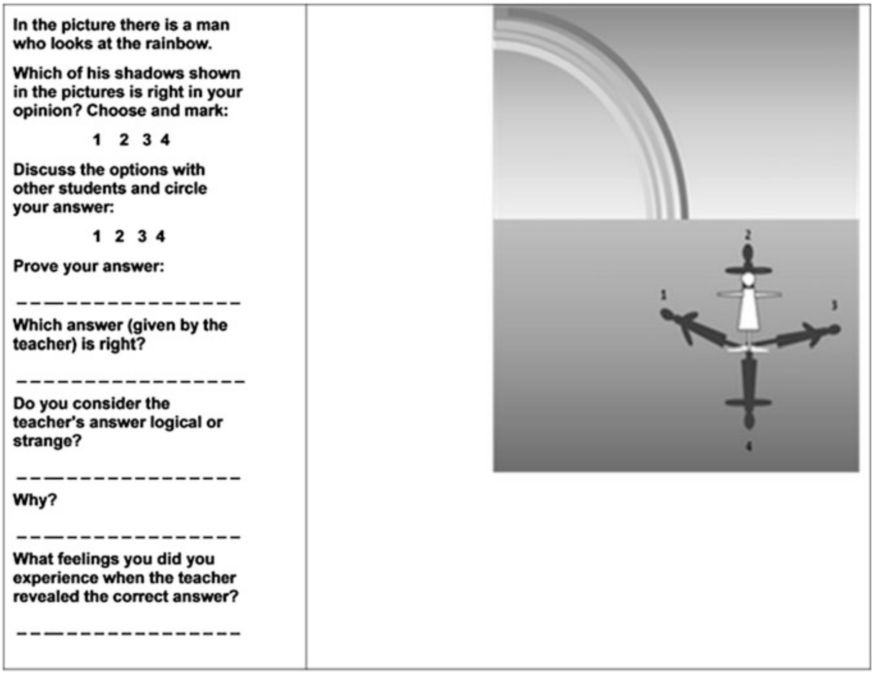

Fig. 2 Final test in the method of selective mobilization of attention

N_f and N_i here stand for the number of correct answers in the final and the initial tests, whereas N_o is the total number of answers.

Thus, for the lesson with the application of the selective mobilization method (N_o = 67), we get the following:

$$g = \frac{N_f - N_i}{N_o - N_i} = \frac{92\,\% - 43\,\%}{100\,\% - 43\,\%} = 0.86 \tag{2}$$

The same calculation for the control group (N_o = 52) results in the following:

$$g = \frac{N_f - N_i}{N_o - N_i} = \frac{67\,\% - 47\,\%}{100\,\% - 47\,\%} = 0.38, \tag{3}$$

As it turns out, the lesson with the use of selective mobilization method is twice as effective as the "traditional" lesson.

Therefore, activation of the probabilistic prognosis in the framework of the selective mobilization method allows changing the role of the students, transforming them from passive and indifferent listeners into goal-oriented, emotionally involved participants, interested in the outcomes of their studies. As a result, the effectiveness of learning increases significantly.

We used the method of selective mobilization on mathematics lessons. Let us consider an example of an initial test used on a school algebra lesson dedicated to the rules of exponentiation (Fig. 3).

Different possible answer options in this test were formulated, based on the previously revealed misconceptions of the students in the particular field of algebra.

In all the three options the answer is "1", but the calculations are different.

The right "path" to the answer is shown in option A, along with the erroneous intuitive answers B and C. Exponentiation is sometimes mistakenly interpreted by the students as multiplication of the base by the exponent, as represented in option B. Answer C is the result of an incorrect use of the rules of a negative number exponentiation given an even or odd exponent value. Therefore, if a teacher ignores the way the students think, and is only interested in the final result ("right" or

A:

$-1^{200}-(-1^{40})-(-1)^{161}=-1--1--1=-1+1+1=1$

B:

$-1^{200}-(-1^{40})-(-1)^{161}=-200+40+161=1$

C:

$-1^{200}-(-1^{40})-(-1)^{161}=-1^{200}-(+1)-(-1)^{161}=+1-(+1)+1=+1-1+1=1$

Three students received the following solutions one exercise in algebra.Which answer is correct? *Choose and mark*:
A B C
Discuss your answer with the other students and *mark* it down afterwards: **A B C**
Which answer is the right (that given by the teacher)? _ _ _ _ _ _ _ _ _ _

Fig. 3 An example of an initial test given on a lesson of algebra, dedicated to the rules of exponentiation, which allows using probabilistic prognosis “wrong”), then he/she will not notice, and accordingly, won’t be able to help them correct misconceptions B and C.

This test, used as a part of the selective mobilization method, allows students to identify their own primary misconceptions that constitute a basis for probabilistic prognosis. Thanks to this, students are at the peak of their concentration specifically in the moments of a lesson essential for the understanding and correlation of the identified misconceptions.

Similar results were shown in our application of the method in a group of college students [28].

5 Probabilistic Prognosis, Emotions and Memory

So how does the discrepancy between the probabilistic prognosis and the real incoming information influence the memorizing of that particular information? Several tests were conducted to provide an answer to the question.

One of the tests involved high school students (N = 86), to check the memorizing of pictures [27, 28], [32]. The students were shown a card with 14–19 simple and clear pictures on it for a short period of time (10–15 s). After the cards were taken away, the students had to name the pictures they remembered. There were three different versions of the pictures:

1. On the first card there were 18 pictures. 17 of them contained animal images (such as goat and goose) and the odd one was a motorcyclist.
2. On the second card there were 14 pictures: 13 sportsmen (including a motorcyclist) and on the odd one was a goat.
3. The third card had 19 pictures: 18 vegetables and 1 goose.

Thus, on every card there was an odd, “unexpected” picture, which did not match the rest of the images.

The results of the test were very impressive: the “unexpected” pictures were much better memorized than the “ordinary” ones. We can see this clearly on the following diagrams (Fig. 4).

The motorcyclist on the card with animals was memorized almost three times as often as on the card with sportsmen.

The goose on the card with vegetables was memorized almost twice more often than the goose on the card with animals.

The same result was achieved in our verbal tests with memorizing words that were read to the students: unexpected stimuli that do not match our probabilistic prognosis are memorized much better.

How can we create the incompatibility between a student’s prognosis and the important information we want him to remember?

In some cases it is useful to take some material from the history of science [24, 33, 34].

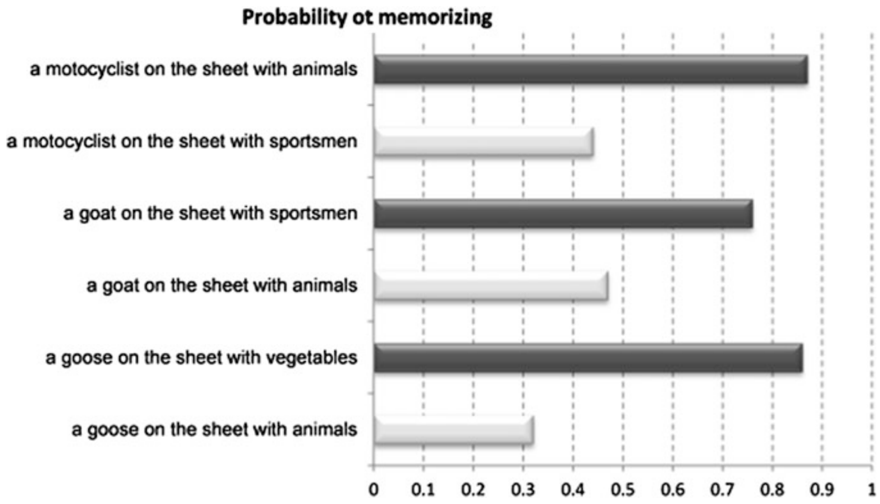

Fig. 4 Memorization of unexpected objects is more efficient

By way of example, we will describe a lesson in which the notion about the dual nature of light (the corpuscular and the wave theories) is studied. In order to make the lesson more emotional, we can structurize it like a detective story [27, 32].

At the beginning the teacher presents Newton's corpuscular theory. According to this theory, the light is a stream of particles moving with different velocity, which depends on the medium in which they are moving. This theory explains very well the rectilinear propagation of light in a homogeneous medium, the reflection of light from mirrors, the refraction of light passing from one medium to another one, where the velocity of the light propagation is different (for instance, from air to water or glass). Once the students have a clear conception about the geometrical optics, they will understand the following explanation without difficulties.

The sunlight goes through a big triangular opening in a non-transparent plate. The light spot which appears on the screen has also a triangular shape (Fig. 5a).

If the sunbeam comes through a small triangular opening, the light spot on the screen will not have a triangular shape but a round one. The shape of this spot will coincide not with the shape of the opening but with the shape of the light source (Fig. 5b).

If we make the opening small enough, we will receive the *camera obscura*. On the screen we will see the inverted image of the light source; the shape of the hole on the plate will have no influence on the shape of the light spot.

Now, the teacher asks: "What will happen if we make the hole in the plate even smaller?" The students raise their suggestions and guesses.

The teacher shows them the results of the experiment when the sunbeam passes through a very small hole (Fig. 5c). The shape of the light spot on the screen coincides neither with the shape of the opening, nor with the shape of the light source. The result does not coincide with the expectations of the students either.

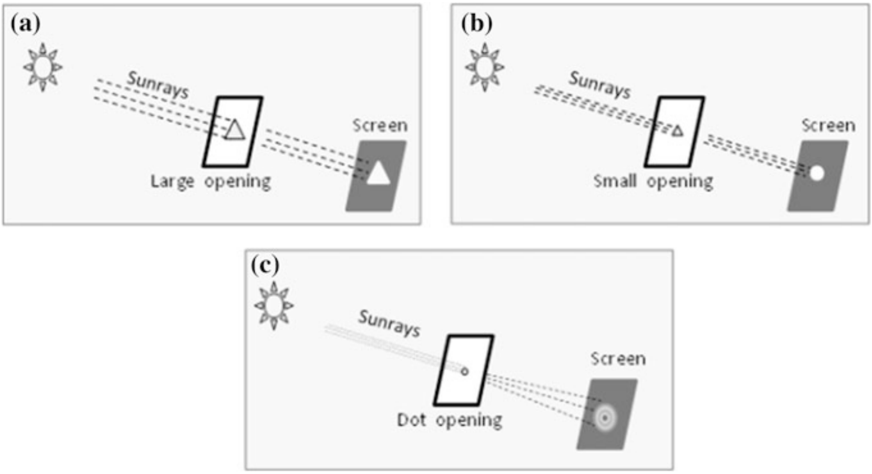

Fig. 5 Experiments with light passing through openings of variable sizes. Unexpected result in 3-d experiment raises the students' attention during explanation of the light's wave nature

Concentric circles appear on the screen, which is something completely unexpected for the students and does not fit into their former knowledge about the nature of light. What is the reason for that?

