Authors draft of the chapter published by SPRINGER as: Dodig-Crnkovic, G. (2022) Cognitive architectures based on natural infocomputation. Philosophy and theory of artificial intelligence 2021. Vincent C. Müller (Ed). Springer, SAPERE series, vol 63.

Cognitive Architectures Based on Natural Info-Computation

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Keywords: Cognitive Architectures, Natural Information, Natural Computation, Naturalized Cognition, Cognitive Evolution, Extended Evolutionary Synthesis, Basal Cognition

Abstract
At the time when the first models of cognitive architectures have been proposed, some forty years ago, understanding of cognition, embodiment and evolution was substantially different from today's. So was the state of the art of information physics, information chemistry, bioinformatics, neuroinformatics, computational neuroscience, complexity theory, self-organization, theory of evolution, as well as the basic concepts of information and computation. Novel developments support a constructive interdisciplinary framework for cognitive architectures based on natural morphological computing, where interactions between constituents at different levels of organization of matter-energy and their corresponding time-dependent dynamics, lead to complexification of agency and increased cognitive capacities of living organisms that unfold through evolution. Proposed info-computational framework for naturalizing cognition considers present updates (generalizations) of the concepts of *information, computation*, *cognition,* and evolution in order to attain an alignment with the current state of the art in corresponding research fields. Some important open questions are suggested for future research with implications for further development of cognitive and intelligent technologies.

1. Introduction

In 1958 John von Neumann wrote "The computer and the brain" (von Neumann 1958)- the book describing information processing architecture of computers as based on then-current understanding of brain organization, with separate memory, input/output unit, arithmetic/logic unit, and a control unit. Von Neumann architecture is still in use. However, understanding of the brain have changed radically (Gazzaniga et al. 2019) (Damasio 2021), as well as the possibilities of distributed concurrent and intrinsic natural computing (Crutchfield et al. 2010)(Burgin and Dodig-Crnkovic 2015).

We may hope that new understanding of the brain and cognition as well as computation possibilities (information processing, structures, and dynamics) will bring about new nature-inspired (biomimetic) cognitive computational architectures. One development in that direction is neuromorphic computing, inspired by human brain function. Compared to von Neumann architectures, it puts very different requirements on the cognitive computational system, such as: the use of the same elements for processing and memory/storage of information; variation of electrical properties according to the Hebbian learning (electronic synapses), auto-oscillation generation mode, stable chains of signal transfer, and capacity of self-organization into 3D systems for the materials used for electronic compounds, all of which is mimicking intrinsic brain functions, (Erokhin 2022).

A recent overview of 40 years of research and practical applications in cognitive architectures, (Kotseruba and Tsotsos 2020), addresses the adequacy of existing cognitive architectures in modelling of the *core cognitive abilities in humans*, including perception, attention, action, memory, learning, and reasoning. Apart from presenting the state-of-the-art of the research through 84 human-level cognitive architectures, authors briefly mention deep learning, and why it does not qualify as *unified model of cognition in humans.* We will come back to the relation between recent developments in deep learning and understanding of (human) cognitive processes. Interesting recent work (Stocco et al. 2021) presents an analysis of the *human connectome data* that supports the notion of a "*Common Model of Cognition*" for *human and human-like* intelligence across multiple brain regions and cognitive domains. However, our focus is not on human and human-like cognition, but on the evolutionary origins of cognition and its development from basal cognition to the diversity of forms of cognition in all living organisms.

The present account introduces natural computational cognitive architectures, not included in (Kotseruba and Tsotsos 2020), in the first place because they do not address exclusively human level cognition, but treats all living beings as cognizing agents. In this naturalistic approach, the underlying assumption is that cognition in nature is a manifestation of biological processes (that subsume chemical and physical levels) in all living organisms *from single cells to humans* (Dodig-Crnkovic 2007; Jagers op Akkerhuis 2010; Lyon 2005, 2015a; Lyon and Kuchling 2021; Maturana and Varela 1992; Stewart 1996).

Recently (Piccinini 2020) made a step beyond the usual assumption that cognition (and intelligence) necessarily presuppose human agent. Piccinini addresses biological cognition in any organism with nervous systems as a result of neurocomputation. This approach does not go the full way to include all living organisms, even those without nervous systems, in spite of new findings of biologists that "*cognitive operations we usually ascribe to brains—sensing, information processing, memory, valence, decision making, learning, anticipation, problem solving, generalization and goal directedness—are all observed in living forms that don't have brains or even neurons.*" (Levin et al. 2021) Similar arguments for biogenic nature of cognition can be found in (Lyon 2015b; Lyon et al. 2021).

