Design of the Artificial: lessons from the biological roots of general intelligence

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Our desire and fascination with intelligent machines dates back to the antiquity's mythical automaton Talos, Aristotle's mode of mechanical thought (syllogism) and Heron of Alexandria's mechanical machines and automata. However, the quest for Artificial General Intelligence (AGI) is troubled with repeated failures of strategies and approaches throughout the history. This decade has seen a shift in interest towards bio-inspired software and hardware, with the assumption that such mimicry entails intelligence. Though these steps are fruitful in certain directions and have advanced automation, their singular design focus renders them highly inefficient in achieving AGI. Which set of requirements have to be met in the design of AGI? What are the limits in the design of the artificial? Here, a careful examination of computation in biological systems hints that evolutionary tinkering of contextual processing of information enabled by a hierarchical architecture is the key to build AGI.

Thomas Hobbes' account of mechanical combinatorial theory of cognition in Leviathan, Blaise Pascal's mechanical calculator and Gottfried Leibniz's alphabet of human thought were among the contributions of late Renaissance and early 17th century visionaries to the dream of building intelligent machines. Late 18th, 19th and 20th centuries witnessed more rigorous attempts to both formalize theories of intelligence and create intelligent machines. The unfinished programmable mechanical calculating machines of Charles Babbage in late 19th was followed by the development of formal logic, Turing's view of computation and intelligence. In 20th century, we have witnessed the emergence of the field of Artificial Intelligence, its promises, winters and its re-emergence in the recent decade. IBM's deep blue victory over Gary Kasparov was among the success stories, though it relied on strategies completely different from human intelligence. The legacy of the triumph of machines was sustained when Google DeepMind AlphaGo beat Lee Sedol in the game of GO. Additionally, recent advances in experimental neuroscience and computing power has led to much excitation about the further extension in applications of neuro-inspired computer vision [7]. Despite the success of brute force algorithms of IBM Watson, and Reinforcement Learning of Google DeepMind AlphaGo, our machines and algorithms are still bereft of Artificial General Intelligence (AGI). The most advanced AI algorithms are far behind the dramatic portrayal of AGI, Hal9000, in 2001 Space Odyssey.

Why has no approach, so far, come even close to AGI? Why did symbolic computation, despite its early promises [25] not succeed in achieving AGI? Was it simply because no one knew how to build a general database of commonsense knowledge? [23]. Neural networks, despite early criticism, have shown wide applicability in a variety of tasks after the rapid expansion of computing power. The magic seems to have been residing in computing power and the scale of the network. Yet still, these networks have no trace of AGI. If the intelligence is not simply equivalent to building a synthetic brain [3], what is the essence of intelligence? Here, I try to provide a new viewpoint that characterizes intelligence as a mechanism deeply intertwined with the core essence of biology, i.e. a specially designed hierarchical architecture that provide the capacity for contextual information processing.

In recent years, the bold and ambitious aspiration to develop intelligent machines is mixed with a recognizable shift towards bio-inspired designs. In mimicking the flight of insect in design of the RoboBee [20] or in mixing biological and electronic elements in RoboRay [26], the key to success has been in understanding the physical limits of the materials used in making flexible lightweight systems. The efficacy of these systems are mostly dependent on the communication capacity among the electronics (or bio-electric interface) and processing power of their elements. In more direct attempts to mimic intelligence, the design of novel neuromorphic computing architectures has been mostly focused on achieving brain-like energy efficiency in spiking neural networks embedded designs [9, 24]. On the algorithmic front, the successful deep learning [18] and recurrent network [13] mimicry of brain networks are mainly focused on intrinsic organization of the biological network.

The assumption is that such mimicry entails intelligence despite missing many other elements in physical imitation of biological systems. What is missing from the Von-Neumann architecture and the bio-inspired non-Von-Neumann approach is an understanding of the computational limits that arise due to the organization of biological templates as complex systems embedded in their environment. This oversight is not very surprising since the designers of (both software and hardware) machines emphasize the functional aspects of a living system in their attempt to duplicate its performance. In the behavioral and functional dichotomy of intelligence, as proposed by [33], the functional approach is concerned with the intrinsic organization while the relation between the object and the outside world is relatively secondary to the structure and internal properties. The emphasis on func-

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tional aspects and reliance on high speed components has high energetic costs. Most efficient neural networks, especially the more bio-inspired ones like Deep Learning, need many computational cycles to reach a desired outcome. This too has added to the energetic cost of computation and part of the new efforts in the bio-inspired frontier (neuromorphic architecture) are geared to resolving this issue.

