Answering Curious Questions about Artificial Intelligence*

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Abstract. Using the contemporary theories and views of computing and of cognitive systems we indicate plausible answers to the following frequently asked questions about artificial intelligence: (i) where knowledge comes from?; (ii) what is the "computational power" of artificial cognitive systems?; (iii) are there "levels" of intelligence?; (iv) what is the position of human intelligence w.r.t. the "levels" of intelligence?; (v) is there a general mechanism of intelligence?; (vi) can "fully-fledged" body-less intelligence exist?; (vii) can there exist a sentient cloud? (viii) how can new knowledge be generated? The answer to the first and the last question stems from the novel view of computation which is seen as a knowledge generating process. For the remaining questions we give qualified arguments suggesting that within the large class of computational models of cognitive systems the answers are positive. These arguments are mostly based on the author's recent works related to this problematics.

Keywords: cognitive systems, computional models, non-uniform evolving automaton.

1 Introduction

Let us consider the following eight questions from the domain of artificial intelligence, all motivated more or less by curiosity: (i) where knowledge comes from?; (ii) what is the "computational power" of artificial cognitive systems?; (iii) are there "levels" of intelligence?; (iv) what is the position of human intelligence w.r.t. the "levels" of intelligence?; (v) is there a general mechanism of intelligence?; (vi) can "fully-fledged" body-less intelligence exist? and, last but not least, (vii) can there exist a sentient cloud? (viii) how can new knowledge be generated?

Undoubtedly, these are interesting questions to which qualified answers can only be obtained within the framework of the contemporary theories and views of computing and of cognitive systems. The mere fact that we are able to answer the above mentioned questions indicates that the underlying theories are really quite

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matured. We will see that when looking for the respective answers, our quest will be based on very recent results in epistemology and theory of computer science, indeed. The respective results concern a novel view of computation or non-standard computational models of cognitive systems.

The new view of computation is based on the recent work [1] where computation is seen as a knowledge generating process. Such an approach differs from the classical approach which sees computation as a process transforming information. The new approach concentrates to the main purpose of computation – i.e., knowledge generation – which presents the basis of intelligence. The non-standard computational models of cognitive systems used in the sequel cover a truly large class of systems. They present an important tool for investigation of cognitive systems since until now no cognitive mechanisms among natural cognitive systems (living organisms) have been identified that could not be modelled computationally. Our arguments will be based on four computational models each of which captures a different aspect of computational cognitive systems. In all cases, the answers are based on the recent work co-authored by the present author.

2 Answering the Questions

In order to give qualified answers to our questions we will refer to the recent results from philosophy of computation and to various non-standard computational (or algorithmic) models of general computational or specific cognitive systems.

The first and the last question concerning the origin of knowledge will be answered by referring to the recent idea that defines computation as knowledge generation process. The remaining answers will refer to various models of non-standard computations. While general computational models are suitable for answering very broad questions concerning the "power of AI" (questions (ii),(iii) and (iv)), answering a more specific question (v) and (vi) will need a fairly evolved model of an embodied cognitive agent with a specific internal structure. Question (vii) will be answered with the help of answers (v) and (vi) and of yet another unconventional model of general computations. Answer to question (viii) follows from (i) and (v).

2.1 Where Does Knowledge Come from?

Knowledge seems to be essential ingredient of intelligence: only knowledgeable agent can make the best of its intelligence. But – what is knowledge? What is the source of knowledge? How does an agent acquire it?

The questions related to the notion of knowledge are traditionally studied in epistemology which is the branch of philosophy concerned with the nature and scope of knowledge. Being a philosophical discipline, epistemology is more concerned with the definitions of knowledge, its characterisation and its relation to related notions such as truth, belief, and justification, and less in principles and mechanisms of knowledge acquisition and creation. Nevertheless, exactly the latter concern is central for understanding and designing knowledge processing algorithms which seem to be necessary for any artificial system displaying intelligence.