The discrepancy between the real results of the experiment and the students' prognosis acquires emotional significance; it boosts their attention and interest in the further explanations by the teacher. Using the questions, which arise in this situation, as well as the increased attention and motivation of the students, the teacher begins his explanation about the wave hypothesis of light. Thus, the rectilinear propagation of light, the reflection of light from mirrors and refraction of light acquire another interpretation; the phenomena, which could not be explained by the corpuscular theory of light (such as the interference of light), become clear.

We applied here a psychological method used in detective stories: using the discrepancy between the most probable prognosis of the reader (or listener) and the actual information he/she receives to create emotional reaction. Furthermore, we did it without distracting the students from the scientific content of the lesson but, on the contrary, on the basis of the material of the lesson.

The comparison with a detective story does not deprecate pedagogical principles. The Latin "detego" means to "open", "expose", "discover". This is exactly what we hope will happen in the student audience. Our goal is to discover, open, and expose to them the concealed nature of certain phenomena and processes, which can be revealed only through scientific research or experiment. The best idea is to let students feel that they perform an actual "discovery" of the right answer before the teacher explains it to them. Examples from the history of science used properly are a powerful tool for achieving this goal.

If, on the contrary, we give students an answer before a question even crosses their minds, it does not facilitate learning.

6 Conclusion

In literature dedicated to effective methods of physics teaching, there are examples of lesson plans requiring that students make a prognosis (for instance, before a demonstrational experiment [35]). In the article [35] it was proven that it raised the interest level in the students. We are convinced that this increase can be explained by the involvement of the probabilistic prognosis mechanism of anticipation. Experiment showed that in case there was dissonance (the demonstration itself provided the right answer), the motivation of the students increased sharply, and, consequently, the lesson was more effective.

Misconceptions, sometimes unconscious, based on personal experience allow the students to make fast decisions in cases of uncertainty [22, 32, 36].

A teacher who is familiar with the intuitive and sometimes erroneous perceptions behind students' decisions can transform passive students into active and co-involved participants. In some cases it is useful to integrate materials from the history of science into a lesson.

It is important to emphasize the significant difference of the tests we used: their role is completely diagnostic and not evaluative. We do not give marks for students' replies, which creates a trusting atmosphere in the classroom.

Probabilistic prognosis helps students identify their intuitive perceptions at the beginning of the lesson, even before the new material is explained. It changes the role of the student during the lesson. In case of dissonance between the prognosis and the right answer, students experience a strong emotional reaction and selectively mobilize their attention when the important material, specifically relevant to them, is being explained. Behavior of the students becomes goal-oriented and their desire to adjust their perceptions makes them active creators of their own knowledge. At the same time, the strong emotional reaction contributes significantly to the memorization level.

In conclusion, the probabilistic prognosis mechanism of anticipation has been used as a basis for the selective mobilization method, improving the memory of the students and raising the learning effectiveness of our physics and mathematics lessons.

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Anticipation | Computational Creativity

Bill Seaman

Abstract The paper will outline the role of anticipatory systems as part of a set of computationally driven creative processes. Here the goal is to both use the computer as a tool functioning in the service of human creative processes e.g. authoring a system to help compose generative music, as well as to begin to explore "learning" and the abstraction of creative processes in terms of autonomous computational creativity. Anticipation is here undertaken in a mindfully-aware manner, as drawn from the deep study, understanding and articulation of human creativity. Thus, this research seeks to define the driving problems in authoring autonomous generative computational systems through the pragmatic application of biomimetics and bio-abstraction, drawing in part on the study of human anticipatory systems that play an active role in creative processes.

Keywords Computation · Creativity · Computational creativity · Machinic creativity · Re-embodied intelligence

1 Introduction—Anticipatory Systems

Robert Rosen wrote one of the seminal texts on anticipation called *Anticipatory Systems*. He *anticipated* much of what this series of conferences seek to examine:

> I have organized [this volume] around the concept of anticipation, which is fundamental in its own right, and which connects naturally to a cluster of other concepts lying at the heart of natural science and of mathematics. Strictly speaking, an anticipatory system is one in which present change of state depends upon future circumstances, rather than merely on the present or past. As such, anticipation has routinely been excluded from any kind of systematic study, on the grounds that it violates the causal foundation on which all of theo-

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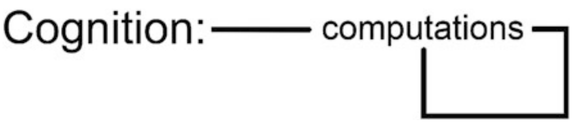
> retical science must rest, and on the grounds that it introduces a telic element which is scientifically unacceptable. Nevertheless, biology is replete with situations in which organisms can generate and maintain internal predictive models of themselves and their environments, and utilize the predictions of these models about the future for purpose of control in the present. Many of the unique properties of organisms can really be understood only if these internal models are taken into account. Thus, the concept of a system with an internal predictive model seemed to offer a way to study anticipatory systems in a scientifically rigorous way [1].

As we begin to explore the authorship of organism-like machines, though biomimetics and bioabstraction, such a book becomes central in outlining a series of specific perspectives that illuminate the concept of anticipation in terms of differing kinds of systems. The creation of computational generative art systems requires the writing of specific code informed by various biological and in particular conceptual processes. Yet, the fact that we are seeking to generate emergent systems points to a strange kind of predictive model, a model that predicts something that is intentionally not fully known—that is emergent in nature. Thus it predicts a kind of behavior or outcome of surprise and/or novelty.

When we undertake a decision making process we undertake a “mental simulation” related to potential future outcomes. In “Perception of the Future and the Future of Perception” (first given as an address in 1971 but published much later in *Observing Systems*) [2], von Foerster was also interested in thinking about ‘thinking about’ the future. As we think about a relationality between the human and the computer, in the same volume von Foerster also expressed the idea that



[2].

Rosen in *Anticipatory Systems* states: “Intuitively, we would expect the concept of a system to involve some kind of inter-relation between the percepts it generates, and which then become identified with corresponding relationships between external qualities which generated them” [3]. In Generative works of art one abstracts and computationally re-embodies qualities and relations that can potentially generate percepts in a focused manner. Rosen goes on to say “Briefly, we believe that one of the primary functions of the mind is precisely to organize percepts. That is, the mind is not merely a passive receiver of perpetual images, but rather takes an active role in processing them and ultimately in responding to them through effector mechanisms” [3]. This is where we build up a sense of aesthetics, and of the potentials for the authorship of generative processes. Here computer code functions as the “anticipated” organizing mechanism, and/or becomes operative as part of an “anticipated” interactive human/computer system. Rosen discusses “Encodings Between natural and Formal Systems” —“In authoring generative systems we seek to encode natural systems into formal ones in a way which is consistent…” Rosen [4] This is the case with generative systems, we seek to author a system that would function in a manner appropriate to that which is being modeled.

Rosen compares a natural system to a formal one:

> A natural system is essentially a bundle of linked qualities, or observables, coded or named by specific percepts which they generate, and by the relations which the mind creates to organize them. As such a natural system is always incompletely known; we continually learn about such a system, for instance by watching its effect on other systems with which it interacts, and attempting to include the observables rendered perceptible thereby into the scheme of linkages established previously. A formal system, on the other hand, is entirely a creation of the mind, possessing no properties beyond those which enter into its definition and their implications [5].

Yet, we seek in a sense to transcend Rosen's statement through the operative nature of our formal computational systems—we seek emergent phenomena that arises through combinatorics and/or artificial life processes, as well as through complex loops of processes that make percepts operative and newly relational over time. Perhaps this falls under the notion of a formal system's "implications," or perhaps we are working on systems that are different to the ones described above. We seek to make a system that can generate aspects of "novelty" out of formal elements and processes—to surprise…

2 Computational Creativity

Margaret Boden in her book *Creativity and Art—Three Roads to Surprise* defines creativity as "the ability to come up with ideas or artifacts that are new, surprising, and valuable." There are many questions related to whether computers can be creative in and of themselves. Margaret Boden in *Creativity and Art* states, in relation to the difficult questions of computational "consciousness, intentionality, and the role of 'brain-stuff' and/or embodiment":

> Since the notoriously controversial problems remain unsolved, I nowhere claim that computers are "really" creative. If and when I mention creativity in computers I am really asking what aesthetically interesting results can computers, generate and how? And just what might lead someone to suggest that a particular computer system is creative or that its functioning is somehow similar to creativity in human beings [6].

Computational Creativity has been defined by the *The Association for Computational Creativity* as "the study and simulation, by computational means, of behavior, natural and artificial, which would, if observed in humans, be deemed creative." They have held four conferences to date [7]. Seaman early on discussed the notion of *Re-embodied Intelligence* [8]. *Re-embodied intelligence* can be defined as the translation of media elements and/or processes into a symbolic language enabling those elements and processes to become part of an operative computer-mediated system. The ability to "translate" the aesthetic conceptions of an "author" into a form that is operative within a technological environment is fundamental to the creation of interactive (and other forms emphasis the author) artworks. We will consider "intelligence" as referring to activities we have in the past considered intelligent, like "playing chess say or recognizing visual images" [9].

In the creation of artworks the artist employs modes of thinking that might be considered illogical, nonsensical, intuitive, metaphorical, non-linear etc. The intelligence embodied in an individual's art practice, functions in the service of their poetics. This process of re-embodiment is entirely anticipatory. Initially one must become "mindfully aware" of the aesthetic processes. Varela, Thompson and Rosch in *The Embodied Mind* speaking about mindfulness/awareness suggest:

> Its purpose is to become mindful, to experience what one's mind is doing as it does it, to be present with one's mind. What relevance does this have to cognitive science? We believe that if cognitive science is to include human experience, it must have some method of exploring and knowing what human experience is [10].

So for the purposes of this paper, Seaman will take a Second Order Cybernetic approach, placing himself as an artist inside of the system, exploring a series of human/computer relations and potentials through introspection and a history of education in the arts informing this position. Thus, this study becomes part of a social and cultural milieu as well as ongoing experience gained through over 30 years of artistic practice [11]. In the long run, learning systems may also become enculturated. Seaman posits that there is an interesting change going on where simulation (discussed above in the definition of Computational Creativity) and actuality, pivot and shift. At a certain point one is not simulating an image—one is generating a computer-based image that is of-itself. As we move toward the exploration of intelligent systems, especially in terms of robotics and autonomous learning systems, we can anticipate systems with real-world functionality that are no longer just simulations. This conflates the definition of natural and formal systems as discussed by Rosen above, especially when the system is emergent in nature.

