Information, complexity, and dynamic depth

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University of California, Berkeley, 2012

Abstract

Why are computers so radically different than brains in terms of phenomenology? The difference is one of complexity but not complexity in mere numbers of elements, interactions, operations per time and space, or even generative difficulty. We argue that the difference is dynamical. We propose a measure of the complexity of a system that is largely orthogonal to computational, information theoretic, or thermodynamic conceptions of structural complexity. In contrast, we propose a complementary measure of system complexity that captures a system's degree of internal causal convolutedness and hierarchic dynamical organization. We term this measure a system's *dynamical depth.* This is assessed in terms of the degree to which it exhibits discrete levels of dynamical organization in which successive levels are distinguished by their inverse relationships to entropy production and constraint generation. A system with greater dynamical depth than another consists in a greater number of such nested dynamical levels. Thus a mechanical or thermodynamic system has less dynamical depth than an inorganic self-organized (e.g. morphodynamic) system, which has less dynamical depth than a living or mental (e.g. teleodynamic) system. Dynamical depth can provide a more precise and systematic account of the fundamental difference between computation (low dynamical depth) and cognition (high dynamical depth), or inorganic chemistry (low dynamical depth) and living chemistry (high dynamical depth) irrespective of their structural complexity. Taking both dimensions of complexity into account is necessary to clearly distinguish between information processing understood in merely structural terms and information understood semiotically.

1. Introduction: Information and interpreting systems

Essays on information very often begin with the classic discrimination between matter, energy, and information. However, their most conspicuous similarity is that they consider information to be indissolubly connected to a physical difference of matter and energy. The common initial point of their reflections is that a distribution of materials or energy in space and time (e.g. a sign or signal medium) must have a structure, i.e. it needs to have a heterogeneous consistency, in order to possess potential information out of which a receiving system may produce actual information. An absolutely homogenous physical object cannot carry any potential information. This basic insight recapitulates Gregory Bateson's famous aphorism that "a bit of information" is "a difference which makes a difference."

We consider this insight to be also the main pre-assumption of the most influential theory of information up to the present, which was originally formulated by Claude Shannon. In 1948 he introduced a method for precisely quantifying the information of a communication signal or medium, which ultimately reduces the measure of information to a measure of physical difference. Although not explicitly saying so, Shannon seems to consider physical difference to be both necessary and sufficient to measure the potential information content that a given medium can convey. His theory has two implicit main pillars because his reduction of potential information to physical difference requires two different conceptions of physical difference: First, there have to be distinguishable physical entities which may be temporal (i.e. successive parts of a temporal sequence)[1] or spatial (i.e. simultaneously existing parts of a material medium).[2] Second, these distinguishable physical differences must occur with different probabilities across space and/or time, than their "expected" or "natural" probabilities in order to convey a specific "message." Shannon's concept of information is thus ultimately a probabilistic concept. He essentially uses the same formula that Ludwig Boltzmann developed to define thermodynamic entropy – since both are measures of uncertainty or unpredictability of an ensemble – in order to define information. For this reason Shannon information is often called "Shannon entropy." This means that the higher the entropy or unpredictability of a received medium or sequence the higher is its potential capacity to convey information.

This necessarily leads to the third and maybe most peculiar characteristic of Shannon's thinking (although not as basic as the two already mentioned fundamentals of his theory): "The less probable an event is the more information it furnishes." (Weizsäcker 1981, 278) If the receiver of a hypothetical sequence cannot formulate expectations about the order or succession of the received states (e.g. signs) then each one that is received carries maximal information for that medium. This can occur, for example, if the sequence in question is absolutely random, (i.e. where the occurrence of each sign is equiprobable in each position). In such cases, the uncertainty (i.e. surprise factor) of receiving a given sign at any point would be maximal. In contrast, if there are significant differences between the probabilities of occurrence of different signs, then

[1] The succession of electromagnetic impulses received by a radio telescope is a sequence of different energy levels distributed in time.
[2] The aperiodic structure of DNA molecules or letter sequences on a printed page are physical structures consisting of discernible physical entities (nucleotides, alphanumeric characters) distributed in space (and which may or may not be interpreted sequentially).

receiving a very probable sign is not surprising. Thus it is sometimes argued that Shannon information measures the average *potential surprise* provided by a received sign or signal. It measures an average "distance" between what *could* have occurred and what actually occurs.

But as remarked both by Shannon, and by Warren Weaver, who wrote a companion introduction to the theory (which was published along with Shannon's paper a year later), this is a special technical use of the term "information" that is not equivalent with its more general usage. Outside the area of computational and communicational technology an incautious use of Shannon's conception of information has misled thinking about information for decades. Because of its explicit identification of information with entropy, i.e. a measure of disorder and unpredictability, it necessarily ignores meaning and reference. In this respect it is often described as a "syntactic" concept of information. This difference is exemplified by the fact that a totally disordered or random spatial or temporal sequence of physical differences carries maximal Shannon information but lacks any internal organization and therefore cannot represent any semantic and referential value. In addition, Shannon's theory of information does not make any claims about the causality of the processes involved in creating, expecting, or evaluating the usefulness of information.