First of all – what is knowledge? It is an elusive notion which resists any generally accepted definition. If we are after a short definition, one of the shortest ones could be *"knowledge is facts, information, skills or behaviour enabling problem solving"*. In Wikipedia, one can find a more extended definition:

> Knowledge is a familiarity with someone or something, which can include facts, information, descriptions, skills, or behaviour acquired through experience or education. It can refer to the theoretical or practical understanding of a subject. It can be implicit (as with practical skill or expertise) or explicit (as with the theoretical understanding of a subject); it can be more or less formal or systematic. [2]

Now – where knowledge comes from? In their recent paper, Wiedermann and van Leeuwen [1] have offered an interesting answer: *knowledge is the result of computation*. More precisely, they have coined a novel view of computation, seeing it as a process generating knowledge. In [1] the following thesis is proposed:

Thesis 1. *Computation is the process of knowledge generation.*

This thesis is supported by the evolution of application domains belonging to various type of computation. Roughly, the respective development starts with the classical Turing's acceptors and recognisers [3, 4], producing single bit of knowledge, proceeds via scientific computing delivering knowledge in the form of solutions of mathematical problems, further through operating systems, which generate knowledge controlling the behaviour of computer systems, and ends, so far, with the current search engines and question-answering systems delivering general encyclopaedic knowledge. The trend towards artificial general intelligence (AGI) systems capable to produce any human–like knowledge is clearly visible.

It is important to realise that a computation generates new knowledge based on the knowledge that is implicitly represented in the design of the computational system or is even explicitly stored within the knowledge base of such a system. Thus, one can say that knowledge generates knowledge.

It is advantageous to see knowledge contained in any computational system as a certain (more or less formalised) theory that is pertinent to a knowledge domain over which the system works and which is used by the systems in order to deliver its output.

If an agent can learn, then there are many ways for it to acquire knowledge: by reason and logic, by scientific method, by trial and error, by algorithm, by experience, by intuition, from authority, by listening to testimony and witness, by observation, by reading, from language, culture, tradition, conversation, etc.

The purpose of the *knowledge acquisition processes* is to discover new knowledge, enter it into the system and to order it into the knowledge already existing in the system. That is, in order the enable its later reuse new knowledge must be properly embedded into the existing theory representing an agent's current knowledge. Hence, any knowledge acquisition process builds and updates the existing epistemic theories. In this sense, knowledge acquisition is also a process of knowledge creation within, or 'inside' the respective computation. This again can only be done via computation.

We conclude with the answer that knowledge comes from computation.

2.2 What Is the "Computational Power" of Artificial Cognitive Systems?

In answering this question we are only allowed to exploit a minimal set of properties of cognitive systems on which majority of us agree. Minimality in this case means that removing any property from our list will result into a systems which could no longer be considered to be a typical cognitive system. It is generally agreed that the minimal set of such properties is: *interactivity*, enabling repeated communication of a system with its environment, to reflect environment's changes, to get the feedback, etc.; *evolution*, i.e., a development of a systems over its generations, and, last but not least, a potential *unboundedness over time* allowing an open-ended development of a cognitive system.

Note that classical Turing machines which since Turing times have often been considered as "the computational model of mind" cannot model any fully fledged cognitive system – simply because such machines do not possess the above mentioned three properties. Hence their computational abilities and limitations cannot be considered to hold for cognitive systems.

Having in mind the above mentioned three properties of cognitive systems, in [5, 6] a very simple computational system – called *non-uniform evolving automaton* has been designed capturing precisely those properties.

Formally, a non-uniform evolving automaton is presented by an infinite sequence of finite–state transducers (FSTs). An FST is a finite-state automaton (FSA) working in a different input/output mode. Like any FSA, it is driven by its finite state control, but it reads a potentially infinite stream of inputs and translates it into an infinite stream of outputs. A non-uniform evolving automaton computes as follows: the computation starts in the first transducer which continues its processing of the input stream until it receives a so-called *switching signal*. If this is the case the input stream is "switched" over to the next automaton in the sequence. In general, a non-uniform evolving automaton is an infinite object. However, at each time a single transducer having a finite description is active. Switching among the transducers models the evolution of the system. The transducers in the sequence can be chosen in an arbitrary manner, with no classically computable relation among them. Thus, there might be no algorithm for generating the individual automata given their index in the sequence. This is why the evolution of the system is called non-uniform. In order to better model the "real" cognitive systems we may require that a specified subset of states of a given transducer is also preserved in the transducer in the sequence. In the language of finite transducers this models the persistence of data over generations of transducers. The switching signals are issued according to the so-called *switching schedule* that again can be a classically non-computable function. It comes as no surprise that a non-uniform evolving automaton, possessing non-computational elements, is a more powerful computational device than a classical Turing machine. For more details and the proof of the last claim, cf. [7]. Thus, the answer to the second question is that *interactive, non-uniformly evolving, and potentially time-unbounded cognitive systems (be it real or artificial ones) posses a super-Turing computing power: they cannot be modelled by classical Turing machines.*