Grounded in the empirical and theoretical work on cognition and its evolution in nature (Walker et al. 2017) (Dodig-Crnkovic 2017a), from basal/ basic/ primitive/ elementary/ cellular, to complex form of human cognition (Dodig-Crnkovic 2014, 2020; Levin et al. 2021; Lyon et al. 2021; Manicka and Levin 2019; Stewart 1996), with natural information processing (natural computation) as a basis, info-computational approach can be used to identify several topics in the research of cognition that need more study.

First of all, in order to understand cognition, we must put it in the context of process of evolution (Dobzhansky 1973). The process of evolution of nervous system and brain, as well as sensory organs which are central for human cognition, deserve special attention.

Lyon with collaborators propose "reframing cognition by getting down to biological basics" in an article that is part of the Philosophical Transactions of the Royal Society B theme issue 'Basal cognition: conceptual tools and the view from the single cell' which explores in depth the cognition on the single-cellular level in its evolutionary context. (Lyon et al. 2021).

As a contribution to the attempt at bridging the gap between high level human cognition and the unicellular basal cognition, it is instructive to study intermediate steps. Recently we could read that "Brainless sponges contain early echoes of a nervous system", as described in Science News. In sponges we can trace back the origin of capacities of "higher order" cognition, resembling those existing in the human nervous system, which point to the evolution of nervous cells from the ordinary somatic cells of simple organisms. This recent discovery of "neuroid cells" in sponges attracted a lot of publicity showing that some cells evolved ability and specialized in connecting inside (digestive system) with the outside (source of food), having genes in common with neurons, and playing similar role for simple and complex organisms. Neuroid ("proto-neural") cells are in contact with cellular cilia, a short microscopic hairlike structure on the surface of cells, either causing currents in the surrounding fluid, or, in some protozoans, providing propulsion, according to https://www.dictionary.com/browse/cilia. Signals from neuroid cells prompt cilia to start or stop waving, and thus control feeding, (Pennisi 2021).

The rest of the paper is organized as follows. Section 2 presents naturalized cognition and human thinking, fast and slow, while Section 3 addresses the open questions of cognitive architectures and natural info-computation. Section 4 offers conclusions.

2. Naturalized cognition and human thinking, fast and slow

> *"Thus the organic body of each living being is a kind of divine machine or natural automaton which infinitely surpasses all artificial automata. For a machine made by the skill of man is not a machine in each of its parts... But the machines of nature, namely, living bodies, are still machines in their smallest parts ad infinitum. It is this that constitutes the difference between nature and art, that is to say, between the divine art and ours."*
>
> *(Leibniz 1898) Monadologie §64, p. 254.*

Cognitive architectures started as a research field with the goal to model *human mind* and build *human-level artificial intelligence*. By connecting models and mechanisms with observed cognitive/intelligent behaviors, they contributed to cognitive science and AI. However, cognition in nature appears throughout biological systems (Almér et al. 2015; Baluška and Levin 2016; Lyon 2005, 2015a; Lyon et al. 2021) and it is important to understand its evolutionary development from the basal/basic/elementary cognition to the human level cognition, (Levin et al. 2021; Manicka and Levin 2019).

This naturalized evolutionary approach to cognition is based on the view of hierarchical recursive structure of information processing in nature, in living organisms from cells, to tissues, organs, organisms and their groups – all of them communicating at different levels of organization by exchanging specific types of information – physical (elementary particles, electro-magnetic), chemical (electric, molecular), biological, and symbolic (signs, languages).

In humans, two basic *functional abstractions* of cognitive system have been proposed, System 1 (reflexive, non-conscious, automatic, intuitive information processing, which is fast) and System 2 (reflective, conscious, reasoning and decision making, which is slow) (Kahneman 2011; Tjøstheim et al. 2020).

Within AI, the field of artificial neural networks with deep learning have made an impressive progress in modeling perception on the level of data/signal processing. Deep learning level corresponds to Kahneman's fast, intuitive System 1. Current developments in AI (addressing *human-level cognition*) are continuing towards modelling System 2, symbolic reasoning (Russin et al. 2020).

It has long been recognized that mechanisms of cognition based on natural computation are far more sophisticated than the machine-like classical computationalist models based on abstract symbol manipulation (Kampis 1991). They conform to the view expressed by (Witzany and Baluška 2012) that *rule-based machines are not good enough models of natural cognition*. Compare to the Leibniz insight from the quote above.

Natural/physical/intrinsic/morphological/ computation presupposes embodiment of information processing. *Embodiment is the fundamental feature of cognition*, which implies that *valence, affect, feelings and emotions* must be taken into account as constitutive elements in the models of cognition (Damasio 1999; Dodig-Crnkovic 2017a; Dodig-Crnkovic and Giovagnoli 2017; Lyon and Kuchling 2021; Watanabe et al. 2017). They affect both System 1 and System 2 information processing.