Proposition of controlling behavior through negative feedback as the mechanism behind teleological behavior [33] led to the notion that artificial intelligence and building a synthetic brain are not equivalent. Feedback as a control mechanism for achieving adaptation in a changing environment untangled the mysterious aspect of teleology [37]. Interestingly, early attempts at designing intelligent machines based on teleological behavior showed some delivered promises [11]. Walter Grey's tortoises, *Machina speculatrix* and *Machina docilis* manifested complex sets of behaviors (phototaxis, search for energy source and conditioned reflex behavior) and could maneuver around the room autonomously. The teleological approach, though properly recognizing the limits of functional approach, eventually rendered cybernetics immovable from a qualitative level [3]. The reason that neither functional nor behavioral teleology have succeeded in advancing artificial intelligence above and beyond task-specific advancements is likely rooted in the hierarchical organization of the nervous systems and their modification and optimization through interactions with the environment. It is possible that what sets biology apart from other systems is the contextual (functional) algorithmic features in biological computation. The context-dependency of biological systems can be defined as a top-down causal information exchange that is unique to their multi-scale organization [42]. While the thermodynamics of information tells us that information is physical [17] and within the bounds of Landauer limit [4, 16] could be converted to energy [27, 41], the information at the macroscopic scale can affect microscopic scale in biological systems [42].

It has been suggested that the supervenience of aggregates over microscopic elements may potentially point to macro-scale causally superseding micro-scale [12]. If macroscopic dynamics can change causality direction then there is the possibility of a strong causal emergence at multiple scales of an information processing system such as the brain. Top-down causality provides a possible platform for offloading the computational complexity onto cells [29]. One can conclude that through "information to energy conversion" and "top-down supervenience" goal-directed macroscopic contextual information processing can recapitulate microscopic dynamics. Of course, in such an information-theoretic landscape, a successful model should tell us how to convert macroscopic goals into computational rules embedded at the scale of networks (neural assemblies) and individual neurons (with potential extension to intracellular computation). The evolved structure that provides the additional top-down causal path (and thus a bidirectional causality), renders information not as mere metaphor of the degree of randomness (as framed by Shannon [35]) but gives it a semantic flavor [22]. This notion of information processing in biological systems is not just a symbolic analogy of modern-day technology (such as Descartes' hydraulic pump analogy, Freud's steam engine analogy and the popular "brain is a computer" analogy), but rather it truly embodies the physical nature of information [22, 34].

If the nature of intelligence is rooted in a contextual, non-local information control and feedback, then it follows that there is no blueprint for the solution and the correspondence between the causality of information and microscopic dynamics of the nervous system. It is essential to note that this claim does not negate the role of the physical substrate (molecules, neurons and networks) of information flow, but rather portrays the non-optimality and non-uniqueness of the multiscale contextual causality of information processing. In such a setting, the need for heuristics in exposure to new environments/problems becomes evident. "Trial and error" as the fundamental heuristic strategy derived from experience with similar problems [28] and a method of problem solving and error elimination under various forms of selective pressure [32] stands as the likely candidate. Unsurprisingly, it has been suggested that chess masters do not rely on flash of insight or superior memory or faster processing, but rather implement a heuristic selective and non-exhaustive trial and error in the tree of possible moves [38]. Since the non-optimality and non-uniqueness of trial-error seem to be the essence of AGI as well as byproducts of contextual information processing, one may ask where and how they could be superior to the alternatives?

Ashby provides an interesting example of the superiority of a trial and error approach [1]. In his example of finding a particular combination of 1000 on/off switches, a simultaneous (parallel) individual testing of all switches (average of 1 second) outperforms serial and all-or-none test of switches (respectively, average of $5x10^2$ and 10^{301} seconds). As the number of the possible states of the problem grows, the time needed for any intelligent design to find the optimal solution grows non-linearly. In contrast, trial and error which relies on little knowledge and is problem-specific seems to be the optimal path to reach a solution even though that solution may not be optimal. This contextual, non-local feedback causal aspect of intelligence is very similar to the DNA serving as the backbone but not blueprint of the cellular computation. In the case of DNA, it is the interaction of the genes in response to the cell's environment that leads to the expression or suppression of other genes [3, 42]. It is the interactions of the genes and not their products, i.e. enzymes, that carry the information that materialize one possibility among many possibilities based on the genetic composition [22]. The reason for such isomorphism between genetics, immune system and intelligence is the nature of information itself. The allure of the biology is not in its search for the optimal solution but rather is beholden to its fundamental roots in trial and error as a tinkering mechanism in response to the environment [15]. As a result, simply by adapting the evolutionary principles, robots can show forms of intelligent behavior [30] that are systematically different from the mainstream ones. Although for a system to be fully capable of AGI, one has to go above and beyond evolutionary robotics and implement the principles mentioned here.