It must be noted that Ada Lovelace at the very beginning of computer programming in 1842, in her *Notes to the Analytical Engine* discussed the potentials of exploring different kinds of relational elements. In her Notes by The Translator written to clarify the textual work entitled Sketch Of the Analytical Engine Invented by Charles Babbage by L. F. Menabrea, Lovelace made some very relevant remarks:

> The Analytical Engine is an embodying of the science of operations, constructed with particular reference to abstract number as the subject of those operations… Again, it [The Analytical Engine, emphasis Seaman] might act upon other things beside number were objects found whose mutual fundamental relations could be expressed by those of the abstract science of operations and which should be also susceptible of adaptions to the action of the operating notation and mechanism of the engine. Supposing for instance, that the fundamental relations of pitched sounds in the science of harmony and of musical composition were susceptible of such expressions and adaptions, the engine might compose elaborate and scientific pieces of music of any degree of complexity or extent… It may be desirable to explain, that by the word operation, we mean any process which alters the relation of two or more things, be this relation of what kind it may. This is the most general definition and would include all subjects in the universe [12].

As a programmer/artist, in order to author such a system, each operative relational element can potentially be "anticipated" in the authorship of coding. Lovelace articulates the 'universal' nature of this approach pointing to the computer as an open system. Yet, the relationality of media-elements and processes brought about through exploration within such systems can be emergent in nature. In specific situations, where the system exhibits a particular level of complexity, paradoxically one can anticipate aspects of aesthetic emergence as an arising state of the system.

The creation of generative artworks can take a series of different forms. Seaman and John Supko are co-leaders of the *The Emergence Lab* in Duke University's new program in Media Arts + Sciences. Last spring they taught a class in *Generative Arts* exploring approaches to image, sound/music and text. Seaman has a long history of creating artworks that are emergent in nature. Anticipatory systems are used in a number of different ways in the creation of these works. In terms of anticipation, every different potential artistic variable as well as the processes that might be called up to operate on those variables, can potentially be considered (anticipated) in the authorship of generative work. A series of variables can be discussed from the perspective of still and time–based image production, generative music/sound, and generative text.

2.1 Some Anticipatory Approaches to Image

In the creation of generative works of art, be they interactive and/or a stand alone generative systems, anticipatory approaches play a central role. In Seaman's practice chance processes are used within 'ranges' of chosen media variables, drawing from media-element databases [13, 14]. Here one can potentially "load the dice" in terms of the heightening the probability of calling in particular media-elements by loading the system with media that already has a set of aesthetic qualities—an overarching sense of color, composition, subject matter, and overall aesthetic etc. This might include the loading of a particular database of still images, digital video works, 3d images, or time-based animations in 2D or 3D. Each media element becomes an anticipated variable module. Along with these media elements, a series of time-based media processes can also be considered. This might include how the media-elements enter the time-based image (e.g. does it dissolve, slide, or cut in—there are many different kinds of transitions that can be explored). The way time unfolds in the work is also anticipated—the speed of playback—e/g slow motion, extremely fast motion etc. Additionally the nature of repetition of the image; the scale of the image; the angular position of the image (flat texture map) in 3d space e.g. the image might be skew to the frame or intentionally presented in an odd/shifting perspective over time. The level of the transparency of the images can also be explored. In terms of the final authorship of the code, the work can be tested in an iterative manner and the code can be adjusted and altered to better reflect the aesthetics of the artist/author/programmer. This "adjustment" alters the probability of the occurrence of particular events. This programming enables a form of controlled anticipation, yet it is also paradoxically open given the chance elements and processes involved in the programming, and the combinatoric nature of the layered composite time-based image that is generated. Although the database is finite, the layering and combinatorics associated with the work, as well as the application of different media processes in time, render it emergent in nature.

Along with the generation of the image, related music and sonic material can be generated via a number of computational means. I speak below about some of the sonic parameters that can be explored in an anticipatory manner. In terms of image/sound relations Seaman seeks to create a metaphorical resonance. Here aesthetic coherence that juxtaposes visual attributes with sonic qualities is explored in terms of image/sound pacing, rhythm and mood. In terms of this kind of work of art, one lays out a set of qualities that pave the way for the "reading" of the work in an abstract manner that continues to unfold over time. The viewing of the work over an extended period of time, enables the viewer to anticipate how the work will continue to unfold. In this sense the work [and many other experimental works] defines (and anticipates) its own viewing expectations as part of its own structural strategy.

2.2 Anticipatory Approaches to Music/Sound

In terms of music/sound, every different kind of sonic aesthetic variable can be "anticipated" in code authorship. John Supko calls this Parameterization [15]. We return to the notion of re-embodied intelligence discussed above. In this case if one was to compose a piece of music, what kinds of relations and qualities would one find of interest to include. On approach is to take a finished work and carefully analyze it in terms of all of its aesthetic qualities. Then one seeks to abstract each of these qualities into a system that enables and heightens the probability of certain events to arise. This is especially true if one is interested in chance processes being incorporated in the work. One can also compose a work with very specific branching structures but these are more formal in nature. Sonic variables that Seaman has explored in differing works include rhythm, pitch, sonic dynamics, vocal intonation, form, timbre, duration, meter, sequence (repeated pattern), tonality, dissonance/consonance relation, harmony, texture, orchestration, register, sounding on the beat/off of the beat, the layering of noise elements, and elements of chance.

One approach Seaman has returned to in a series of different audio pieces has been to work with loops and combinatorics. He uses Ableton Live (and pro-tools in the past) as a program to build the loops in. Initially generative works were made with tape loops in the early 80s. In this case Seaman builds these loops exploring the sonic variables listed above. Ableton also has a series of effects built into the program so the sound can be highly crafted. Thus, each loop is computationally 'composed'. This functions as a "loading of the dice", similar to the notions discussed above in relation to imagery, where the sonic aesthetics are crafted with great care. This approach to the system anticipates that each loop will be played with another from the system-set at some point in time. These loops are created to repeat in exactly the same place with the same duration. One can also intentionally explore loops of differing lengths that explore permutations of changes over time.

Seaman has taken this approach in other works. As the same-duration loops are added in one at a time, Seaman listens to how these work together in differing combinations, both as pairs and as multiples intermingling. Each addition of a new loop means much testing in terms of turning them on and off. Yet here Seaman comes up against the vast number of permutations that one arrives at as more and more loops are added to the system. Sometimes up to 50 loops are explored in one system. At a certain point, not "all" permutations are tested but a kind of "averaging" where a subset are tested together. It is anticipated that if the loop works with the subset of multiple other loops musically, that it will have a strong probability of sonically "working" with the entire system in terms of the aesthetic parameters that are being modeled. As more and more loops are layered together there is also an emergent sonic quality that arises.

Seaman has collaborated with Daniel Howe in creating an engine to play back these loops sets. The engine has some interesting parameters that the user of the system can alter: these include the number of loops that will be called in at one time and the number of loops that will change/stay the same after a specific number of repetitions. One can also play the system by turning loops on and off during playback. Seaman performed his work "A China of Many Senses" at Duke University, singing and speaking live on top of specific loops.

Seaman is now collaborating with John Supko on a work called s_traits. In this work Max MSP has been used as a "controlling" or "anticipation" engine, where after our discussions John has authored many different "patches" seeking to explore a alternate approach to the sonic variables. Discussion of this work will be the source of a different paper. One concept under discussion is the notion of modeling "listening" as a way to trigger new events. When the system "hears" a particular quality it is listening for, it may add in material from a particular database. This approach also moves away from locking in loops, and explores non-regular juxtapositions informed more from experimental and contemporary classical music. Supko authored a series of "remix" engines as a way to explore permutations quickly via human/computer interaction. The outcome of use of these systems was used to build modules that can be called in from a database. Here one can also use meta-tags in terms of facilitating "anticipation" of particular sonic variables or qualities—drones, rhythms, specific pitches etc., where the audio system "listens" and responds based on particular parameters that have be pre-authored. Audio files from a folder with a particular meta-tags may also be called into the ongoing composition. Here a form of code-based synthetic perception is used to inform analysis and anticipated feedback in terms of choosing new computational elements and processes to unfold over time.

2.3 Interactivity

Seaman has also explored interactive systems that enable a listener to call in and/or position differing audio loops in virtual space. This was quite a unique approach in that all of the variables are anticipated, but here the participant makes a mix through their positioning and subsequent navigation of the generative space. Again, there are probabilities at work. In this case the participant can also “anticipate” potential navigation based on the sonic choices that they make from a database to be positioned in the virtual world. One can also “perform” the interactions as a compositional methodology.

2.4 Textual Anticipation

Although there are many systems that generate text, Seaman has chosen to explore a method of exploring Re-embodied intelligence for a number of his works, starting with his media/text generator—*The Exquisite Mechanism of Shivers* [16]. To first derive the variables for his generative text Seaman wrote a singular complex sentence. He divided this into 10 segments. He then carefully, one at a time began to write a series of substitutions. This enabled him to craft the vocabulary and also anticipate shifts in the meaning of the text. Like the creation of the generative music variables, Seaman could begin to build up the sentences seeing how the substitution would work in relation to the differing contexts that the alternative linguistic variables would bring about. This also meant Seaman could keep to a particular grammar and syntax in a patterned manner. In particular, Seaman anticipated the generation of multiple meanings/readings through polysemy in the choice of words, often employing homonyms. Yet, like the music, as the system became larger the combinatorics became astronomical in number. Seaman again would explore a series of substitutions in terms of how they worked poetically, yet the system would later continue without testing every substitution. Here Seaman anticipated the generation of emergent texts, yet loaded the dice by inserting very specific vocabulary.

Markov Chains and N-Grams. Many experimental media authors explore Markov Chains for generative textual authorship. Daniel Shiffman provides a definition:

> A Markov Chain can be described as a sequence of random “states” where each new state is conditional only on the previous state. An example of a Markov Chain is monopoly. The “next” state of the monopoly board depends on the current state and the roll of the dice. It doesn’t matter how we got to that current state, only what it is at the moment. A game like blackjack, for example, is different in that the deal of the cards is dependent on the history of many previous deals (assuming a single-deck not continuously shuffled.) We can use a markov chain to generate text where each new word or character is dependent on the previous word (or character) or sequence of words (or characters). This is known as an N-gram model. An N-gram model for language predicts a word (or character) W[i] based on the previous sequence W[i-2] W[i-1], etc. Given the phrase “I have to” we might say the next word is 50 % likely to be “go”, 30 % likely to be “run” and 20 % likely to be “pee.” We can construct these word sequence probabilities based on a large corpus of source texts [17].

Thus, again we can “load the dice” by supplying a specific source text or Corpus and exploit the “predictive” nature of such a system. This again explores probabilities, so the anticipatory nature is not fixed but is “heightened” so to speak.

RiTa Toolkit. Daniel Howe has created a toolkit for the exploration of Generative texts called RiTA:

RiTa is designed to be an easy-to-use toolkit for experiments in natural language and generative literature. RiTa is implemented in Java and JavaScript with a single API and optionally integrates with Processing. It is free/libre and open-source via a GPL license.

