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TECHNICAL CONTRIBUTION

Higher-Level Cognition and Computation: A Survey

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Abstract Higher-level cognition is one of the constituents of our human mental abilities and subsumes reasoning, planning, language understanding and processing, and problem solving. A deeper understanding can lead to core insights to human cognition and to improve cognitive systems. There is, however, so far no unique characterization of the processes of human cognition. This survey introduces different approaches from cognitive architectures, artificial neural networks, and Bayesian modeling from a modeling perspective to vibrant fields such as connecting neurobiological processes with computational processes of reasoning, frameworks of rationality, and non-monotonic logics and common-sense reasoning. The survey ends with a set of five core challenges and open questions relevant for future research.

Keywords Higher-level cognition · Cognitive and computational modeling · Artificial intelligence · Reasoning · Problem solving

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1 Introduction

Humans are able to perceive their environments, integrate information into mental models, exchange information, act, feel, derive new information, and they can learn—they are prototypical *cognitive agents*. And their ability to perform successfully in different domains is what makes them superior over typical specialized AI approaches. But the two fields, cognitive science and artificial intelligence, have much in common: Cognition usually refers to an information-processing perspective of mental abilities [47]. This approach gives rise to a fruitful analogy between the hard- and software of computers and the human brain and mind. Cognition can be described by computational processes. Computational processes, including rule-based as well as artificial neural network models, are the current best approaches to describe and/or predict cognitive processes. Several researchers [1, 21] proposed to model human cognition by production rule systems such as *Adaptive Control of Thought Rational* (ACT-R, e.g., [2]).

But what is the definition of higher-level cognition? It often refers to cognitive abilities like language, reasoning, planning, and problem solving. In contrast, low-level perceptions like seeing, hearing, etc., are often not considered to be part of these processes. However, the boundaries are not strict, interpreting complex visual input can require demanding higher-level cognitive processes, and seeing for instance can be influenced by higher modeling processes. Higher-level cognition is connected to the term complex cognition. Complex cognition has been defined, e.g., by Knauff and Wolf [26], as processing of information to make implicit information explicit or to derive new information "with the intention to make decisions, solve problems, and plan actions". Funke [15] points out that "this approach assumes an active and goal-directed information-processing by human beings who are able to perceive their environment and to use their memory. The term 'mental processes' is not restricted to cognitive ones, but includes motivational and emotional processes at the same time". We will use these definitions to define (and contrast) higher-level cognition in the following. Hence we propose to define higher-level cognition by cognitive processes that contain at least the following four aspects (adapted from [15]):

1. Processing of information to derive new information to make decisions, solve problems, or plan actions.
2. It is a goal-directed process; most processes require a form of attention.
3. Diverse cognitive sub-systems are contained, e.g., perception systems, and declarative and procedural memory; these processes and diverse information needs to be integrated.
4. Information needs to be interpreted or exchanged (e.g., language processes are relevant) and information needs to be reframed.

Although there are many possible mental processes involved in cognition, they can be broken down into roughly two aspects: First, how do humans internally represent and store information? Second, how do humans process the information, to perform a task, e.g., derive a conclusion in a reasoning task? In contrast to AI systems that have been built, the human brain is more a "black box" and many cognitive functions and their neural implementations must be "reverse-engineered". Typically, cognitive scientists perform experiments to have data that either support a theory or exclude whole classes of theories. Cognitive theories can be characterized on three levels (inspired by Marr [28]): The theories can describe cognitive processes on a purely symbolic level (e.g., by mathematical differential equations or logic), the theories can be on an algorithmic level (in the form of a computer program), or they can be on an implementational level (e.g., how are cognitive functions implemented in the human brain). All three levels can contribute to an understanding of cognition. A major problem is the symbolic-subsymbolic connection realized in the human brain: We all perceive cognition as symbol manipulation, e.g., in language or reasoning terms. On the other hand, many implementational theories focus on neuronal networks. How does symbolic reasoning emerge from neural networks? This grounding problem poses a great difficulty to modeling cognition.

