PHYSICAL COMPLEXITY AND COGNITIVE EVOLUTION*

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Our intuition tells us that there is a general trend in the evolution of nature, a trend towards greater complexity. However, there are several definitions of complexity and hence it is difficult to argue for or against the validity of this intuition. Christoph Adami has recently introduced a novel measure called physical complexity that assigns low complexity to both ordered and random systems and high complexity to those in between. Physical complexity measures the amount of information that an organism stores in its genome about the environment in which it evolves. The theory of physical complexity predicts that evolution increases the amount of 'knowledge' an organism accumulates about its niche. It might be fruitful to generalize Adami's concept of complexity to the entire evolution (including the evolution of man). Physical complexity fits nicely into the philosophical framework of cognitive biology which considers biological evolution as a progressing process of accumulation of knowledge (as a gradual increase of epistemic complexity). According to this paradigm, evolution is a cognitive 'ratchet' that pushes the organisms unidirectionally towards higher complexity. Dynamic environment continually creates problems to be solved. To survive in the environment means to solve the problem, and the solution is an embodied knowledge. Cognitive biology (as well as the theory of physical complexity) uses the concepts of information and entropy and views the evolution from both the information-theoretical and thermodynamical perspective. Concerning humans as conscious beings, it seems necessary to postulate an emergence of a new kind of knowledge - a self-aware and self-referential knowledge. Appearence of selfreflection in evolution indicates that the human brain reached a new qualitative level in the epistemic complexity.

1. Introduction

Our intuition suggests that there is a general trend in the evolution of nature, a trend towards greater complexity. According to this view evolution is a progressive process with Homo sapiens emerging at the top of the life's

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hierarchy. An alternative opinion is that there is no trend in evolution and we are just one of many leaves on the evolutionary tree. There are several definitions of complexity and hence it is difficult to argue in a quantitative way for or against the validity of each of these views. In my article, I will be focusing on a novel measure of biological complexity (physical complexity) that has been proposed by Christoph Adami.

2. Kolmogorov - Chaitin complexity and biology

One well-known definition of complexity is the Kolmogorov-Chaitin complexity (introduced independently by Kolmogorov (1), Chaitin (2) and Solomonoff (3)). It represents an algorithmic measure of system's randomness (4, 5). It defines the complexity of an object (or a process) by the size of the smallest program for calculating it. For example, a long sequence of digits with a regular pattern (e.g. 01010101...) can be compressed to a much shorter description/program ("repetition of 01") and hence it has a small amount of complexity. In contrast, an infinite random sequence of digits "19255324193625168147..." has no intrinsic structure and cannot be compressed at all. The only way to express the sequence is to enumerate all the digits that it consists of. Thus, Kolmogorov - Chaitin's definition implies that maximum complexity is ascribed to a completely random process that is algorithmically incompressible (Fig. 1, c.f. Ref. 6).

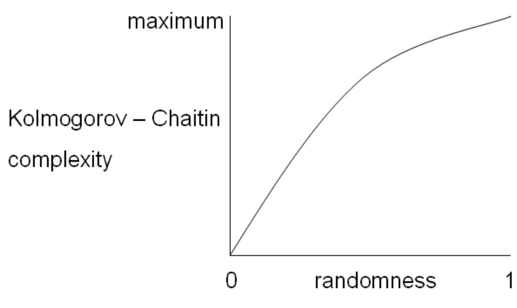

Figure 1.