Some of the features of RiTa include:

- Text-generation via Context-Free Grammars and Markov-chains
- Taggers for Syllables, Phonemes, Stress, Part-of-Speech, etc.
- Modules for tokenization, verb conjugation, pluralization, and stemming
- A user-customizable lexicon with a letter-to-sound phoneme generation
- A standard set of ‘easing’ effects for animation & textual behaviors
- Integration with Processing, ProcessingJS, and NodeJS
- Runs in or outside the browser, with or without Processing (also in Android)
- Integrates with (locally-installed) WordNet dictionary [18].

Here Howe has brought many textual variables into a “toolkit” space that enables authors to experiment and find new approaches to generative text. The toolkit anticipates many different kinds of explorations yet the system is open in terms of how programmers/authors might choose to explore it.

3 Machinic Autonomy—The Future in Generative Systems

We can anticipate a future where computers take on more and more autonomy in the creation of works of art. As we begin to author learning systems of deep complexity, one can anticipate what Ray Kurzweil discusses in his book—*The Singularity is Near* [19]—fully autonomous thinking/learning machines. Of course there is a great debate surrounding this possibility, as well as fear of highly intelligent machines. Seaman and Rössler in their book—*Neosentience—The Benevolence Engine* [20] discusses many different aspects of machine intelligence and robotics related to this topic. There are many deep questions about how we can author/embody a learning system that can become creative, enculturated, and learn about aesthetics. We ask—how will this new machine aesthetics—or Neosentient Aesthetics play out. Certainly we will continue to make systems that enable human/computer interaction in the service of creative production. At some point in time this interaction may be more like working with a collaborator than a tool.

Seaman gave a paper at Duke on Neosentient Aesthetics. Here he pointed to a form of meta-level discourse that might arise. Topic areas include:

- Discuss aesthetics with the Neosentient in terms of their self-understanding.
- Strange Gödelian loop—where the Neosentient might become creative of such a system with it's own "Catastrophy theory", science of Neo-neosentient Aesthetics; movement to a new 'programmed' aesthetic understanding.
- System might learn to reprogram itself or program other new learning systems.
- Intimidating—creating an entity with its own sense of aesthetics. What might this be? [21]

In terms of textual aesthetics, Richard Powers in Galatea 2.0. [22] imagined an autonomous machine that learns a sense of poetics though a training in comparative literature. The book is deeply contemplative and through science fiction anticipates many of the ideas surrounding computation and intelligence, and their problematics. Learning in the human is no simple matter to model. When a learning system learns to write its own code, and can anticipate its own future functionality, we might call this a form of Techno-Lamarkism. At the moment such notions are still science fiction in terms of aesthetic production.

3.1 Modular Codes that Could Be Recombined

In the short term, Seaman is interested in the authorship of a code generator that would contain many different computer codes with differing functionalities. These could be modular in nature and be designed to be combinatoric. In the past he has called such a system—an *Emergent Intention Matrix* [23]. Each of the modular codes would anticipate a particular kind of functionality, yet the system could combine and recombine these functionalities with an emergent outcome. Imagine an App that generates new Apps…

4 Summary

We see that there are many forms of anticipation involved with both computational creativity and emergent poetic systems. We witness here the complexity of systems that are in one sense formal, modeled via biomimetics and bioabstraction, and alternately are emergent in nature, thus showings aspects of novelty and surprise. This might be considered the embodiment of a paradox—making a system that is predictive of something which in essence is intentionally not fully predictable. In terms of creativity in the arts, artists do not exactly copy past aesthetic processes. This would be considered un-original. They must often explore a relation to art history, to past patterns of creativity. The long-term question is, can we author learning systems that can observe artistic processes which in turn can devise new forms which are emergent in nature. This would be a form of machinic enculturation. Such a system would potentially embody all of the processes discussed above as well as begin to learn how to re-program itself to articulate new creative aesthetics. Such a computational learning system would learn how to be creative.

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Art in Progress

Elvira Nadin

Abstract Aesthetic purpose is anticipatory by its nature. In their concrete action—painting, composing, writing, filming, dancing, etc.—individuals involved in aesthetic activities are driven by a goal (obviously projected into the future) that will eventually become an artifact or a performance. The experiment, "Inside Out—A Performance" (Anticipation and Art) took place in the context of a conference that examined anticipation across disciplines. Through the nature of the experiment, aesthetics became a test-bed for ideas pertaining to the expression of anticipation in action.

Keywords Anticipation · Creativity · Interaction · Originality · Technology

1 Preliminaries

All creative work, all inventive work, is anticipatory. The artist or inventor creates, generates—gives birth to, in a way—something that never existed before. She (or he) has a vision—a "seeing" into the future—of what might be or can be. He/she is *goal-driven*, (cf. Rosen's definition: An anticipatory system is a system whose current state is determined by a future state [1, 2]. Yet the goal, no matter how clearly defined in the creator's mind, is open to choices from a large space of possibilities. In the process of pursuing the end work, the creator continuously adjusts to circumstances of all kind: materials used, means of expression, his/her state of mind, and the environment. These are some of the variables that, consciously or less than consciously, inform the artist's decisions. While aesthetic concerns dominate, practical considerations play an unavoidable role.

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On the other hand, it must be kept in mind that an anticipatory system is a "system whose current state depends not only on a past state or states, but also" [and here I add by way of emphasizing] *especially* "on future possible states," [2, p. xxxiv]. The past is embodied in skills, culture, education, influences, materials, techniques, available technologies, and the like. The possible future states are not material in nature, but rather informational, as generated by the artist, or by what informs his/her choices (the latter is usually called "inspiration"). These possible future states pertain to intentionality: the meaning of the work in the artist's mind, its interpretation, and, possibly, to its reception. The public, professional critics, art historians, etc., are part of the interpretation process. Should their interpretations be a matter of concern to the artist, he/she will try to control any possible equivocation about his/her goal.

2 The Interrogation Moment

Some obvious questions arise. One question is of primary concern: To what extent does an artist create something that truly never existed, or even whether art starts from nothing (*creatio ex nihilo*)? It goes almost without saying that the work is always, and irremediably, an expression that includes past states. Like everything born, the work entails a narration, without ever being reducible to it. The role played by the current state of the entity that integrates artist, work-in-progress, environment, etc. is not easy to describe. States succeeding each other are easy to distinguish and account for. But states that represent the aggregate of parallel streams of events emerge as simultaneous, although not always distinguishable. In a theatrical performance, or in a film, this is relevant. However, when the making of an aesthetic artifact is itself a performance, simultaneity cannot be ignored. In awareness of these general considerations, let's sketch a context for understanding how aesthetic expression implies anticipation.

The question of inspiration, already mentioned, comes to mind in regard to how the future is embodied. Let us recall some artists whose work influenced the public to view art in a new light, to view creation in art as singular as it is in life: Seurat and Signac, whose pointillist style, reflecting knowledge of how color is perceived, was way ahead of our knowledge of pixels; Malevich, Lissitzky, and Russian Suprematists suggested that we can view the world through geometry (Mondrian has is own perspective in this regard); post-Revolution Constructivism in Russia exercised its influence on design, architecture, theater, film, dance, breaking the conventions of realism; the Bauhaus "school" of architecture and design built upon the expressive power of syncretism; Picasso, whose Cubism attempted to represent three dimensions and the underlying time component on a support (i.e., a canvas) allowing for only two; the art of "objets trouvés"/"found objects", which suggests that any ordinary object can be seen as art (from Picasso and Duchamp to Nevelson and Koons); Calder's mobiles, which gave a dynamic dimension to sculpture (overcoming the understanding of the genre as static); Jenny Holzer's *word art* (as I would call it since, despite the media she employs—paper, marble, projections, electronic displays, LED, whether static or in motion—her object is the word, with a small *w*); Christo's *art of expropriation* (a fitting name for his practice of taking over objects large and small and decorating them according to his inspiration, or wrapping them as though he were presenting them back to the public as a gift). Such examples (a selection kept at a cultural minimum) might prompt a conclusion that does not necessarily endorse the anticipatory perspective. This is because no matter how original—one could say "anticipatory"—the work of art is, how novel the perspective of the various creators, in creating something new, they do in fact proceed in reaction to past forms of creative expression. In such cases, the past is rejected as having lost the creative impetus. They also explore and promote new means of expression. I recall the "revolution" of electronic art (Laurie Anderson, Nam June Paik). As new means become available, some artists take up the challenge of exploring the artistic means of expression that new technologies offer—especially in the realm of the digital. Manfred Mohr, for example, with his algorithmic art, was one among several pioneers in "computer" art. (Frieder Nake, less celebrated as an artist and more as a computer scientist, could be included among these pioneers.)

After all is weighed in the balance, in effect, an artist, no matter how inspired (or how unoriginal), always creates something that never existed before. By virtue of the uniqueness of each object (painting, drawing, sculpture, etc.) or experience (in music, dance, video, etc.), the aesthetic expression qualifies as the "fingerprint" of its maker. At the same time, the artist escapes the limitations intrinsic in reaction by exploring the possible futures associated with the making of the work. These broad-stroke considerations are more or less the framework for placing the experiment "Inside Out" in the context of the conference *Anticipation Across Disciplines*.

3 Interactive Art

3.1 Engaged Art

Lada Nakonechna belongs to the "School of Engaged Art" (http://chtodelat.org/) in Kiev, Ukraine. "A central component of our school," she states, "is the idea of collective practice. We want to develop a range of models for collective art production while of course continuing to discuss personal projects." The group does not shy away from the descriptor "political," in the sense that its members are in a state of revolt against comfortable art, against art approved by those holding power, in the market as well as in government. Nakonechna wholeheartedly adheres to the group's principle of "involved art." That is, they hold that the object of the artwork, as well as anyone viewing the work in progress, be allowed to take—even be encouraged to take—an active role in the unfolding of the work. No more the romantic image of the artist in the ivory tower, seeking inspiration in isolation;

rather the attempt to engage others, to interact. This choice changes the nature of aesthetic activity. Interaction infuses the process with many more choices, and thus expands the space of possibilities.

Nakonechna is a successful artist. Her exhibitions (works in photography, performance, and drawing) in Europe and in the USA (New York) were well received exactly because of her aesthetic premise. The Hanse Institute for Advanced Study, known for promoting interactions between artists and scientists, discovered her via an exhibit at EIGEN+Art in Berlin [3]. A fellowship at the Hanse Institute gave her the opportunity to create art while in residence. During her tenure at the Institute, she concentrated on drawing, as she has done for the past few years. The experiment associated with the conference on *Anticipation Across Disciplines* is a continuation of the dialog with researchers in various scientific fields. It should be noted that during the previous conference, *Anticipation—Learning from the Past. A Legacy from Soviet/Russian Scientists*, she was already engaged in her experiments. It is probably mere coincidence that a conference on scientists of the early Soviet era (who were pioneers in anticipation and motoric activity) and the fellowship of an artist from modern-day Ukraine took place simultaneously. Lada Nakonechna was able to attend some of the presentations and post-presentation discussions. She became interested in the work in anticipation that was carried out in the early years of the Soviet Union, and could relate to the revolutionary thinking manifested in many fields, the arts included.