Cognitive theories can be described as competence and performance theories. Competence theories try to show what from specific assumptions and modeling approaches can follow. Performance theories aim at making predictions about how the average participant may behave with respect to given answers, typical error, response times, attention focus, etc. These performance measures can serve as test criteria for a cognitive theory. Cognition can cover, as we have seen, many different cognitive aspects. In the following we will mainly concentrate on reasoning.

2 Cognitive Theories

For all parts of human cognition, from memory over language to reasoning, cognitive theories have been developed [2]. In some research areas cognitive theories excel in predicting human performance. Other areas of human cognition are less understood. Let us consider deductive reasoning with quantifiers, so-called syllogisms. Syllogistic reasoning has been proposed 2500 years back by Aristotle and has been investigated for about 100 years from a psychological perspective [45]. The core problems consisting of two premises and the quantifiers All, Some, Some not, and None, form 64 problems. At least 12 cognitive theories have been developed during the last hundred years to explain errors that humans are performing.

A recent meta-study [24] showed that any of the proposed 12 reasoning theories deviates considerably from the empirical data. In other words, there is so far no cognitive computational theory for the 64 syllogistic reasoning problems—that are easy from a computational perspective—where human performance can be predicted. But the problem goes further, because general approaches are rare. There is so far no general or unified theory about human cognition covering several cognitive subtasks. Best approaches are cognitive architectures (see next section); they try to identify common grounds (often parameters) that should be general. An example is the memory activation function in ACT-R that represents the decay of information or the way information is represented and processed. Many cognitive theories of reasoning can be characterized as being logical, model-based, probabilistic, or heuristic approaches [23].

It has been questioned, however, if humans do reason according to propositional or first-order logical accounts. A classical example is the *Wason selection task* [53] that shows that humans make consistent errors in evaluating the *modus tollens* or as a more recent example the *suppression task* that shows that humans may reason non-monotonically [43]. Consequently, recent approaches have focussed on ternary approaches like Kleene and Lukasiewic logic to explain humans deviation [11, 43]. Recently, mental simulation as a more dynamic approach has been introduced [19, 24]. A more extensive description of cognitive theories from an AI perspective can be found in [47]. Another direction comes from the field of psychometric artificial intelligence [4, 6, 7]. The goal is to assess artificial cognitive systems on intelligence tests such as Raven's matrix tests and many other inductive reasoning problems [20, 36, 40]. Again many systems perform well on specific domains—a general approach is missing.

3 Cognitive Models and Architectures

The rise of cognitive modeling is strongly connected to advances in cognitive science and AI. The first emerged about 30 years ago and covers research about reasoning, problem solving, language, and perception and provides the field of research. Research on AI has started at the Darthmouth conference in 1956 and the interest in modeling theories by computer models grew stronger. The advantage is obvious: Once conceptually defined, cognitive theories are algorithmized, theory gaps become visible and theories can make precise predictions the performance of humans.

A possible definition for cognitive architectures is that they are unified approaches implementing assumptions about our cognitive structure, like working memory, and how the information is distributed across assumed cognitive modules. Most cognitive architectures have been strongly influenced by the General Problem Solver (GPS) that has been proposed and developed by Newell and Simon [33]. Most of the existing cognitive architectures are implemented as production rule systems such as GPS. Production rule systems contain production rules and they consist of condition-action-rules that "fire" (they are executed). A sequence of such production rules can be compared to mental processes. The set of these production rules are called procedural knowledge. Another form of knowledge is declarative knowledge, it deals with the representation of facts and knowledge. Examples of such cognitive architectures are ACT-R 6.0, 4-CAPS, and CLARION. ACT-R 6.0[1] as a hybrid architecture [2] consists of psychologically plausible modules for representation (e.g., *visual, aural*), goal representation (*goal, imaginal*) and buffers. Applications of these models are learning, working memory, problem solving, and Human-Computer-Interaction (HCI). SOAR[2] (States, Operators, And Reasoning) [32] can both be used to model cognitive aspects and to deal with AI problems.

A general criticism is that the existing "cognitive architectures" contain too few constraints and that they are often Turing-equivalent, such as ACT-R [1]. Since cognitive modeling aims at excluding cognitive model classes, a Turing-equivalent architecture might not provide enough restrictions.