3. Open questions of cognitive architectures and natural info-computation

With the present development in scientific research as well as cognitive and intelligent computing it is becoming important to update computational approaches to cognitive architectures. Currently, there are several interesting open questions worth more exploration.

Biomimetic design of cognitive architectures. What is "biologically plausible"?

Proposals to learn from nature about cognition are old, (Maturana and Varela 1992; Stewart 1996; Lyon 2005, 2015a; Dodig-Crnkovic 2007; Jagers op Akkerhuis 2010; Lyon and Kuchling 2021), but they have recently gained a lot of prominence in the form of biomimetic design (Joyee et al. 2020). Can our newly acquired insights into cognition on different levels of organization in nature be applied to improve cognitive architectures?

(Russin et al. 2020) argue that deep learning (corresponding to Kahneman's System 1) needs an equivalent of "prefrontal cortex" that would play the role of System 2 (slow, reflective information processes). This is in agreement with (Marblestone et al. 2016), who suggest increased integration of deep learning and neurosciences. Similar ideas are put forward by (Dodig-Crnkovic 2020) with the argument that natural morphological computation should be used to study function of metalearning (learning to learn) in humans (function of prefrontal cortex), other living organisms, and intelligent machines.

Here we should recognize that Bengio's and Kahneman's interpretations of System 1 and System 2 are not identical, which was evident from the discussion at AAAI-2020 conference, Fireside Chat with Lecun, Hinton, Bengio and Kahneman https://vimeo.com/390814190. However, the details of interpretations are not essential for our current exposition.

To this current discussion about how Bengio-Lecun-Hinton's interpretation relates to Kahneman's views, one should add critical voices questioning dual-process theories in general as inadequate, as presented in (Osman 2004) review. Osman proposes replacing the dualist (dual-aspect) approach with "a single-system framework that conjectures that different types of reasoning arise through the graded properties of the representations that are utilized while reasoning and the different functional roles that consciousness has in cognition", arguing for the framework, unifying the different forms of reasoning, identified by dual-process theorists, under a single system. Bengio-Lecun-Hinton's interpretation seems to be closer to Osman who searches for connections between System 1 and System 2, especially Bengio elucidates the role of consciousness for learning (Russin et al. 2020).

Cognitive behaviors and their simulation, emulation and engineering

In the special report "Can We Copy the Brain?" (The Editors of IEEE Spectrum 2017), the founder of the Blue Brain Project, Henry Markram discusses complexities of the brain and necessity of learning about the details of its functioning on different levels of organization. He also discusses possibility to simulate the brain with molecular and cellular level simplified and encapsulated. There are two open questions that run in parallel, providing an opportunity for two-way learning between computing and neuroscience (Rozenberg and Kari 2008). The questions are: first, how cognition works and develops in nature, and second, how we can model, simulate, emulate and engineer it in computational artifacts.

Work of Michael Levin (https://ase.tufts.edu/biology/labs/levin) suggests broad range of applications for nature-inspired cognitive architectures based on biological cognition connecting genetic networks, cytoskeleton, neural networks, tissue/organ, and organism with the group (social) levels of information processing. Levin shows how biology has been computing through somatic memory (information storage) and biocomputation/decision making in pre-neural bioelectric networks, before the development of neurons and brains. (Fields et al. 2020) summarize:

> *"Importantly, neurons utilize ancient mechanisms such as ion channels, electrical synapses, and neurotransmitters that also*

> *operate throughout the body in many non-excitable tissues and predate the evolution of specialized neurons. We here propose a model in which both neuronal signals and non-neural bioelectric patterning signals arise from modifications of conserved basic machinery, and co-evolved to function to control both organismal behavior and development."*

Insights from biocognition can help the development of new AI platforms, applications in targeted drug delivery, regenerative medicine and cancer therapy, nano-technology, synthetic biology, artificial life, and much more.

Computational efficiency of natural computing

Computational efficiency and performance are important features, often left outside when discussing computational models of cognition. However, with the increased ubiquity of computing, this aspect becomes essential. Natural cognitive computing, being particularly resource effective, can provide ideas for future developments towards more resource-efficient computational architectures (Usman et al. 2019) (Nature Editorial 2019).

The question of computational efficiency has also been addressed by biomimetic neuromorphic computing which is mimicking the neural structure and functions of the human brain, together with probabilistic computing, with algorithmic approaches to the uncertainty, ambiguity, and contradiction in nature (Ackerman 2019). More learning from nature about computational efficiency is needed that will inform biomimetic designs of cognitive architectures.