However, although useful for the theory of computation, Kolmogorov-Chaitin complexity does not satisfy our expectations inspired by biology that most complex organisms are neither completely regular nor utterly random but lie between the two extremes of order and randomness (7). What makes living systems *complex* is the interplay between *order* and *randomness* (8). This principle has been supported by recent research on biological networks (9). Complex networks of cellular biochemical pathways have neither *regular* nor *random* connectivity. They have a so called *scale-free* structure (10). A scale-free network contains a small number of *hubs* - major nodes with a very high number of links whereas most nodes in the network have just a few links. "Scale-free" means that there is no well-defined average number of connections to nodes of the network. In case of a biochemical network, nodes and links represent molecules and their chemical reactions, respectively. In such a molecular network, hubs are important molecules that participate in a large number of interactions (e.g. cAMP, H_2O) in comparison to other molecules that take part in a few biochemical signaling paths (11). An important consequence of the scale-free architecture is robustness against accidental failures of minor nodes/links and vulnerability to disfunctions of major hubs. (Note that this may bring interesting insights into the molecular pathophysiology of various diseases.) Surprisingly, recent mathematical analysis of various scale-free networks (including biochemical signaling networks) has revealed *self-similarity* (fractal pattern) in their structure (12). Self-similarity is a typical property of systems that are on the *edge of order and chaos*. Such a critical state (with a tendency to phase transitions) might be useful for optimizing the performance of the system (13). To sum up, we need a measure which would capture the complexity of dynamical systems that operate between order and randomness.

3. Physical complexity

Christoph Adami (14) has recently introduced a novel measure called *physical complexity* that assigns low complexity to both ordered and random systems and high complexity to those in between (Fig. 2). Physical complexity measures the amount of *information* that an organism stores in its genome *about* the *environment* in which it evolves. This information can be used to make predictions about the environment. In technical terms, physical complexity is a *shared (mutual) Kolmogorov complexity between a sequence and an environment* (for mathematical equations see Ref. 14). Information is not stored *within* a (genetic) sequence but rather in the *correlations between* the sequence and what it describes. By contrast, Kolmogorov-Chaitin complexity measures regularity/randomness within a sequence and therefore fails to address its meaning in the environment.[a] Information is a relative quantity - always *about* something, in case of the genome it is about the niche that an organism lives in (16, 17). The theory of physical complexity uses two central concepts of Shannon's theory of information: entropy and information. *Entropy* is a measure of potential information, it determines how much information a sequence could hold. Entropy of a sequence can be compared to the *length of a tape*, and *information* to the *length of a tape portion containing recordings* (14). Physical complexity has the advantage that it is a practical measure, because entropy of an ensemble of genetic sequences can be measured by estimating the probabilities of finding the genetic sequences in the environment.

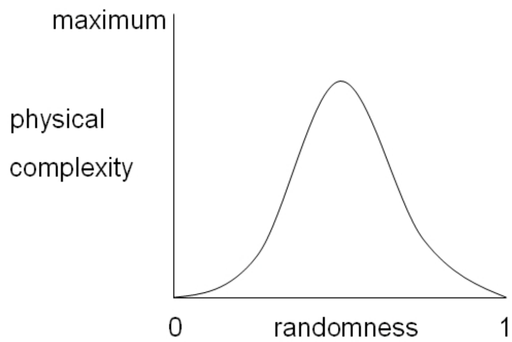

Figure 2.

Evolution is a slow process and therefore obtaining exact data is difficult. How could we test the hypothesis of the evolutionary complexity increase? An interesting option is to study digital evolution (18). Digital organisms (digitalia) are *self-replicating* computer programs (sequences of instructions) that *mutate* and *compete* for space and computer time (19). Thus, digital evolution occurs since the three conditions of evolution are met: *replication*, *variation* (mutation) and *competition/selection* (due to differential fitness/replication rate). Digital organisms have a much shorter generation time (seconds) and their physical complexity can be measured exactly. In this case, *physical complexity* is the information in a digitalia

[a]Interestingly, Chaitin has proposed his own definition of life based on Shannon's concept of mutual information. See Ref. 15.

program that is vital to organism's survival (replication). Of course, digital evolution is a highly simplified model of biological evolution and this creates the possibility of artifact conclusions or generalizations. On the other hand, simplification is at the same time the greatest strength of simulated evolution experiments since it allows us to find and see the forest (general principles of evolution), not just the trees.