Unfortunately, the super-Turing computing power of non-uniform evolutionary cognitive systems cannot be harnessed for practical purposes – it is only needed to precisely capture their computational potential, where the elements of uncomputability enter computing via unpredictable evolution of the underlying hardware and software.

2.3 Are There "Levels" of Intelligence?

For answering this question we will again consider the computational power of cognitive systems modelled by a non-uniform interactive automaton. Namely, for such automata one can prove that *there exist infinite proper hierarchies of computational problems that can be solved on some level of the hierarchy but not on any of the lower levels* (cf. [8]).

The interpretation of the last results within the theory of cognitive systems is the following one. There exist infinite complexity hierarchies of computations of cognitive systems dependent on the amount of non-computable information injected into such computations via the design of the members of the respective evolving automaton. The bigger this amount, the more non-uniform "behaviours" (translations) can be realised. Among the levels of those hierarchies there are many levels corresponding formally (and approximately) to the level of human intelligence (the so–called Singularity level – cf. [9]) and also infinitely more levels surpassing it in various ways. The complexity classes defining individual levels in these hierarchies are partially ordered by the containment relation.

2.4 What Is the Position of Human Intelligence w.r.t. the "Levels" of Intelligence?

There is increased theoretical evidence that the computational power of human intelligence (aided by computers or not) is upper bounded by the Σ_2 level of the Arithmetical Hierarchy.[1] This level contains computations which are recursive in the halting problem of the classical Turing machines. For instance, Penrose [11] argues that human mind might be able to decide predicates of form $\exists_x \forall_y P(x, y)$, i.e., the Σ_2 level. The computations within this class can answer the following

[1] Arithmetical Hierarchy is the hierarchy of classically unsolvable problems of increasing computational difficulty. The respective problems are defined with the help of certain sets based on the complexity of quantified logic formulas that define them (cf. [10]).

question related to the halting of the arbitrary (classical) Turing machines for any input: (*"Does there* exist *a Turing machine which* for all *Turing machines and* for all *inputs decides whether they halt?"*). Similar conclusions have been reached during the last few decades by a number of logicians, philosophers and computer scientists looking at the computations as potentially unbounded processes (cf. [12]).

A more detailed structural insight into the nature of computations in the Σ_2 level of the Arithmetical Hierarchy offers a recent model of van Leeuwen and Wiedermann [12] – so called *red-green Turing machines*. This model characterises the second level of Arithmetical Hierarchy in terms of a machine model.

A red-green Turing machine is formally almost identical to the classical model of Turing machines. The only difference is that in red-green Turing machines the set of states is decomposed into two disjoint subsets: the set of green states, and the set of red states, respectively. There are no halting states. A computation of a red-green Turing machine proceeds as in the classical case, changing between green and red states in accordance with the transition function. The moment of state color changing is called *mind change*. A formal language is said to be recognised if and only if on the inputs from that language the machine computations "stabilise" in green states, i.e., from a certain time on, the machine keeps entering only green states.

The model captures informal ideas of how human mind alternates between two states (accept and reject) when looking for a solution of a difficult decision problem.

Thesis 2. *The computational power of cognitive systems corresponding to human-level intelligence is upper-bounded by the class Σ_2 of the Arithmetical Hierarchy.*

Note that the previous thesis does not claim that the cognitive systems can solve all problems from Σ_2. Nevertheless, the example of the halting problem theorem shows that occasionally human mind can solve specific problems that in general belong to Σ_2 (for more details cf. [13]).