A recent approach aiming at the investigation of fundamental structures of the human mind is CLARION[3] [49]. This system provides a modular structure analogous to ACT-R, where all subsystems are based on neural nets (in contrast to ACT-R). Restrictions in CLARION are emerging from this neural grounding. Task specific cognitive processes, e.g., playing Tower of Hanoi or a human flight simulator, are described by cognitive models. Such models exist for SOAR (for an overview see [27]), ACT-R 6.0, and others. Hence cognitive models are algorithmizations of psychological theories.

A different approach are neurally inspired architectures with one of the most prominent being Nengo [14]. The simplest representation are groups of neurons and connection with weights between these neural groups. Nengo is based on the Neural Engineering Framework (NEF) to compute the "appropriate synaptic connection weights". The current models cover visual attention, working memory, motor selection, and inductive reasoning among others.

The goal of any of these architectures is to make precise performance predictions for the reasoners, e.g., to predict the answer of the participants, the time to give answers, and recently eye movements and brain activations. Simon and Wallach [41] (cited after [46]) argue that good models and generative theories should contain several of the following steps:

1. *Product correspondence*: This requires that the cognitive model shows a similar overall performance as human data.
2. *Correspondence of intermediate steps*: This requires that assumed processes and steps in the model parallels separable stages in human processing.
3. *Temporal correspondence*: This requires that computational process times (or assumed temporal costs) parallels reaction and answer times.
4. *Error correspondence*: This requires that the same error patterns in the model emerge than in experimental data.
5. *Correspondence of context dependency*: This is a comparable sensitivity to known external influences.
6. *Learning correspondence*: This requires a similar or identical learning curve between the humans and the model.

This impressive list already shows that generative theories can be tested and falsified in a number of ways. The more cognitive models fulfill these aspects the more cognitive-adequacy they capture. However, a major problem is that experimental psychological research aims at the mean performance of a group of participants. This can distort the findings. Better models aim at modeling individual performance. To define benchmarks is often not so easy since

1 http://www.act-r.psy.cmu.edu

2 http://www.sitemaker.umich.edu/soar

3 http://www.cogsci.rpi.edu/ rsun/clarion.html

many cognitive models are domain-specific, i.e., they can be applied to the field of syllogistic reasoning, planning with Tower of London, or recognition memory and, hence, they cannot be applied to other domains as well—in contrast to human abilities. So these two aspects may extend the list of Simon and Wallach.

3.1 Artificial Neural Networks

A different perspective on cognitive modeling are subsymbolic models which can be categorized as models on the implementational level [28]. Artificial neural networks [30] or connectionist models are inspired by human neural representations and they are excellent with respect to the learning aspect. Formal neurons are strong reductions of brain neurons. For instance, only the electric potential is modeled, but not, e.g., the neurotransmitter in synapsis. And the ANN-architectures are from their structure more regular than real neurons. Most proponents see connectionism as computation models and not as models of biological reality. Recent advances cover also complex cognition problems like the dynamic water flow problem [38], and number series sequences can be solved by artificial neural networks. The basic idea is to consider such inductive reasoning problems as learning problems, instead of finding "intuitively" a solution, or searching a larger space, a third idea is to learn the underlying function [37]. A disadvantage of an ANN is that there is no obvious connection to the symbolic level (see above), and it is more difficult to develop a complexity measure using artificial networks as underlying computational model.

3.2 Bayesian Modeling

The use of Bayesian cognitive models, i.e. models that are based on Bayes formulae (e.g., in reasoning) has been called the "new paradigm" or the "Bayesian turn". The principle idea is that mental processes are strongly connected to information-processing approaches. Proponents of these approaches, however, claim that, although the human mind might learn using Bayesian inferences, that does not mean that the mind implements Bayesian inferences [51]. Bayesian models can be connected to using heuristics and reasoning about background knowledge [35]. This approach has been successfully applied to inductive learning [50], causal inferences [17, 18, 44], and language processing [8, 54] among others.