Overemphasizing the distinction between information and matter / energy is also common in both technical and non-technical uses of the concept of information. However, no such sharp distinction is implied by Shannon's theory. Indeed, the information theorist Charles Bennett (discussed below) often is quoted as saying "information is physical" to emphasize the importance of avoiding this sort of implicit dualism. However, this should not be construed as claiming that information is identical to its physical substrate either.

Denying the physicality of information often entices incautious scholars to overlook two obvious facts: First, information is always conveyed by distinguishable differences exhibited in some physical medium. Shannon's measure of the information conveyed by a given (physical) medium is a function of the reduction of signal uncertainty it provides, and this is a function of constraint in the variety exhibited by the received signs/signals compared to what was potentially possible (i.e. a reduction of Shannon entropy). But for a physical medium to exhibit a comparatively low probability state (i.e. comparatively low entropy) this difference must have been caused by work imposed from some extrinsic source (Deacon, 2007, 2008). This is true whether the prior expected probability is due to simple thermodynamic effects or to the operation of known tendencies or even purposive processes. Thus, for example, an inorganic physical process that is in a low probability state provides evidence that either something has prevented an increase in its entropy or some work has been done to move it away from a higher entropy state. But likewise, a high probability state of a purposively maintained medium, such as the arrangement of furniture in a room, if instead is distributed in such a way that the furniture is turned over and disorganized in locations, may indicate that a fight or an earthquake took place just previously.

Second, the receiver-interpreter of information also needs to do work in order to discover the reference conveyed by these received physical differences. In other words, work must be done to utilize the received constraints to reorganize some aspect of the receiving system. If there is no such recipient effect, nothing is conveyed. This response thus produces an additional modification of another medium (e.g. that which constitutes the receiving system) which can itself serve as information for further interpretation. Importantly, this recipient response can for this reason be described as being "about" the prior work embodied in signal constraints.

In biological systems the performance of biochemical work requires consumption of energy, and this is typically embodied in molecular form (e.g. in the phosphate bonds of ATP molecules). This transformation of bound energy into work allows organisms to react to the non-random distributions of environmental features in ways that are supportive of their continued existence and reproduction. An external observer could say that the information that they acquire in this way warrants claiming that such systems appropriately represent their environment, i.e. that they *interpret* these medium features as being about something potentially relevant for the persistence of this very capacity.

In this paper we will put special emphasis on analyzing the forms of system-internal material-energetic processes that are necessary and sufficient to utilize information "about" environmental features (i.e. in some way bring system-intrinsic and system-extrinsic features into correlation with one another). Concepts like representation, interpretation, sentience, etc., can in this way be disentangled from their mentalistic connotations for the purpose of generalizing their use in non-mentalistic (e.g. biological) contexts.

Deacon (2012, 549) classifies all such semiotically based phenomena, including both mental and non-mental end-directed relationships (e.g. functions) under the term "ententional phenomena." This inclusive concept of entention is similar to Von Weizsäcker's usage of related concepts in his reflections on information.[3] In his book on the philosophy of nature, *The Unity of Nature,* he says that "information is only what can be understood" (282) and by the term "understanding" he means some form of correspondence between internal information (which a system produces after the receipt of a signal) and the object of reference of a signal or environmental effect. According to

[3] Carl Friedrich von Weizsäcker (1912-2007) was a German leading physicist (close colleague of Werner Heisenberg), and influential philosopher of science.

Von Weizsäcker this conversion of an input to an output via system-internal work does not imply the presence of any kind of subjective experience or mental decision. It is governed by the totality of lawful physical interactions between the elements of the receiving system (ibid. 284-285) that transform energy and matter into work. However, this is not quite sufficient to constitute information "about" something. There is a certain form and level of organizational complexity required. It is the goal of this essay to try to identify exactly what kind of complexity this is.

Even the simplest organisms able to interpret physical differences in their environment as useful or dangerous are complex material *multi-stable dynamic systems*. Such systems typically consist of a large number of interacting components able to be diversely configured into a large number of interrelations. But they are complex in an intermediate structural sense—exhibiting only modestly high Shannon entropy for their compositional detail, because of their many repeated components and structural regularities.[4] In contrast, simple mechanical dynamical systems, such as linked pendulums, exhibit considerably lower complexity in structural terms but high complexity in global behavior, whereas an unorganized thermodynamic system, such as an ideal gas near equilibrium, exhibits very high complexity in entropic terms but low complexity when analyzed at the level of the whole system. This provides a glimpse of an intuitively paradoxical relationship between structural-dynamical complexity of a system and its capacity to utilize signal medium constraints as information about something not directly present. It is not merely that what we might term *semiotically competent systems* are of intermediate complexity, rather their complexity is of a form that exceeds some threshold along a scale that current concepts of complexity fail to measure.