2.5 Is There a General Mechanism behind the Human–Like Intelligent Systems?

This is a very hard question, indeed. It can again be approached from the viewpoint of computations. If there were a different mechanism of intelligence than that we are aware today then there would be a notion of computation different from that we know about today. Note that we are speaking about computations, not about the underlying mechanisms. For all we know about computations today, there are many kinds of computations (deterministic, non-deterministic, randomised, quantum) each of which is characterised by a class of computationally equivalent mechanisms. We believe that this is also the case of cognitive systems which are but specialised non-uniform evolutionary computational systems supplied by information delivered, thanks to their own sensors and effectors, from their environment. (It is their environment that injects the non-uniform information into such systems, and their non-uniform development is further supported by Darwinian evolution.) Thus, one may characterise the mechanism of intelligent systems as any computational mechanism generating the class of computations (resulting further into behaviours) that those systems are capable to produce or utilise. For instance, for such a purpose non-uniform evolving automata will do. However, we are interested in a more refined, more structural algorithmic view of cognitive systems possessing high–level mental qualities, such as learning, imitation, language acquisition, understanding, thinking, and consciousness. What are the main parts of such systems, what is their "architecture", what are the algorithmic principles behind their operation?

The answer is offered by the high level computational models of cognitive agents aiming at capturing higher–level human–like mental abilities. Among them, the most advanced modes seems to be the model named HUGO (cf. [13]) (cf. Fig. 1) which is conformed with the recent state of research in the domain of embodied cognitive systems.

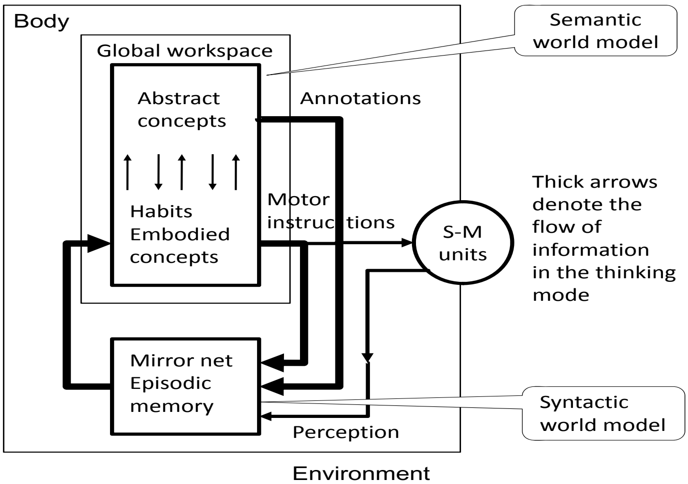

Fig. 1. The structure of a humanoid cognitive agent (HUGO)

The notable part of the scheme in Fig. 1 is the body represented by the sensory–motor units. These units are governed by the control unit consisting of two main parts called *syntactic* and *semantic world model,* respectively. These two world models are realised with the help of neural nets and are automatically built during the agent's interaction with its environment. The syntactic world model builds and stores the "database" of frequently occurring *multimodal units*, i.e., of tuples of sensory information and motor instructions that "fit together", make sense under circumstances corresponding to the given perception and proprioception. This database can be seen as a vocabulary of atomic units of behaviour that have turned out to be good in the past. The semantic world model connects multimodal units into a semantic net that captures often followed sequences of activations (usages) of individual multimodal units. In the series of papers [14], [15], and [13] algorithmic mechanisms are described leading to the algorithmic emergence of higher mental abilities, such as imitation, language development and acquisition, understanding, thinking, and a kind of computational consciousness.

HUGO is not a universal high-level scheme of a humanoid cognitive system in the sense that it could simulate any other such system (like a universal Turing machine can simulate any other machine). This is because HUGO involves embodiment and (thus) morphology (albeit indirectly, via properties of sensorimotor units), and such aspects make the respective cognitive systems unique (for instance, one cannot simulate birds on fish).

Obviously, there might exist other "schemes" of humanoid cognitive agents, but the "validity" of the one we have presented is supported by the fact that, unlike the other schemes, it offers plausible explanation of a full range of mental faculties. Any other scheme with the same range would necessarily be equivalent to HUGO.