Interestingly, Adami's experiments on digital organisms revealed a steady trend toward increased physical complexity in their evolution within a fixed environment (16). According to his theory and simulation data, evolution increases the amount of 'knowledge' an organism (or a population of organisms) accumulates *about* its niche. Since in this context *entropy* is a measure of *potential information*, biological evolution leads to a decrease of entropy. Natural selection turns an *empty tape* into a *filled tape*: entropy into information. The information-filled part of the tape is important for the survival of an organism in the environment. If the selective advantage fixes a beneficial mutation within the population, the amount of information (physical complexity) increases. Adami views natural selection as a *unidirectional filter* (see below the discussion of ratchetting) that lets information enter the genome, but prevents it from flowing out.

Adami's simulations were done in a fixed environment. He discusses that a rapidly changing environment as well as several other factors that were not included in his experiments (high mutation rates, sexual recombination, co-evolution between species occupying different niches) may lead to complexity declines. However, these factors are ambivalent - sometimes they help, rather than hinder, the evolution of complexity (14). Therefore he argues that there are good reasons to expect that the theory of physical complexity will reveal an overall trend towards higher complexity in biological evolution.

4. Physical complexity and the concept of cognitive biology

It might be fruitful to generalize Adami's concept of complexity (which has been primarily thought to describe the evolution of genome) to the entire evolution including the evolution of man (Fig. 3). Physical complexity fits nicely into the philosophical framework of *cognitive biology* which considers biological evolution as a progressing process of *accumulation and application of knowledge*, i.e. as a gradual increase of *epistemic complexity* (20, 21). Cognitive biology provides a broader philosophical frame for Adami's approach since the central idea of his theory of physical complexity is relating complexity to the system's 'knowledge' (information) about its environment. *Physical complexity* can be viewed as a special case of *epistemic complexity*. This becomes clear if we look at many common features of Adami's ideas and cognitive biological ideas. According to the paradigm of cognitive biology, evolution as a whole is a cognitive *'ratchet'* that pushes the organisms unidirectionally towards higher complexity. Epistemic 'ratchetting' operates at all hierarchical levels, from molecules to societies (20). Dynamic environment continually creates problems to be solved (i.e. each niche is a solution problem). To survive in the environment means to solve the problem, and the solution is an embodied knowledge.

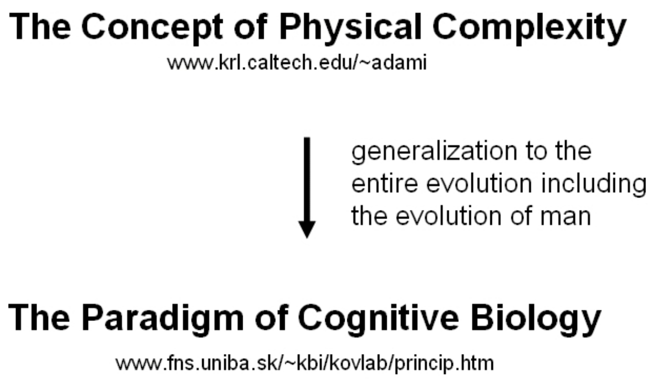

Figure 3.

'Ratchetting' is a general phenomenon that has been usually described in the context of thermodynamics. Cognitive biology acknowledges that progress in evolution has thermodynamical reasons (20). Both cognitive biology and the theory of physical complexity use the concepts of *information* and *entropy* and strongly emphasize that there is a close connection between thermodynamical thinking and information-theoretical approaches. By thermodynamical reasoning we can identify a 'differentiation of a system from environment' as a dissipative 'movement from thermodynamic equilibrium' (22). Biological evolution creates organisms with an ever increasing amount of embodied 'knowledge' and with an ever farther distance from thermodynamical equilibrium (20). Living systems are far away from the equilibrium because of the information stored in their genomes (17). John

Polkinghorne (23) predicts that “by the end of the twenty first century, information will have taken its place alongside energy as an indispensable category for the understanding of nature.” The paradigm of cognitive biology points to the same direction.