2. Measuring Complexity

In his influential essay "The Architecture of Complexity," published 1962, Herbert Simon provides an admirably plain and seemingly self-evident view of complexity: "Roughly, by a complex system I mean one made up of a large number of parts that interact in a nonsimple way." (468) Because of the non-simplicity of their interactions "given the properties of the parts and the laws of their interaction, it is not a trivial matter to infer the properties of the whole." (ibid.) Simon's approach to complexity has been implicitly accepted by almost all attempts to define complexity in different sciences. Since the 1960's many analytic and quantitative definitions of complexity have been offered. There are two main categories: The first category includes methods developed by

[4] See the discussion of measures of complexity in section 2.

information theorists and mathematicians who understand complexity (as did Simon) in terms of a measure of the number of distinguishable components times some measure of the number of possible non-redundant (i.e. random) arrangements of these components with respect to one another. Members of the second category try to capture complexity in terms of the diversity of arrangements that are exhibited "across multiple temporal and spatial scales." (Sporns 2007; see also Christen 1996, 59-65)

2.1. Complexity as randomness

Ray Solomonoff (1964), Andrej N. Kolmogorov (1965), and Gregory J. Chaitin (1966) independently developed closely analogous measures of complexity that apply to sequences of symbols. Measures of this kind of complexity are known as *algorithmic information content* (AIC) or as *Kolmogorov complexity*. In these approaches the complexity or information content of a string of symbols is equated with the length of the *shortest* computer program or algorithm that can generate this string (typically defined in terms of implementation on a universal Turing machine for maximum generality). The algorithm is considered to be a compressed representation of the string. If the string consists of values that represent states of a physical system (e.g. measure values) the algorithm is a measure of the *compressibility* of an abstract representation of a given physical phenomenon.

Charles Bennett (1988) developed a related measure of complexity which was also suggested in a paper by Chaitin (1977) and is called *logical depth* (Christen 1996, 63). Bennett defines logical or algorithmic depth as the *time* that a universal Turing machine requires to execute the shortest algorithm which generates a given sequence of symbols. The logical depth of such a sequence is directly related to its Kolmogorov complexity, but additionally it indirectly takes into account the actual work involved in the process. There are many other algorithmic definitions of complexity (Christen 1996, 63-65), but almost all are based on related assumptions and so for the purpose of the present paper these will be considered variants of the general AIC paradigm.

Clearly the concepts of complexity developed by Solomonoff, Kolmogorov, Chaitin, and Bennett are very similar, and are also related to Shannon's measure of entropy. They treat complexity as the inverse of compressibility and identify ways to compress a signal or its representation (such as a character string) by virtue of discovering redundancies. However, whereas Shannon entropy only takes into account what might be described as superficial statistical redundancy, the various algorithmic approaches can additionally take into account more cryptic redundancies due to recursive aspects of the process capable of generating that representation. In effect, AIC approaches seek to identify the most compressed *representation* of a given phenomenon.

The AIC approach to complexity was implicit in Herbert Simon's (1962) idea that "a system can be *described* economically" if it has redundancy (478; emphasis added). So although Simon did not explicitly define complexity as a measure of non-redundancy in the *representation* of a physical phenomenon, his approach anticipated this later development. The question that remains is whether the complexity of a representation and the complexity of the phenomenon represented are equivalent.

So the question is begged whether or not these methods which apply to representations (typically treated as binary strings) are also adequate to assess the complexity of real physical systems. We discern five weaknesses or limitations in the use of AIC approaches to measure physical complexity. First, even if physical systems are understood as spatial or temporal sequences of physical differences they "do not come readily encoded as numbers" (Lloyd & Pagels 1988, 189). Second, as Chaitin (1977) showed, it is impossible to prove that a certain algorithm is indeed the shortest possible representation of a given sequence. Third, like Shannon's concept of information, AIC and logical depth do not focus on meaning and reference of the representations they analyze but only on their syntactic aspects. Any assessment of the complexity of physical phenomena needs to also consider any semantic (referential) and pragmatic (normative) aspects of these representations, especially since these aspects are indissolubly connected particularly to biological and cognitive systems. Fourth, information theoretical concepts of complexity only characterize descriptions of physical systems, not how they came about or how they are causally organized. In this sense they refer to the "map" and not to the "territory." This may or may not reflect the causal complexity of a dynamical system. Fifth—and this is the biggest problem for all methods which connect complexity to non-redundancy or randomness—the concept of complexity underlying AIC and logical depth is *counterintuitive*. The information theoretical concepts of complexity attributes higher complexity to an entirely stochastic system than to an ordered one. Whereas the former cannot be represented by a shorter program because "no aspect of its structure can be inferred from any other" and therefore "it is its own simplest description" (Simon 1962, 478), the latter can be compressed because of its internal regularities. Thus, the information-theoretical and mathematical approach to complexity *only* identifies complexity with incompressibility in one dimension of organization, whereas real physical systems may not be so reducible.