2.6 Can "Fully–Fledged" Body–Less Intelligence Exist?

With the only exception of HUGO the previous models of cognitive systems were general, "disembodied" computational models capturing certain aspects of cognitive systems which we showed were enough to support the answers to our questions. Nevertheless, HUGO has been the only computational model for which we have been able to design algorithmic mechanisms arguably supporting the development of intelligence. For this to happen it was crucial that we have considered a complete cognitive agent inclusively its body represented by its sensorimotor units. The body has been an instrumental part of our agent allowing him not only to interactively learn his environment (to make himself situated in it) and thus, to build his internal structures (most notably the syntactic and semantic world model and episodic memories) on the top of which higher mental abilities have arisen so to speak "automatically" (cf. [15]). Agent's understanding of its own actions and perception has been grounded in the multimodal concepts formed by his sensorimotor units. From this viewpoint, the remaining models, lacking the body, could at best be seen as seriously crippled models of cognitive agents. Could such purely computational, body-less models retain the cognitive abilities of the embodied models of cognitive systems? It seems that contrary to popular beliefs that embodiment is condition *sine qua non* for intelligent agents, this belief is only partially warranted. Namely, according to the "theory" behind the HUGO model, embodiment is necessary in order intelligence to develop. However, once the necessary structures (and again, most notably the internal world models and the episodic memories) are developed, the agent (e.g., HUGO) can be *de-embodied*. That is, all its sensory-motor units can be removed from it, except those serving for communication (speaking/hearing or reading/writing). The resulting agent will work in the "thinking mode" using the cycle denoted by thick arrows in Fig. 1, being not able to develop any new skills and concepts related to sensorimotor activities. The de-embodied agent will "live" in a simulated, virtual world provided by his internal world models. His situation will thus remind the circumstance described in the philosophical thought experiment "brain in the vat" (cf. [16, 17]).

2.7 Can There Be a Sentient Cloud of Gas?

Written by by astrophysicist Sir Fred Hoyle the nowadays cult science fiction novel "The Black Cloud" [18] appeared in 1957. When observed from the Earth, this cloud appeared as an intergalactic gas cloud threatening to block the sunshine. After a dramatic attempt to destroy the cloud by a nuclear bomb the scientists came to a conclusion that the cloud possessed a specific form of intelligence. In an act of a pure hopelessness, they tried to communicate with it and, to their great surprise, they discovered a form of life, a super–organism obeying intelligence surpassing many times that of humans. In return, the cloud is surprised to find intelligent life-forms on a solid planet.

By the way, extra–terrestrial sentient oceans, planets, and suns occur quite often in numerous sci–fi novels.

How plausible is the existence of such sentient super–organisms? To answer this question we will invoke another result related to non-standard machine models of computations – so-called *amorphous computing systems*. From a computational viewpoint, amorphous computing systems differ from the classical ones almost in every aspect. They consist of a set of similar, tiny, independent, anonymous and self-powered processors or robots that can communicate wirelessly to a limited distance. The processors are simplified down to the absolute necessaries in order to enable their massive production. The amorphous systems appear in many variants, also with nano-sized processors. Their processors can be randomly placed in a closed area or volume and form an ad-hoc network; in some applications they can move, either actively, or passively (e.g., in a bloodstream). Depending on their environment, they can communicate either via radio, via signal molecules, or optically, or via whatever wireless communication means. The investigation of such systems has been initiated by the present author by the beginning of this century (for an overview, cf. [19]). Amorphous computing systems appear in many forms and the simplest ones can consist of processors which are, in fact, simple constant depth circuits. Genetically engineered bacteria can also be turned into an amorphous computing system [20]. The main result that holds for such models is that all of them they possess universal computing power. This means that they can simulate whatever computation of a classical Turing machine. For the simplest amorphous computing systems such a simulation is unbelievably cumbersome, because the underlying amorphous computing system can compute but with the unary numbers. This will cause an exponential slow-down w.r.t. the original computation.

Now we are in a position to formulate the answer to the question of this subsection. The "cloud" can be seen as a specific amorphous computing system.

According to what has been said previously, such a system can simulate the computational part of, e.g., HUGO that was mentioned in the previous subsection. The whole super–organism will not be completely body–less, since its processors have locomotion and communication means, and possibly other sensors and actuators. According to what we know the cloud will be able, over the entire existence of the Universe, develop a form of intelligence that will be appropriate to the environment in which it lives. The "slowness" of its thinking does not matter, taking into account travel time needed to investigate the potentially unbounded space. Undoubtedly, Darwinian evolution will also apply to this case. Interestingly, recently physicists have discovered inorganic dust with life-like qualities [21].