5. Self-referential cognition - a ‘Big Bang’ of complexity in cognitive evolution?

Concerning humans as conscious beings, it seems necessary to postulate an emergence of a new kind of knowledge - a self-aware and self-referential knowledge. We not only know, we know that we know. We not only have informations but we possess informations about informations (meta-informations) as well. Cognitive biology itself is an example of the self-referential knowledge. It is a theory (knowledge) about accumulation of knowledge. Appearence of selfreflection in evolution indicates that the human brain reached a new qualitative level in the epistemic complexity. One may speak of a cognitive ‘Big Bang’. The expression of this cognitive ‘explosion’ that occured in human species may be found in the development of science, art, culture and religion. Many writers have noticed this interesting phenomenon. Gilbert Keith Chesterton wrote that “man is not merely an evolution but rather a revolution.” Since the most primitive men drew pictures and the most intelligent monkeys don’t, “art is the signature of man” (24).

What are the mechanisms of self-awareness? Can we describe the emergence of self-referential knowledge in the mathematical language of empirical science? Is it possible to extend the theory of physical complexity and formalize the meta-knowledge which is characteristic for our species? Interestingly, Gödel’s theorem shows a basic limitation of formal methods due to self-reference (25). His results demonstrate that it is impossible to achieve a complete knowledge of a (nontrivial) formal system with the means available within the system. To fully understand the formal system one must go outside the system (otherwise one falls into inconsistencies). It is interesting to apply this principle to human cognition. According to the computationalism, our mind basically functions as a certain (unknown) computational algorithm. However, a Gödelian line of thinking would suggest that we are not able to find this out because we cannot step out of the algorithm. If this reasoning is valid then there are two possibilities: either we are no mechanical machines or we are machines but we cannot know it because of the limitation imposed by computational selfreference. It is the limitation of an observer in "Cartesian prison" (26). In a paraphrase of Stephen Hawking's words (27): we don't see the mind from the outside. Instead, we and our models, are both part of the mind we are describing. Thus, a theory of human cognition is self-referencing, like in Gödel's theorem. One might therefore expect it to be either inconsistent, or incomplete. So it seems to be improbable that a *complete* and *consistent* formalization of *human epistemic complexity* is possible (28).

Based on Gödelian and other arguments, some authors argue that the evolutionary leap from 'pure' cognition to self-referential cognition might have been governed by some novel noncomputational principles. (It should be noted that Gödelian arguments are highly controversial and the interesting debate about their validity continues. See e.g. Ref. 29, 30, 31.) To account for the emergence of consciousness, new physical principles (32) or known physical (quantum) principles operating in the brain in a special way have been suggested. An interesting quantum brain proposal was published by Jeffrey Satinover (33) that combines findings in computational neuroscience, nonlinear dynamics and quantum physics. Since indeterminism observed in quantum events is sometimes interpreted as a fundamental time asymmetry (34), it is tempting to speculate that if quantum brain hypotheses contain some truth then a deeper link might connect thermodynamic, cosmological and epistemic 'ratchetting' processes (for introduction to quantum 'ratchetting' see e.g. Ref. 35).

If it is not possible to entirely reduce emergent human consciousness to neuronal computation (28), then an interesting philosophical question arises, namely what kind of *emergence* is responsible for it. Mark Bedau distinguishes nominal, weak and strong emergence (36, see also Ref. 37). If a new kind of causation powers (so called 'downward causation') has been brought about by the emergence of selfreferent cognition, then we can call it a *strong emergence*, according to Bedau's definitions. The existence of *downward causation* belongs to intensely discussed topics in the philosophy of science. I a recent article, George Ellis (38) describes a hierarchical view of the complexity of the universe with the autonomously effective mind at the top of it: "the higher levels in the hierarchy of complexity have autonomous causal powers that are functionally independent of lower-level processes. Top-down causation takes place as well as bottom-up action, with higher-level contexts determining the outcome of lower-level functioning..." These words resemble the Satinover's hypothesis (33) of a hierarchy of nested networks (similar to Hofstadter's "tangled hierarchy", Ref. 39). An attractive speculation is that the strong emergence might be related to quantum phenomena since quantum theory postulates that quantum events cannot be reduced to some form of bottom-level microscopic law governing their outcomes (41, 40). In addition to information, the downward causation (or - in Aristotelian terms - the *inside-out causation*, Ref. 42) seems to be a very interesting topic for discussion and research in complexity science in the next years.

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