3.2 Art in Progress

The performance *Inside Out* (see *Announcement*, Fig. 1) that engaged the group of researchers in anticipation resulted in a category of drawings that qualify as the

Fig. 1 Invitation to interaction. Artist's studio at the Hanse Institute

integration of an aesthetic goal, spontaneity (in choosing subjects from the video stream), randomness (nobody “organized” the interest of the persons captured through the video camera as they walked, talked to each other, or watched the artist in her living studio). Something that never existed and, due to Nakonechna’s method, will never exist again emerged.

As a matter of fact, each expression of anticipation is irrepeatable. Recalling one of the most daring ideas of Nikolai Bernstein [4] in describing human expression through motion, it is “repetition without repetition.” Given the philosophy of art that Nakonechna adheres to, she emphasizes interaction. “Instead of simply trying to activate the viewers to think about the figures in the work [...] he gets involved in the work by becoming part of it and directly affects its outcome,” [3, p. 3]. But to what extent is interaction anticipatory? We have to focus on what were the possible future states that affected the interactive process of executing her art project. An artist who deals with a static subject (tangible or envisioned) feeds back only to herself in choosing among the possibilities that arise while planning and executing a work. Such an artist has almost complete control over the current state of execution. An artist given over to interaction seems confined to reacting to her interlocutor. Obviously, there is the possibility of simply accepting or rejecting the subject’s contribution.

Since Nakonechna became familiar with the concept of anticipation and internalized it, her own work reflected this perspective. Her project gained “a new dimension” as she submitted her choices to selections guided by future possible expressions. She did not film or videotape, she rather integrated the “living” into the drawings. “Art has no borders. It breaks borders,” is part of her aesthetic credo. With awareness of anticipation, she comes to the realization that “Art is process, questioning, discovery.” The artist sees herself in the subject and as subject. Art is a discussion that begins in the self. It is never her goal to preach or describe. She ascertains equality and wants to create a situation of equality between artist and viewer, to lead both viewer and artist to think, to debate. The anticipation is, of course, implicit.

The aim of Nakonechna’s project at the Hanse Institute was to deal with “movable, changeable” subjects. The most obvious expression of anticipation was her plan for carrying out the project. She designed a new kind of studio—an open studio that made interactions possible. Its one wall of glass, separating the studio from the outside world, faced the Institute’s grounds, and had more than a physical influence on execution of the project. (See Fig. 2, on which the window frames are projected onto the paper and integrated in the artist’s work.) The video camera was set up to capture what would go on outside, on the other side of the glass wall. A modern (and much smaller) version of the *camera oscura*, it projected not an upside-down image that a *camera oscura* would yield, but a mirror image on the opposite wall. Here the artist had installed a large roll of drawing paper—about 80 cm high and several meters long—on which she penciled in the images projected. The rate of change of scenery determined the speed and effect of the act of drawing. That is, if there was no change, she worked more slowly and penciled in

Fig. 2 "Inside". The artist at work on the image projected by the video camera. Far left: part of a completed panel

finer detail; if there was much change and movement, she penciled in broad, vertical strokes of an outline, to be filled with detail at a later time.

The action that took place outside the studio could have been videotaped or filmed, for later reproduction at her discretion. But her medium of expression is the opposite of the "cold" media. It is drawing, probably the most ancient of aesthetic expression, of ritual quality. This is the anticipatory dimension that she does not want to trade in for the perfection of "mechanical" recording. The aura of drawing gives her work the uniqueness that an artist desires to attain. Thus she would have an artistic rendering of what transpires on the Institute's grounds. That was one goal of her project. The main goal, as mentioned above, was to deal with "movable" objects, that is, the living entities circulating the grounds—mainly humans, but also animals (pets and wild). Moreover, her hope was to attract people to see her at work and to "engage" them in artistic production, even if only by watching (see Fig. 3). This interactivity depended on many contingencies. The dialog envisaged was not one of words exchanged, but of co-presence.

4 Contingency

Contingency seemed to be a major factor in executing her project. The day she started, it showered in the morning. By 1:00PM, the rain had stopped and the conference participants, who had been encouraged to view her working, proceeded

Fig. 3 Outside. An observer becomes an object of art

en masse (25 individuals) to the studio. This was in fact a bit overwhelming. The viewers acted naturally: they milled around the grounds, some small discussion groups formed; most of them eventually approached the window and peered into see the artist at work. Obviously, the rush of subjects was overpowering, and she had to choose which to include on the large paper before her. These are selections that give life to the image. She had already penciled in the background. Now she had to hurriedly pencil in the subjects. She used broad strokes of the pencil to form a sketch of each subject. Later on, she filled in details; that is, she used penciled in darker lines, smaller lines to produce what would look almost like a black-and-white photograph of the area she was reproducing. Figure 4 reproduces one of the images resulting from a busy day in the studio.

This short record of details from the event is meant to suggest what transpired and how anticipation figures in the creative process. New artistic processes make new demands on the artist; but some seem constant. In discussing the computer animation that was succeeding animation based on hand drawings, Lasseter [5] presents some ideas that seem applicable to interactive art:

> To stage an idea clearly, the audience's eye must be led to exactly where it needs to be at the right moment, so that they will not miss the idea […] Staging, anticipation and timing are all integral to directing the eye. A well-timed anticipation will be wasted if it is not staged clearly.

How much control the artist has over each of her interactive works is not different from the question of how much control we have over our lives. In general, she "knows" how she wants a project's structure to unfold, but she had less control over

Fig. 4 Outside In. One result of an experiment in interactive art

the unfolding than does an artist dealing in isolation and with a static subject. Weather and light were factors she could not control, but which solved themselves. At the Hanse Institute, she found a “safe” place to work. But how does such a structure (and structure in general) influence her work? In a closed environment, protecting her from interference, she cannot influence outsiders. Thus a conflict arose: working in a safe environment vs. need to be “seen,” to be not only observed, but especially interacted with. In her artistic process, she anticipates a “critical” interaction with the public. Yet, when people managed to enter the workshop, she did not open a dialog, but “tried to guess the viewer’s thoughts.” Anticipating “double exposure”—viewers who would stand where there was already a drawing —she planned for positioning herself in order to influence where the viewer stands. During the times no one showed up, she manipulated to some degree the images she had already captured.

Was the artist Lada Nakonechna happy with outcome? “It is easy to say ‘happy’ or ‘successful’.” The project was not out of what she ordinarily does. It was an experience: good, but not great. In the end, she felt she could not meet her main goal, but attained many small goals. One was to construct a situation in which the artist is placed appropriately. Another goal was communication:

$$\text{artist} \leftrightarrow \text{viewer} \leftrightarrow \text{artist as viewer}$$

“to view as a stranger in order to see something differently,” to get people to recognize the artistic process as art in its own right. Very important to Lada Nakonechna is that “the viewer should ask what the artist is doing. The process

should open a line of communication.” She is not sure if viewer/subjects asked such questions of themselves.

Allow me to end by inviting the reader to think about art and the artistic process, and his/her role in the life of a work. And to ask: To which extent is a work of art—and art in general— the expression of anticipation?

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Political Anticipation and Networks: Creating Anticipatory Systems for Government and Society

Marie-Hélène Caillol

From now on, tomorrow determines today

Abstract LEAP was established in response to the need for future-oriented programs for the European Union. Political Anticipation transcends the outdated paradigm of permanent, centralized, hierarchic, and isolated institutionalism by networking throughout the entire European Community. Just as every cell in a living organism plays a part in the functioning of the whole body, so do individuals, connected through modern technology, have an important role, on the local, national, and trans-European levels. Informed by trends, Political Anticipation attempts to guide policy in full awareness of possible outcomes. This stands in stark contrast to the deterministic, reaction-based, and big classic outmoded patterns prevalent in the European Community today.

Keywords Anticipation · Decentralization · Networking · Hierarchic/non-hierarchic · Transparency

1 Introduction

"Political Anticipation" was developed by the European think-tank Laboratoire Européen d'Anticipation Politique (LEAP) in 2005. It was conceived as a future-oriented decision-making tool that applies the concept of freedom of informed choice as opposed to principles of determinism. Political Anticipation aims to diminish the influence and weight of past practices on the future and affirms that human beings are active participants in creating the government and society they desire. In view of this, it is imperative that citizens become aware of and

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understand the mechanisms at play in building the future, as well as ways to contribute to this goal.

2 A Short History of Political Anticipation

Created in 2005, LEAP is anchored in the development of organizations and actions that, in Europe, date back to 1985. Prior to this (as early as 1972), anticipation related to politics and social systems was approached in the USA by Rosen [1, 2], and by Bezold [3]. In 1996, the Santa Fe Institute Economics Program addressed the anticipatory characteristics pertinent to economic processes—enmeshed as they are with political processes [4]. In Europe, anticipation was formally approached by Godet [5], Yolles and Dubois [6], and Adamkiewicz [7], among others. Franck Biancheri (1961–2012), a French political scientist concerned about the democratization of the European Union (EU) was the moving force behind Political Anticipation in Europe [8]. During his 25-year long career (which included several important governmental posts), Biancheri, together with the networks he initiated and guided, developed a unique competence in anticipating major socio-political evolutions.

The first documented attempt at anticipation dates back to June 1989 when Biancheri wrote a recommendation that Europe should consider preparing itself for the collapse of the Soviet Union. According to this document, Europe would have to contend with the consequences of such a major systemic change through addressing the key question of the new role of Central and Eastern European Countries (CEECs). At the time, the media and political leaders considered the event that Biancheri anticipated highly unlikely. Six months later, as the Berlin Wall was being torn down, the European Union entered a state of emergency. Unprepared for this momentous change, the EU ended up engaging in a chaotic and undemocratic expansion process that is accountable for today's Euro-Russian crisis.

Another significant and documented anticipation analysis concerning the crisis in 1999 [9] was presented. The independent report on fraud and mismanagement in the EU prompted the (infamous) resignation *en masse* of the European Commission (led by Jacques Santer). The above-mentioned political anticipation was based on the analysis of the Maastricht Treaty; it concluded that the Treaty had significantly changed the nature of the European Union, primarily in terms of scope and budgeting. The analysis went so far as to request that the *modus operandi* of the European institutions go through a rethinking process in order to prevent questioning of the EU's transparency and legitimacy.

In 1997, Biancheri initiated the Europe 2020 project. In 1999 this project evolved into a think tank to be guided by the concept of "anticipation." More precisely, the project focused on consideration of possible future states, intended to guide current procedures for elaborating the most effective political, social, and economic strategies. A series of high-level "anticipation" seminars (entitled *EU Governance 2020*) were conducted between 1999 and 2002. Themes related to EU governance reform and expansion were discussed with representatives of the European Union, civil servants from various countries, and diplomats. The perspective of political anticipation informed the seminars. Biancheri's contribution was acknowledged in the publication of *Vision 2020* [10] among others.[1]

Political Anticipation was formally established in 2005 through a new think-tank, Laboratoire Européen d'Anticipation Politique (LEAP)—in English, the European Laboratory of Political Anticipation. In 2006, LEAP launched the *Global Europe Anticipation Bulletin*, published monthly. In January 2006, it reported on an "upcoming global systemic crisis" [11], seen as the set of changes entailed by the process of collapse of the global influence of the USA. Early 2007, the subprime crisis was anticipated in detail [12]. Based on this consistent work of anticipation, LEAP was approached by the Sorbonne. Its intention was to formalize the empirical method of Political Anticipation and to launch training courses. In 2009, the first series of training sessions on political anticipation was initiated in partnership with the Sorbonne's Department of History. One year later, the first formalization of the *Method of Political Anticipation* was published [13].