Brains are (physical) computational systems with a dynamical broken symmetry of information that finds relatively stable states [14]. But how does a system which harbors context-dependent behavior remain stable? The answer lies in Ashby's law of requisite variety, which states that "If a system is to be stable, the number of states of its control mechanism must be greater than or equal to the number of states in the system being controlled" [2]. As a result, systems with higher internal variety are more capable of responding to predictable scenarios and are better suited to face unpredictable situations. To achieve a higher number of behaviors, the system needs to increase its intrinsic variety. To do so, the system must rely on a higher number of computing components and a higher number of connections between these computing elements. However, there is a cost of increased connectedness among the components. Up to some level of increased connectedness, the dynamics of the system is stable. However, at some critical threshold, it suddenly becomes unstable [10]. If the big system is organized in a modular fashion, it is more likely that individual modules/blocks preserve their stability in the face of perturbations [21], though there is a limit to the number of random interactions and they should be fixed in time [6]. This desired stable collective information processing can be harnessed through competitive dynamics [8] where modular composition provides the possibility of asynchronous or synchronous recruitment of sub-assemblies. It follows that as the system's variety grows, so does the need for the organization of information and the capacity to reshape the structure as information grows. Evolution has found a solution for this and that solution resides in multiscale organization of biological systems.

Simple life forms are capable of rudimentary computation equipping them with simple behaviors such as chemotaxis and movement. In more complex life forms, specially multicellular animals, behaviors are controlled by the nervous system. Rudimentary nervous systems (such as jellyfish) are in the form of a diffuse nerve net. As the organism's behaviors get more complicated, the nervous system becomes organized in ways to adapt to the greater repertoire of the needed behaviors. Comparative structures of the nervous system in C. elegans, fruit fly, mouse, Macaca Mulatta and humans show increasing levels of internal variety, organized in a hierarchical fashion. Ashby's law of requisite variety demands a higher internal variety to match the more complicated sets of behaviors. Yet, the needed bigger nervous system is not just composed of a very large neuronal net with shallow depth. Instead, the more advanced nervous system is structured as a hierarchical system. These advanced systems are still composed of microscopic elements involved in the similar types of rudimentary intracellular computation (as in single cell organisms) as well as computations that are built upon a network of cells organized as tissue. As we discussed above, this form of architecture helps to provide dynamic stability of the system while enabling a much larger repertoire of computations.

An unsurprising outcome of a hierarchic structure is that increasing network depth may provide an efficient way for achieving abstraction of information through renormalization [19]. This aspect may represent why and how deep learning has been more successful than its predecessors in certain domains. Though, it is important to recognize that the more complex the nervous systems is, the more hierarchical organization is present. Such non-decomposable hierarchy is a hallmark of complex systems [37]. It is essential to recognize that this hierarchical architecture of complexity provides the chance for repair, modification and improvement of different parts of the system without the need to halt the operation of the system. Simon's parable of the two watchmakers Tempus and Hora [36, 37], and their distinctive systems of shallow and serial vs modular and hierarchical approach to watch assembly, reflects how the compositionality of hierarchical complex system can give them a significant edge. Similarly, not only does the hierarchical nature of advanced nervous systems provide a better chance for the repair, modification and improvement of different parts, but also these different subassemblies can be recruited to parallel computational tasks and thus the space of compositional computations greatly expand. Note that evolutionary tinkering also benefits from such hierarchical modularity. These modules can be reused in the re-design of the species' next generation or can be borrowed and implemented in the construct of other species [15]. Whether we study the nature of computation in the nervous system or we wish to design robust AGI, these principles will be crucial.

Note that this notion of intelligence directly opposes all attempts trying to formalize intelligence as an inductive process. Bayesian inference advocating for strong generalization from few examples relies on inference from inference over hierarchical generative models [40]. Because of the reasons mentioned above, bayesian formalism is simply incapable of reaching the desired (non-optimal) generality of intelligence. Note that the trial and error is probably the most fundamental element of all knowledge gathering systems. In fact from an epistemological point of view, even the core of scientific discovery is not based on induction [31]. In contrast to bayesian approach, the complex intelligent behavior has roots in non-symbolic information transfer and arises as a result of interaction of the system with the environment.

In the design of AGI, the emphasis should be on behavior-oriented Artificial intelligence emerging adaptive intelligence in a continually changing environment [39]. Only in such case the relation between scales and the bidirectional causality in biological computation finds a proper meaning. It follows that the context-dependency entails a specific intrinsic multiscale organization of information and provides the ability to interact with the changes in the environment. Thus the limit of an intelligent system is shaped by a core element of complex systems, i.e. multiscale organization, the requisite variety and trial and error. Surprisingly, in formalizing a theory of intelligent systems, these were not considered together before. In an influential essay ("As We May Think"), Vannevar Bush envisioned a future where computers support humans in many different activities [5]. If we truly intend to reach such stage, bio-inspired design will be our solution but only if we take into account the contextual aspects of cognition and intelligence. Evolution has been very successful in creating AGI through trial and error. That blueprint is in front of our nose and ours to mimic.

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