Time aspect of cognitive models of naturalized cognition

Cognitive models today take the mind/brain to be reactive, with information processing starting with a stimulus and ending with a response (Bechtel 2013). However, cells are inherently active, neurons are sustained oscillators, exhibiting electrochemical oscillations even in the absence of stimuli. Input data/information presents stimuli that *modulate existing endogenous oscillations*, (Bechtel 2013). In the book "Rhythms of the Brain" (Buzsáki 2009) describes the important role that spontaneous activity of neurons plays. Spontaneous firing of neurons is the very basis of human cognition when it comes to its time aspects. A self-organized timing of oscillations has co-evolved as the main organizational principle of neuronal activity. Global computation (on multiple spatial and temporal scales) is enabled by small-world-connectivity of neurons in the cerebral cortex. In a small-world setting, any two of nodes are connected through a short sequence of intermediary nodes. Cortical system is in a metastable state, synchronized through weak links between network oscillations in constant interactions. Oscillator frequency determines periods of receiving and transferring information.

Based on studies of oscillations, neural computations and learning, (Penagos et al. 2017) propose that "*precisely coordinated representations across brain regions allow the inference and evaluation of causal relationships to train an internal generative model of the world.*" Training starts while awake, and processing continues during sleep when periodic nested oscillations induce hierarchical processing of information. Authors suggest that "general inference, prediction and insight" supporting an internal model for generalization and adaptive behavior is enabled through periodic states of sleep.

Related is the synaptic plasticity of the brain which changes its connections through the long-term potentiation (Hebbian and non-Hebbian), considered to be a basis for learning and memory. Oscillatory behavior is not only characteristics of the human brain. Similar oscillatory rhythms have been observed in the brains of mice. Being made of *oscillators, biological neural networks are able to filter inputs and to resonate with noise.* Unlike those observed oscillatory time behaviors in the biological brains, that appear as a result of their physical embodiment, artificial neural networks have no such temporal coupling and synchronizing mechanisms. It is an open question how essential this oscillatory behavior and metastability are for "fine tuning to the world" and if their function can be obtained in a different way.

On the global level of unified theories of cognition, time aspect (Anderson 2002) manifests itself in terms of Newell's *bands of cognition* (Newell 1994)—the biological "10 millisecond band", cognitive, rational, and social ("long-term") bands. How important is it to have all of them represented and how detailed? Here we talk about understanding of temporal aspects of cognition as organized hierarchically in a metastable state, constantly tuning to the environment. Coordination obtained through communication is central for connecting different levels, from molecules to thoughts, in the same coordination dynamics (Kelso et al. 2013). Through the interplay with the environment this process results in *eigenstates* (Foerster 2003). Technological approaches to cognitive models of brain-like computer, based on frequency-fractal computing are proposed by (Ghosh et al. 2014) and (Singh et al. 2020). In short, time aspect of cognitive models of naturalized cognition deserves more attention.

4. Conclusion

Modelling cognitive processes as natural computation/physical computation/morphological computation (natural information processing), we can better understand cognition as it evolves in living beings (Dodig-Crnkovic 2017a).

Identified open questions deserving further attention include biomimetic design of cognitive architectures and meaning of the expectation of biological plausibility for understanding of cognition and for technological applications; cognitive behaviors in nature and their simulation, emulation, and engineering; taking advantage of computational efficiency of natural computing, and deeper understanding of time aspects of cognition on hierarchy of levels of organization and in evolutionary context.

The info-computational framework considers state of the art in the research and applications of information and computation, as well as relevant parts of information physics, information chemistry, bioinformatics, neuroinformatics, computational neuroscience, complexity theory, self-organization, and the developments in the theory of evolution, for naturalizing cognition. It requires generalization of several fundamental concepts, as follows:

Information is seen as the fabric of the universe/nature. For a cognitive agent, information is the basis or reality on which behavior is based.

Computation is *information processing (dynamics of information).*

Cognition is characteristics of all living forms, not only humans or organisms with nervous systems. Cognition is a network of life-sustaining processes that enables every living organism to perceive its environment, react adequately and adapt so to survive as individuals and species.

Evolution is understood as *Extended evolutionary synthesis*, which considers that not only random mutations, but also sequences of changes caused by laws of physics and chemistry (that can be described as *morphological computation*) leads to the development of new structures which are then exposed to natural selection (Jablonka and Lamb 2014; Laland et al. 2015).

Parallel development of our understanding of cognition as natural phenomenon and its technological implementations inform each other in a recursive manner (Rozenberg and Kari 2008)(Bondgard and Levin 2021). As we have seen, learning from nature and biomimetic design necessitate interdisciplinary approaches to computing as exemplified in approaches in (Dodig-Crnkovic 2017b), also argued for in (Esposito et al. 2018).

Development towards biomimetic architectural design inspired by natural intrinsic morphological computing promises new resource-effective cognitive architectures on different levels of complexity – from basal cognition that can be used in nanotechnology to complex cognition needed for social robotics.

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