3 Political Anticipation: One Image, Some Principles, a Subject of Exploration

Imagine a sailing ship, called *Political Anticipation*, at sea heading towards a harbor. The boat must contend with icebergs and storms, and must keep its course as it deals with wind, high waves, and strong countercurrents. "Political" refers to the perspective from which strategy and decision-making are considered, taking current conditions (e.g., icebergs, storms) into account. "Anticipation" considers the variables (waves, winds, currents), which are possible future states that should be taken into account in order to optimally steer the ship as it pursues long-term goals, i.e., safe harbor; medium term goals, i.e., possible course adjustments; and short-term goals, i.e., setting the appropriate direction towards the harbor. The waves and winds and currents are changeable, as are political trends. Even though winds and currents are allies in propelling the ship forward, they will never set the ship on the right course towards the harbor without the sailors' expertise. LEAP's analyses and understanding of trends is indeed key, so that those in charge can optimally coordinate all the elements and set the right course that will lead the "ship of state" onward.

In short, the Political Anticipation is a very accessible and common-sense methodology based on the assertion that the human beings *must* be aware of their connection to and influence on a future state, so that they can learn to better set the current course of events leading to the desired future state. Each encompassing analysis includes the following points:

[1]See, for example, Archive of European Integration (2002): http://aei.pitt.edu/230/.

1. Understanding the object of study: long-term goals, short- and mid-term trends, breaking points, trend accelerators/decelerators;
2. Optimal information, taking into consideration interdisciplinary perspectives, differences in history, language, national, ethnic, and social realities;
3. Optimal grounding in transnational societal reality, with the aid of technology (Internet) and networking, and in awareness of the overall guiding perspective;
4. A necessary state of mind: objectivity, independent thinking, courage to face the risk of being wrong and being opposed (sometimes very strongly), openness, and flexibility (in order to adjust to new events or realities);
5. The scientific basis and methods of the study: elaboration of hypotheses, validation processes, evaluation.

In his proposal for political anticipation (*avant la lettre*), Rosen [1] recommended submitting anticipation in politics, economics, and social issues to his (M,R)-System (modeling-relation system). LEAP's methodology is less formulaic, but, in our opinion, more effective, because it deals with complex reality directly, without reducing the various aspects of the analyzed reality to categories (such as effectors) to fit a system. Political anticipation is intended for policymakers in a complex world [14]. It is no exaggeration to state here that the ability to perceive and decide among the many future scenarios is vital to development, if not survival.

LEAP is aware that its method is an incomplete science and therefore prefers to present it as an open field of exploration, inviting researchers in both humanities and hard sciences to better understand the specific features of Biancheri's success in applying the anticipatory systems perspective to politics and related fields.

4 Capacity to Anticipate Versus Incapacity to Adapt

The European Community (as today's European Union was called until 1992) was the epitome of a centuries' old paradigm: pyramid, top-down, hierarchical organization. Biancheri took note of this *modus operandi* of a group of countries, collaborating on equal footing, for which linear pyramid-based governance was actually ineffective—even counter-effective. The old paradigm, in which structures such as those dominating the European Community, was giving way to a new one, more effective for the modern, technology-based world [15, 16]. Networking proved to be a more efficient way of operating in the new civilization of non-hierarchy, non-linearity, impermanence, and decentralization dominant in progressive societies around the world. Although LEAP operates in the trans-European area, it "thinks globally," since the EU is affected by trends from around the world. From the time he created his first trans-European organization (Association des États Généraux des Étudiants de l'Europe—AEGEE/the European Students Union) in 1985, Biancheri was connected to European and global social and political realities via the networks of collaborators and followers he created. LEAP considers that this multi-point, multilingual, and transnational (i.e., "multi-sensor") connection to human society through networks—real and virtual—to a large extent accounts for its collective anticipation skills. An enhanced organic connection to reality is indispensible to "sensing" upcoming changes and identifying paths to deal smoothly with these changes. Through the Internet and network-based structures, LEAP perceives how it can educate people to think from the perspective of anticipation—of possibilities rather than probabilities.

A major challenge for political anticipation is to convince organizations (private companies and organizations, state-run institutions) to take the anticipatory approach. The current global systemic crisis has been anticipated by isolated individuals, but also collectively within organizations. Nevertheless, the latter happened to be incapable of turning their collective capacity to perceive oncoming changes into a systemic capacity to prepare for them. Thus LEAP is increasingly concerned about contributing to the invention of tomorrow's organic and anticipatory systems of governance. The term *adaptive* is often used, and sometimes more easily understood; but it connotes reaction to a past situation. LEAP prefers *anticipation* as the richer concept, transcending probability through possibilities. In the words of the cybernetician von Foerster [17], "Act always in such a way as to *increase* the number of *possibilities*." We believe that network-based organizations can develop this feature.

4.1 Growingly Dysfunctional Systems of Governance

Institutions around the world are in a state of self-induced "suffocation" under the weight of centuries-old practices and regulations, which even in the 20th century proved ineffective. For instance, a single EU country, in the framework of its dealing with the euro crisis, must proceed under legal constraints imposed by the International Monetary Fund (IMF), the Organization for Economic Cooperation and Development (OECD), the EU as an organization, as well as by the country's own (democratic) system of decision validation. All these legal frameworks were well thought, duly negotiated, and voluntarily agreed in the previous decades, in times of low crisis, by each country in concert with the others. The reason for this supra-national effort is obvious: in a globalized world—a world with huge discrepancies in size of nations—it was necessary to create clusters of nation-states sharing converging interests in order to ensure some influence on a global scale.

Despite good intentions, several problems arise from this architecture.

1. A problem of democracy: these supra-national entities are turning national governments into mere executors of their legal requirements, at the expense of elected governments' prime mission of serving the people who elected them.
2. A problem of relevance: the supra-national level, originally designed to enhance the capacity to serve its members' collective interest, lacks the grassroots articulation and connection to reality to understand problems other than theoretically, and therefore to address them other than on a legal, or even ideological, basis.

3. A problem of efficiency: The combination of “hardware” entities, all based on the 19th century model of nation-states, accumulating layers and layers of pyramidal (top-down) systems with linear chains of command and information, has led to a level of complexity that results in sheer dysfunctionality.
4. A problem of timeliness: This very complicated and disconnected system acts in a purely reactive mode. Even if the individuals within are capable of anticipating changes, and even if in some cases this capacity can be shared throughout the system, in the end the system runs into every problem as if it hadn’t noticed it at all. (Imagine a Titanic full of passengers with mini-radar devices spotting the iceberg, but the captain remains sealed off in his command post.) The system then reacts to events, with a two-fold procedure. The first aims to solve the problem, in the realization that in complex systems it is too late to address a crisis when the crisis is already there. The second is to elaborate yet another set of rules in order to avoid repetition of the problem. Paradoxically, this creates the conditions for that very problem to arise again. A good example is the new “Cold War” between NATO and Russia. Each side sees the other as an enemy to its way of life, instead of considering possible forms of cooperation beneficial to all concerned.
5. A problem of adaptability: In the constantly changing reality of a highly interconnected world, these supra-national entities should be capable of adjusting a current state in full awareness of possible future circumstances, instead of regularly creating more such entities.

The euro crisis provides a very good example. First, it raised questions of democracy, leading to a political crisis that weakened the ability of any EU state to respond to a geopolitical crisis. Thus the whole of Europe is caught up in crisis, instead of the affected country. The EU invented the euro currency but never anticipated a euro-crisis. A new institutional embryo—let’s call it “Euroland”—is established in reaction to an emergency, and soon ends up competing with its mother institution, the EU.

As chaotic situations pop up around the world, LEAP dedicates its efforts to elaborating political and institutional systems that not only analyze a previous system’s failings, but, more important, identify new mechanisms, new ways of operating, while reasserting collective interest and stability. In the face of such challenging responsibilities, Political Anticipation aims to come up with useful elements for a solution.

5 Context and Anticipation

Anticipation is the sense that enables a *living* system (biological, social, political) to adapt to change. It is the “sense of context” [18] that takes change into account and defines and implements the adaptation (structural or temporary) needed to integrate that change. Otherwise change leads to shock, and shock is conducive to irrational and unpropitious reactions conducive, in turn, to system failure. It may well be that the current speed of change increases as systems become more complex. But it could also be that uncontrolled complex systems increasingly create change. In both cases, enhancing the structural capability of political and institutional systems to deal with change is key. That is, such systems must realize that the need to anticipate (envision possible changes) and to act in consequence (adapt or adjust) is a vital challenge for our globalized societies.

5.1 Globalization, High-Speed Transportation, Internet: Time and Space Reconsidered

In the past two decades, it is not so much an official agenda of globalization that has changed the world's structure, but the new technologies, which have "democratized" globalization. That is, an agenda classically believed to be elaborated and implemented by economic and political elites alone, in fact (in most places in the world) is enjoyed by every individual who has access to digital technology, especially the Internet. The result is a profoundly interconnected social and economic global structure: countries, companies, non-government organizations (NGOs), and the ordinary citizen are all interconnected through a gigantic network. This network turns global humanity into an "organic" system in which things happening in one part of the planet end up having an impact in many other places. The world has de facto become one organic body—a gigantic *living* entity, hence dependent on anticipation for survival. Unfortunately, there are still too many centralized structures that, each acting in disregard of the entity, undermine it. (The Greek debt crisis easily comes to mind as an example.)

The *space* of actions has been dramatically reduced, and not only through rapid transportation. Each computer becomes a microcosm, a reduction of its user's world wide web of connections through a globalized access to news (for the time being, language differences remain a greater barrier than any objective space requirement), to his/her network of international "friends," project collaborators, customers, and clients. Live, real-time online discussions via social media, news from all over the world available anytime from anywhere, high-speed trains and low-cost airfares result in an almost complete annihilation of space-related constraints. In respect to time, it is becoming quite clear from this interconnectivity that what will come tomorrow is more the result of what is being done today than what was done yesterday. Consequently, news headlines and individual conversations are full of the future. Everyone has something to say about what might happen as the result of a certain decision or event. The Internet connects the future to the present as much as it connects far to near. Every level of decision takes into account upcoming developments. The Internet connects the future to the present as much as it connects far to near. In fact, the future has been integrated in an enlarged present. Our grandparents used to purchase their tools on the basis of past experience and the expectation of permanence. Today, buying a computer does not require any analysis of past computers, but the anticipation of upcoming technological developments that suggest when exactly to buy, and which brands and models best reflect these developments.