And could such a cloud be many times more intelligent than people? This is hard to say because its intelligence will be of a different nature than ours. But the principles of evolution and operation of its intelligence will be the same as those of us. Computational arguments can again be invoked showing that even an amorphous computing system of galactic size will not be able to solve problems beyond the Σ_2 class of the Arithmetic Hierarchy (cf. [13]).

2.8 How Could New Knowledge Be Generated?

Essentially, the above mentioned question asks, whether an artificial cognitive system can be creative. A cautiously positive answer – which we are ready to offer – must at least indicate a constructive way how this is possible.

In Subsection 2.1. we have already mentioned that the purpose of the knowledge generation process, i.e., the purpose of any computation, is to produce new knowledge in reaction to the external or internal requests. But how is it possible for a computation to generate new knowledge that would not have been contained, in some way, in the initial data (read: in the knowledge base) of the computation at hand?

This is an interesting problem whose difficulty stems from the fact that known epistemological processes of knowledge generation are usually described as extrapolations of repeated observations, or of known facts, as some variants of an induction process. In this process, there is no creativity aspect: knowledge is merely transformed from one form to an other. This allows for no better explanation (or reasoning) than *"it has been so in the past, so it will similarly be in the future"*. However, it is reasonable to expect that the ability to create new knowledge must also include the ability to create new explanations of observed or conjectured facts which cannot be obtained by generalising the past experience or by putting the known facts together in some unexpected way.

So how could new explanations or conjectures be generated? One of the answers seems to be in the notion of analogy.

Analogy has been studied and discussed since classical antiquity by philosophers, linguists, scientists, lawyers and writers, and more recently also by cognitive scientists. The history of the subject is very rich. There are many definitions of analogy. For instance, *"analogy is reasoning or explaining from parallel cases";* or *"analogy is a figure of language that expresses a set of like relations among* *two sets of terms"*. As an example, consider the analogy "*city* to *street* is like *country-side* to *river*".

What all these definitions have in common is a direct or indirect reference to natural language, to understanding, reasoning, explanations, and creativity. Within the theory of artificial cognitive systems all these notions are notoriously known as hard problems. Understanding of the underlying mechanisms evolves only slowly and therefore it is not surprising that the notion of analogy has seldom been approached from the viewpoint of requirements on the mental abilities of artificial cognitive agents.

One such a quest has recently been described in [22]. Here the author has shown the mechanism of analogy solving within the model of a humanoid cognitive agent described in Subsection 2.5. The proposed solution requires extensive searches over the agent's knowledge base that seek parallel semantic relationship among concepts entering into the analogy that are stored within the agent's semantic world model. Discovering of an analogy amounts to discovering of, in a sense, 'parallel' relationship between the concepts defining the analogy, or, in general, between two theories involving several concepts. This contributes to a better understanding of either theory since it enables to expect relations holding in one theory to also hold in its pendant theory. This is an important element of insight, explanation and understanding. Insight, understanding and explanation make only sense within a theory. They must follow from known facts or beliefs and rational thoughts. However, some theories can be based on incomplete facts or on wrong beliefs (cf. the flat earth theory). A discovery of semantic inconsistencies between alternative theories leads to a falsification of either theory. This seems to be the main source of new knowledge and thus, the main engine of progress (cf. [23]). Unfortunately, the respective mechanisms are so far poorly understood.

3 Conclusions

We have seen that using the recent novel view of computation, recent results from non-standard machine models of the contemporary theory of computations and the current ideas on the working of non-trivial cognitive systems we are able to answer the questions that until recently have been the domain of sci–fi or of philosophy, at best.

On one hand, the answers deny the ideas of some sci–fi writers or of some prodigies of science (cf. [9]) concerning the existence of super–intelligence. On the other hand, they also support futuristic ideas concerning the development of alien intelligence in alien environments using alien forms of life.

It is encouraging to see how recent achievements of theoretical computer science, and especially, the theories of non-standard models of computations and the computational theory of cognitive systems that are seemingly unrelated go hand in hand in our quest for unraveling the secrets of intelligence.

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