4 Employing Automated Reasoning

Cognitive science as the interdisciplinary scientific study of the mind and its processes includes research on intelligence and behavior. In the cognitive paradigm, knowledge representation using methods from AI and computer science, the human consciousness and situations of the real world are described by natural and formal languages as cognitive processes. The assumption is that there are cognitive processes in the human brain which can be formally represented together with related knowledge by computational means.

In order to automatize this reasoning process, several calculi for automated reasoning have been developed. The study of automated reasoning [39] as an area of computer science and mathematical logic dedicated to understanding different aspects of reasoning helps to develop computer programs that allow computers to reason completely, or nearly completely, automatically. The development of formal logic played a major role in the field of automated reasoning. In the early years, it concentrated on the development of calculi for classical propositional and first-order logic. Reasoning with the *modus ponens* or *modus tollens* has a direct counterpart in automated reasoning systems.

Effective reasoning procedures make applications such as question-answering systems possible. For this, language knowledge has to be exploited to extract the logical content of the question. This is, e.g., the procedure in the LogAnswer system [16]. After that, together with background knowledge, answers can be derived by an automated reasoning process. Background knowledge is available via online resources like the Wikipedia encyclopedia[4] on the one hand and provided on the other hand by knowledge bases in form of ontologies like Research Cyc [29], Yago [48], or others.

4.1 Common-Sense Reasoning

In contrast to plain automated reasoning, systems implementing approaches of higher-level cognition must be able to deal with large knowledge bases, because they exploit implicit background information and thus must have access to a variety of knowledge that often cannot be restricted to a clearly specified and restricted domain. On the one hand, these knowledge bases are often inconsistent. On the other hand, they may be incomplete, i.e. not sufficient to solve a given problem. Thus, in the context of incomplete and inconsistent knowledge, we still have to reason validly. This requires mechanisms to draw conclusions even in cases of incomplete or inconsistent knowledge. This is even more important for higher-level cognition, since human reasoning does not strictly follow the rules of classical logic (see above). It requires a number of different approaches from abductive and defeasible reasoning, and finally common-sense reasoning.

[4] http://www.wikipedia.org

According to Mueller [31], common-sense reasoning is the sort of everyday reasoning humans typically perform about the world. It allows to derive knowledge about continuity and object permanence, e.g., if a person enters a room, then afterwards, the person will be in the room, if she has not left the room. Additionally, there is no bilocation, i.e., a person cannot be in two places at once. If a person moves from one location to another, and carries an object, then the object moves the same way. We have knowledge about objects, events, space, time, and mental states and may use that knowledge. All this implicit background knowledge is part of everyday human reasoning and must be added to a cognitively adequate automated reasoning system.

4.2 Defeasible Reasoning and Argumentation Theories

We often derive conclusions under the assumption that nothing abnormal is known, i.e., that we do not have evidence that the conclusion is false. According to Nute [34], human reasoning often is defeasible in consequence: For instance, if a reasonable person receives a letter stating that she had won a million dollars, the first consideration deals with the question: Is there any evidence that the letter is a hoax or misleading? And only then the reasonable person may make plans to spend the money. Sometimes, in everyday life, we may arrive at conclusions which must later be retracted when contrary evidence becomes available. The contrary evidence defeats earlier reasoning.

Defeasible logic programming together with argumentation theory is considered a logic programming formalism which relies upon defeasible argumentation. It has proven to constitute a simple—yet expressive—language to encode rule-based knowledge with incomplete and potentially inconsistent information. It combines strict logical rules and defeasible rules. Answering a query in defeasible logic programming gives rise to a proof for the query, involving both strict and defeasible rules, called argument. In order to determine whether the query is ultimately accepted as justified belief, a recursive analysis is performed which involves finding defeaters, i.e. arguments against accepting the argument, which are better than the argument (with respect to a preference criterion). The references [5, 9, 13] provide a good overview on the field. There are also ranking theories of knowledge [42].