5.2 Global Complexity and Organicity Require and Enable Political Anticipation

It goes without saying that the complex, interconnected, organic world described above *must* enhance its ability to anticipate future possibilities. It becomes incumbent upon complex entities to look farther ahead than months, even years, because they need more time than simple entities in order to prepare for change. (To return to the ship metaphor: a super tanker relies on radar to see far enough ahead in order to have sufficient time to adjust course; a small vessel can rely on short-range vision.) The complex, interconnected, organic world also provides the tools for an enhanced capacity to anticipate future contingencies: the Internet facilitates information delivery on the scale needed for anticipation; moreover, it provides access to information from practically all possible sources—the arts, cultural events, sports, political actions, economic developments, local events, and so much more, from low to high. Although many governments curtail their citizens' access to the Internet, and even plant misinformation, their attempts only prove the power and potential of the world-wide web.

5.3 Global Organic Social Body and Its 19th Century Institutions

In today's globally oriented society of people, interconnected, informed about everything they are interested in, there is a tendency to take it for granted that they have an enhanced capacity to understand events and to anticipate the possible directions in which they may lead. It is unfortunate that with all this information available, the institutions entrusted with steering the most propitious course are grounded in principles reflecting 19th century thinking. However well these models (centralized, hierarchic, linear, sequential) may have worked since 1800 (the beginning of the Industrial Age), they have already proven their ineffectiveness for our post-industrial age. Paradoxically, these institutions are run by highly educated, well-informed, and forward-looking individuals. But they must function in a prison-like framework in which each department, isolated from the interconnectedness of current human pragmatics, operates. Above all, there is a structural incapacity of these institutions to properly "read" the information conveyed to them, and to propose solutions based on new realities. Their deterministic attitude is, "If it worked well in the past, it will work well for the future. If it does not, it is not the fault of the system." This is the typical "Cassandra syndrome": the institution is structurally incapable of engaging the changes suggested by the prediction; the signal is too weak and the effort too important. Consequently, the choice made is "Do not believe what she (Cassandra) says and change nothing!"

Such institutions are structurally incapable of anticipating where trends might lead. For example: a revolution will always lead to democracy. Or: Independence will lead to progress. (And no one ever anticipates failure!) They are bound to determinism: Do this and that, and such and such will result. That's the way it has worked before, so it must work that way always. (For example: If it works for Germany, it will work for Greece.) For this reason, despite the effort some institutions make to create within themselves a capacity to anticipate changes (forward study units, interaction with civil society organizations, democratic mechanisms), the established political and institutionalized systems are functionally incapable of accommodating; they can only move when pushed by problems.

The challenge of improving the efficiency of our institutional and political systems, whether national, supra-national or international, is twofold:

1. To enhance the connection to reality;
2. To improve the capacity to translate information into action.

In the 19th century, the aim was to prevent change, especially political change. Economic change took its own course: rapid, "revolutionary" change (it is called the Industrial Revolution for a reason). Operating within a historic paradigm of slow progress, centralized authority, institutionalized hierarchy, homogeneity of the social order, the deterministic mindset often failed society as the years and decades went by. In the 21st century, change happens so fast that it often takes people society by surprise. And despite the fact that people are used to change, political and institutional systems never act in anticipation of it. The general aim of political and institutional systems being social stability, it is necessary for them to understand changing realities, to analyze trends, developments, and even extreme events [19], in order to come up with policies that lead to the most effective outcome. We need to switch from a creationist vision of political and institutional systems—meant to be valid for eternity—to a Darwinian view—constantly adapting in order to survive.

The characteristics of today's global environment that compel the system to change probably also provide tools for the future political and institutional engineering.

5.4 Anticipation and Networking

Political Anticipation emphasizes that understanding ongoing trends and anticipating possible developments is relative to the quantity and quality of the information gathered.

> Information is what co-relates an anticipation. […] Information is the ultimate substratum of anticipatory processes. Anticipatory systems are systems of information, themselves subject to interaction with other systems [18, p. 101].

Consequently it is vital that a superior information gathering system must be put in place. The principles of this good information consist of making sure the information gathered creates the conditions for objectivity. That is, it must reflect a diversity of sources: mainstream and marginal, general and specialized, right and left, from different countries and in different languages, all considered in the holistic environment.

Being part of a network characterized by diversity is a key factor in maintaining complete connection to realty and creating the proper environment for anticipations. Indeed, the capacity to anticipate can be improved by enhancing the connection to reality through networking. Thus, political and institutional systems are well advised to structurally connect themselves to the existing global network of information and interaction.

A network is a non-hierarchic, non-linear system of links that connect the nuclei of the system in a self-organizing way. This means that no nucleus is permanently connected to all other nuclei in the system, but only as the situation requires. The world-wide web is, of course, the best known network; it facilitates the exchange of information from any point to any other point. Sometimes the networks go through a hub, i.e., a center common to all lines in the network; sometimes they do not need the hub and connect only to the systems deemed necessary.

6 Towards an Organic System of Governance

How do 21st century pragmatics apply to political and institutional systems? What could a modern institution be like?

It should be decentralized, its components connected through networks of people and instruments rooted in their environment. Today there is no need for huge buildings that shut government workers off from reality. They can remain in the place that adds value to their work—connection to a specific environment, for instance, to nationality, to a profession—as they punctually combine the value in a common project through online communication or conferencing. Modern political and institutional systems can consist of light structures, technical secretariats mostly, that coordinate meetings, decisions, and actions of ad hoc, self-organizing networks.

Such entities should be project-based, and impermanent, that is, lasting only as long as the purpose (the project) justifies them. The world is full of meaningless institutions and organizations. Imagine if the United Nations (UN) was replaced by self-organizing networks of organizations tackling a common regional problem, involving only those other participants that can actually help. Instead, it has become a super-expensive center of nations, most of which have no stake in problems that are not of importance to them, and which have nothing in common with the principles that the UN is supposed to uphold. Such organizations weigh on society; through their cost, influence, and uselessness they are actually counterproductive.

The identification of specific problems could result in the creation of temporary coordination secretariats connecting networks of experts and animating them around a common objective. They will be interconnected through the reality, the actuality of a situation or question. Each system can be connected to the other systems into a global network of institutions. Again some uncomplicated administration offices can connect part or all of these institutions on the basis of specific de facto projects, concretely activating connections among these organizations. These are the conditions for a non-pyramial/non-hierarchic global system of governance.

There is something fractal about networks. Indeed, it is anticipated that each component of a network can itself form a network, forming "natural" connections with new members, all equal. A municipal waste management worker can be seamlessly integrated into a supra-national network of experts on the environment. Indeed, in a network-based system, the individual is the basic component, the projects are the connections, and the institutions are the hubs.

6.1 How an Organic System of Governance Becomes "Naturally" Capable of Anticipating

Turning political and institutional systems into networks and hubs enhances their perception of social realities. The inherent fractality of networks facilitates the network's capability to understand trends and anticipate future developments. It is the sum of the capacity of individual components to understand trends and anticipate future developments.

Thus the network creates the conditions for an upward leverage of the quality of information, understanding of trends, and anticipation of upcoming changes for both society at large, as well as for the individuals making it up. For example, trees, through the interconnection of their roots, inform one another of the risk of contagion from a diseased tree. The tree system creates the possibility for each tree to adapt. The combination of these individual adaptations results in the adaptation of the forest altogether [20]. Here we see that adaptation of a complex structure is possible through the collective adaptation resulting from individual mini-adaptations, easy to implement.

Political anticipation claims that this natural mechanism is applicable to social entities when these entities are organized in networks—when they are "organicized"—and therefore become able to collectively integrate Darwinian adaptations.

6.2 Back to the Individual

Of course this collective capacity can only benefit from the individual components' increased awareness of the basic principles of good anticipation. It therefore appears important to set up rules to rationalize this new requirement of taking the future (better yet, possible futures) into account at every level of each individual's life, whether professional or personal. That's the purpose of Political Anticipation: to provide as many individuals as possible with simple tools that will make them aware that they are dealing with the future on a daily basis, that they are being told many different things about this future, and that they must be able to make their own judgments from the apparent possibilities—or to create new possibilities.

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Interactive Living Space Design for Neo-Nomads: Anticipation Through Spatial Articulation

Asma Naz

Abstract Recent advances in embedded computing technology of microchips and sensors have given rise to computer-mediated, human-centered interactions and emergent mobile lifestyles. Interactive system design driven by embedded computing collaborates with architectural design in the realm of habitable interactive architecture to generate and facilitate human interaction with built environment. However, the potential of interactive technology as a design means in the anticipatory spatial thinking of traditional architecture is still largely unexplored. This paper proposes design possibilities of an interactively modifiable living space that aims to accommodate evolving lifestyles of highly mobile, information age professionals, also referred to as *neo-nomads*. The proposed design investigates anticipatory dimensions of interactive technology in generating possible spatial articulations through human-space interaction to meet design goals.

Keywords Anticipation · Interaction · Interactive architecture · Embedded computing · Spatial articulation · Neo-nomad · Mobility

1 Introduction

Architecture is essentially a spatial entity with distinct spatial functions. Anticipatory architecture provides design allowances for possible spatial solutions to prepare for emergent needs. Anticipation allows design to make decisions at current condition by looking into prior and possible future conditions [1]. Concepts and model scenarios are generated in architecture as abstract representations of possible future actions and interactions that have not been realized yet [2]. Specific

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design attributes are introduced in architectural design to grant it anticipatory capacity to achieve its goal.

Many researchers and practitioners predict human-centered, embedded computing technology to play a crucial role in our interaction with surrounding built environment in the coming years [3]. Embedded computing has increased mobility and given rise to a new breed of highly mobile, technology-dependent, wireless professionals, or *neo-nomads*, who can work and communicate remotely [4]. Popularly known as Silicon Valley workers, this specific segment of the population inhabits a dematerialized world of portable computing, mobile technology, digital and social media, and continuous online presence. The past decade has witnessed a rapid increase in the number of new generation freelance professionals characterized by their digital dependence and nomadic “location independence” in pursuit of remote jobs at various technology hubs around the world [5]. In San Francisco, the booming industry of internet, social media and smart phone technology has brought in a recent influx of tech literate, young professionals and entrepreneurs [6]. Silicon Valley workers are currently facing a severe housing crisis due to space shortage, higher rent, and job growth [7].

The phenomenon of transitional living of rapidly growing information-age professionals has prompted researchers to seek new design vocabularies for computer-mediated spatial solutions [8]. One of the main criticisms of the current trend of habitable interactive architecture is its disregard towards spatial thinking of traditional architecture [9]. These researchers urge designers to explore interactive technology as a creative design means in the conceptual, aesthetic, and functional aspects of architectural space-making to meet emerging needs and lifestyles [3].