4.3 Non-Axiomatic Logics

One problem with classical logic formalisms may be that explicitly axiomatized logic is suitable only for an idealized situation. The initial knowledge is represented as axioms, and all solutions to the problems are provided by the theorems derived by deduction. However, in realistic situations it must be assumed that only insufficient knowledge and resources are available. Therefore, Wang [52] proposes a non-axiomatic reasoning mechanism aiming at artificial general intelligence, which is less anthropocentric than specific approaches from cognitive science. The theory contains grammar and inference rules. While grammar rules define the format of the representation language used in the system by specifying how an acceptable sentence can be composed from words and phrases, inference rules define the patterns of valid reasoning in each inference step, where certain sentences are derived (as conclusions) from some given sentences.

5 Current Directions, Projects, and Works

The number of book publications about higher-level cognition is steadily rising and contains many popular bestsellers [3, 22, 25]. This shows the high interest of researchers and of the society in higher-level cognitive processes such as reasoning and decision making. New research paradigms and approaches concentrate on combining methods from different fields, questioning assumptions, and investigating complex tasks.

The recently ended SFB/TR 8 *Spatial Cognition*[5] has approached the question of the “acquisition, organization, and utilization of knowledge about spatial objects and environments, be it real, virtual, or abstract, human or machine”. It has combined methods from AI, cognition, linguistics, and robotics. The findings covered many research areas, lead to exciting collaborations and findings about the way human represent reasoning.

Another interesting question is whether past research has considered the wrong frameworks while evaluating human answers. As outlined above, humans do significantly deviate from predictions of classical propositional logic. So, if we evaluate human reasoning with respect to propositional logic then human reasoning can be considered erroneous. If, however, human answers are compared to predictions made by Lukasiewic logic than the answers do not deviate strongly [10–12]. Such questions about the underlying framework is investigated in the SPP 1516 *New Frameworks of Rationality*.[6] It covers this interest by combining research interests of philosophers, psychologists, and computer scientists to understand and identify implicit assumptions and characteristics about human reasoning especially concentrating on inductive domains.

[5] http://www.sfbtr8.spatial-cognition.de

[6] http://www.spp1516.de

Connections between higher-level cognition and symbolic computation models and the neural implementation grow stronger. Cognitive and computational models grow more complex, for instance, Spaun [14] consists of 2.5 million neurons and the trend increases to build realistic neural models of the human brain, e.g., in the Human Brain Project[7] of the EU and the BRAIN Initiative of the US-American National Institute of Health.[8] These investigations can have consequences on a neuronal foundation of higher-level cognition and in general to research investigating *Mind-Brain-Mapping*. Connected is the question if we can link our brains to external devices.[9]

6 Conclusions

Higher-level cognition and computation is a vibrant, multi-layered field and covers many other disciplines from psychology, cognition, computer science, artificial intelligence, and robotics. Theories and models about higher-level cognition can cover *symbolic*, *connectionistic* or *hybrid* models and include one or several modeling levels. Although many models are specific for some cognitive tasks architectures aim at combining theories towards a unified approach of cognition integrating several cognitive aspects, from working memory over perception to problem solving and language. AI has provided many ideas, approaches and tools to describe human higher-level cognition approaches. The advantage of implemented algorithmic theories is that they make precise predictions, can be implemented in artificial agents, can be evaluated, combined and improved. Despite a deeper understanding of human cognition and many exciting results some challenges remain. Some of these important challenges can be characterized as following:

1. What is the appropriate cognitive-adequate representation for symbolic processes in human cognition?
2. How can the symbolic-subsymbolic gap be overcome? What can we learn from the neural representation for higher-level cognition?
3. How can cognitive theories be adequately assessed? What could be general benchmarks?
4. Can cognitive models be turned into effective computational theories and, if yes, with which formalism?
5. What makes embodiment so central for human cognition? What are possible consequences for cognitive systems and artificial intelligence?

These five questions (and possibly many others) can lead to important improvements to build better cognitive systems, to provide a deeper understanding of human psychology and the interplay with neurobiological processes and helps us to understand the particularities of human cognition.

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[7] http://www.humanbrainproject.eu/de

[8] http://www.nih.gov/news/health/sep2013/od-16.html

[9] http://www.brainlinks-braintools.uni-freiburg.de

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