This paper proposes design possibilities of an interactively modifiable space through spatial articulation in real time. Here, *spatial articulation* refers to modification of overall visual quality of space, i.e., character, feel, and appearance, by manipulating the variables of visual space perception. These variables include, but are not limited, to light, material, color and texture [10]. The design goal is to support neo-nomadic lifestyle. Occupant has the ability to dynamically change spatial quality of a sensor-driven interactive living space for the purpose of satisfying emotional and psychological requirements associated with daily living. These generally include feelings of security, intimacy, creativity, contemplation and spirituality. This paper analyzes proposed design concept to demonstrate the process in which interactive architecture anticipates to achieve its goal.

2 Background

This section provides a brief overview of space-making traditions in anticipatory architecture and the relation between architectural space and human emotions. It further discusses the notion of interaction in architecture, current trends, and criticisms of habitable interactive architecture.

2.1 Space-Making in Anticipatory Architecture

Space creation, reorganization and articulation techniques of traditional architecture extend beyond the physical boundaries of space. Spatial narratives are constructed at conceptual, creative, aesthetic, and psychological realms structured around subjective human perception, imagination, and emotion. Perceptual process of visual quality of space depends on the visual properties of architectural elements that construct it and their interrelationships [11]. These properties include color, material, texture, size and shape.

Anticipatory architecture explores spatial possibilities in both functional and experiential aspects of design. Each space-making element brings with it anticipated intentions of possible spaces and functions that may form around it. A degree of uncertainty is acknowledged in the design process of anticipatory architecture. Possibilities in spatial transformations, layouts and articulations are offered to prepare for needs that may arise in regards to evolving environmental, demographic, social, cultural, economic and technological factors.

Various traditional and vernacular architecture offer space use possibilities through modularity, courtyard systems, and movable partitions to accommodate diurnal and seasonal domestic activities [12]. Anticipatory architecture also explores the interrelationships between light, materiality, and form for possible spatial articulations to create sensory perceptive, visually engaging spatial experiences. Through formal manipulations and juxtapositions, Corbusier's Chapel of Ronchamp uses the capacity of natural light, materiality, and color to explore dynamically evolving experiential spaces.

2.2 Aesthetic and Emotional Spaces

In *The Poetics of Space,* Bachelard explains the perceptual process of space as a subjective reconstruction of memory and imagination [13]. The spatial, architectural imageries and sensations associated with one's memories of past lived spaces are intertwined with symbolic meanings, dreams, and subjective interpretations. The openness, enclosure, warmth, lightness, and darkness of the "fragments of space" of past domestic habitat are charged with emotions and feelings of safety, solitude, intimacy, creativity and/or danger [13, p. 9].

Renowned architect Louis I. Kahn believed that a room's size, surfaces, openings and lighting combined have an influence on the occupant's mood and action in that space [14]. Many architects actualize spaces with psychological and emotional dimensions by exploring the cultural and temporal meanings of natural light, material, color, and texture. The psychological and metaphysical aspects of character, temporality, permanence, or impermanence of natural light and material provide imaginative dimension to the perceived space [15]. Aesthetics of space rely on the meaningful emotions that emerge from subjective meanings, essences and sensuousness of light and material as sensory elements [16]. Some spaces have aesthetic dimensions that carry higher levels of consciousness. The large central space of Kahn's Exeter Library has no other programmatic function but to provide inspiration and excitement [17].

2.3 Human-Space Interactions and Interactive Spaces

In this paper *interaction* is understood as a simple input-output mechanism that is similar to McCullough's definition of a "deliberative" two-way exchange between man and machine [18, p. 20]. An action or input must be reciprocated with a deliberate response or output in order to complete an interaction. In architecture, human-space interaction occurs when physical space changes shape or appearance in response to an input or action from the user. An occupant can interact with an enclosed physical space by adjusting movable partitions and modifying its spatial quality. As an active participant in this interaction, the occupant personalizes and customizes living space by formulating physical, emotional, aesthetic, and social meanings [19].

In recent years, human-centered information technology has moved towards socio-cultural, artistic, mobile, and embodied human interactions [18]. Technological innovations have facilitated new forms of human-space interaction [20]. In interactive architecture, interaction between human and built environment is enabled by integrated or embedded computing technology in the form of microchips and sensors. The "interactive essence" of computing technology can enable buildings or spaces to embody interconnectedness of information technology, respond to human and environmental input, and acquire sensitivity to behavior [21, p. 25]. These include the potential for constant formal and visual change, reconfiguration, and personalization. Sensors receive signals from users and reciprocates automatically [22].

Embedded computing has also triggered "embodied" interaction with the physical world in real time against physical and social settings [23, p. 102]. The last decade has seen an upsurge of innovation in interactive materials that inspired development of a variety of spatial art installations of urban scale with both embedded and embodied computing. Materials, especially textiles, with embedded sensors change color and luminance, move and shrink or expand in response to human touch and sound [24]. These spatial studies explore bodily and sensory engagements with space, and challenge traditional ways of perception, navigation, and interaction with space [19].

2.4 Current Trends of Interactive Architecture

In the emerging field of interactive architecture, buildings embody wireless interconnectedness, use sensor operated kinetic elements and controls for space and energy optimization, and explore communication possibilities of programmable digital surfaces [25]. Some researchers predict embedded computing technology to change human relationship with built spaces in the coming years and stress the urgency of research on computer-mediated spatial solution for contemporary “information-able” architecture [21, p. 25]. However, a growing number of researchers and practitioners criticize current practices of habitable interactive architecture for their market-driven goals and surface-deep focus on gadget and media design [8]. Others criticize the preference of digital displays of interactive systems over the aesthetic and functional roles of physical, material spatiality of the building [9]. They urge designers to understand and integrate traditional architectural space-making practices in their exploration of computer-mediated interactive living spaces.

3 Anticipatory Interactive Space Design

This section introduces an interactive architectural design concept that is anticipation-driven. The design begins with a goal to support the neo-nomadic lifestyle that involves accommodation of psychological and aesthetic requirements associated with daily living. Design aims to evoke and enhance feelings of security, creativity, intimacy, spirituality, contemplation or any other moods and emotions that the occupant desires. Design is analyzed and exemplified with respect to its capacity to generate possible spatial articulations to meet its goal.

The proposed design constitutes a single space enclosed by programmable, interactive planar surfaces. Embedded sensors can track user input and articulate space in real time by modulating light, material, color, and texture of walls, floor, and ceiling (Figs. 1 and 2). Occupant thus has the ability to modify any or all interior surfaces and customize living space in an attempt to suit his/her psychological needs. The living space also has the capacity to respond to environmental input. With abstract representations of modulated light, material, color, and shadow, interior space reflects external weather conditions, and diurnal and seasonal changes to perceptually situate occupant with the physical world (Fig. 3).

3.1 Enabling Anticipatory Capacity

In the design planning stage, known needs, desires, and expectations are identified and probabilities are predicted to establish a possible future design state that has an impact on the present state [26]. Background research is performed at the early conceptual phase of the design process to determine design criteria for the neo-nomadic *action-space*. Possible future design states are established based on observations, literature, and subjective personal experience in regards to individual, socio-cultural, economic, and technological aspects of neo-nomadic lifestyle. Study

Fig. 1 A single space enclosed by modifiable interactive surfaces

suggests a dematerialized context for target occupants who are highly adaptive to new settings and have no fixed sense of belonging [27]. A transitional, temporal, and highly optimized living space is proposed for target occupants that can potentially support their minimalist lifestyle and constant mental shift from living to work, personal to social, and physical to digital.

Specific attributes are integrated in the design to grant it the anticipatory capacity to achieve its goal. One design attribute is the interactive surface with embedded sensors that has the capacity to modulate appearance of architectural surfaces in response to human input. Interactive surfaces also have the capacity to generate human-space interaction. The other attribute is the application of traditional space articulation technique with light and materiality that, if examined and understood, has the capacity to create strong, sensory spatial experiences. The design infers interactive technology to trigger human-space interactions that articulate space in real time and produce a set of spatial possibilities.

Fig. 2 Manipulation of surface texture, color, light and shadow can change the visual quality and character of a living space. User can customize one or more enclosing surfaces in an attempt to suit his psychological needs

The sensory-rich spatial articulations with light and materiality are constructed around subjective perception, imagination and emotion. Through sensory engagement, design sets a stage for possible psychological scenarios to emerge.

Fig. 3 Interior surfaces can be modified to reflect abstract representations of external weather conditions, diurnal and seasonal changes

3.2 Anticipation in Human-Space Interaction

For a space that is impermanent and dynamically evolving, the anticipation in architectural elements that construct it is challenged. The interactive surfaces shift to the foreground as active participants engaged in a continuous dialogue with the occupant in the human-space interaction process of an interactive space [25]. This dialogue is facilitated by possible experiential qualities of living space formulated around human emotion, its influence on perceptual process of space, and meaningful connection to human experience.

The human-space communication relies on satisfactory subjective interpretation of spatial goal or creation of new goals [25]. Each spatial experience is informed by prior experience and interpretation of spatial feedback that can potentially inspire new sets of anticipation. The occupant decides to interact in anticipation of possible spatial feedbacks. The occupant's awareness of his/her decision-making abilities changes his/her relation to domestic space.

Here, human-space interaction is a creative exploration of experiential space-making. Creative and aesthetic processes are driven by imagined ends with underlying anticipations of possible outcomes [1]. In a constant personalization and customization of space, the occupant's creative exploration of space-making has imagined goals, driven by formulation of possible physical, emotional, social, and aesthetic meanings and interpretations. Aesthetic experience is also sought in the real-time interaction with architectural spatiality, as well as in the temporality of materials [28].

3.3 Testing Method

Models can be created to test and verify if user's interaction with space and response to spatial changes reflect design anticipations [29]. Cave Automatic Virtual Environment (CAVE), a four-sided, room-sized Virtual Environment can be used to simulate proposed interactive space at full scale (1:1). This technology can closely recreate the reality of authentic physical world experiences and allow the user to move and view space with enhanced feeling of presence [30]. A small group of target occupants can experience and interact with simulated interactive space. The user's subjective perception of space, aesthetic and emotive responses, as well as space usage preferences can inform designer the extent to which designed anticipation has been realized. The testing process may inspire creative, playful exploration of space. It can thus challenge and redefine conventional expectations and interactions with domestic living spaces and give rise to new sets of design anticipations.

4 Conclusion

The design attempts to provide a platform for further research and experimentation in the realm of interactive architecture that is physical, tangible, and essentially spatial in nature. This study attempts to investigate possible human interactions in and with emerging computer-mediated living spaces. It also explores the capacity of interactive technology to participate in the anticipatory design process of architecture. Test results of Virtual Environment simulation can potentially enrich future research in defining the field of interactive architecture. In the wake of a severe housing crisis affecting Silicon Valley workers, the paper proposes a possible design solution that is humane and aesthetic and which focuses on space optimization.

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