This understanding of complexity therefore produces a paradoxical problem in that it effectively treats a maximally disordered system and the random string of characters that represents it as more complex than ones that exhibit interesting and/or unprecedented properties, such as being alive or being conscious. Intuition suggests instead that a thoroughly random and maximally unpredictable, i.e. maximally incompressible, sequence (state to state, character to character) is simple in its organization.

Clearly, the related definitions of complexity of Kolmogorov, Chaitin, Solomonoff, and Bennett are well-suited for analyzing abstract sequences of symbols or numbers. In this respect it is not counterintuitive to claim that π has a higher complexity than the number 2/3 which is a simple periodic number (0.6666….). But they lead to counterintuitive results when applied to physical systems. In order to understand the complexity of real physical systems we need a more subtle measure that more accurately reflects features of a system's causal properties, not just the complexity of its representation.

2.2. Complexity and physical structure

In the last three decades natural scientists, especially physicists and biologists, have introduced concepts of complexity that focus on the organization of natural entities and not merely on the regularities and irregularities of their formal descriptions.

The simplest way of quantifying complexity on the basis of structure is to count the number of a system's elements and/or interactions between them (Sporns 2007). For example, some biologists (e.g. McShea, 1995) offer definitions of organism complexity based on the number of different cell types, the number of components, and the organism's morphology, i.e. the number of structural elements and their combinations (Christen 1996, 74). Others define biological complexity "related to the diversity or lack of self-similarity" of the interactions within a hierarchically organized system (Huberman 1992, 130, see also Huberman & Hogg, 1986).

The term *effective complexity* was introduced by Murray Gell-Mann and Seth Loyd (1995, 1996, 2003) to split the Kolmogorov complexity or algorithmic information content of an object into two separate parts, its regularities and its random features. Its effective complexity is defined as the AIC of the *regularities* alone, i.e. the length of the shortest algorithm that can generate the regularities of an empirical system or sequence of symbols (Ay, Müller, & Szkola 2010). The concept of effective complexity has been criticized as being too sensitive to subjective criteria contributed by an external observer who decides which parts of the system are to be considered regular versus irregular.

Adami and Cerf (2000) developed a related concept of *physical complexity*, a quantity particularly useful in biology. It can be applied to "any sequence of symbols that is about a physical world or environment." (Sporns 2007) Physical complexity is "an instance of effective complexity" Gell-Mann's (Adami 2002, 1087). It is defined as the Kolmogorov complexity (AIC) of the bio-molecular sequences (e.g. genomes) of a population that encode the adaptations of the organisms to specific features of their environments. The physical complexity of a genetic sequence is the amount of information coded in the genetic material of an adapting population that is about the environment to which it is adapting. This information is "given by the difference between the entropy of the population in the absence of selection, and the entropy of the population given the environment, that is, given the selective forces that the environment engenders." (ibid.) All entropies are calculated by measuring the distribution of the genes and calculating the Shannon entropy of this distribution. It is an attempt to measure the information encoded in a genome which allows an organism to make predictions about its environment and hence increases its chance of survival (ibid.). It also can be used to measure the genetic similarity of individuals belonging to the same population.

The concept of *predictive information* (Bialek 1999) is based on the principle of the extensivity of entropy (Sporns 2007). Systems are called "extensive" if their entropy grows linearly with the increase of the number of their elements. Since the entropy of systems that contain causally interacting elements will tend to be a nonlinear function of their size, the degree to which a system deviates from extensivity can be used to measure the degree of the interconnectivity of its elements. In this respect predictive information is a measure of what might also be described as network complexity.

Neural information (Tononi et al. 1994) is a measure of complexity that is related to predictive information. Despite the name, neural information is applicable to all kinds of empirical systems not just brains. "One of its building blocks is integration" which "is computed as the difference between the sum of the component's individual entropies and the joint entropy of the system as a whole." (Sporns 2007) The concept of integration also measures the degree to which a system's entropy deviates from additivity (i.e. linearity).

Finally, Seth Lloyd and Heinz Pagels introduced the concept of *thermodynamic depth* in an effort to overcome the lack of causal relevance of the concept of logical depth and of computational conceptions of complexity in general (see 2.1.). Thermodynamic depth was conceptualized as a quantity that characterizes "the evolution of a state and not the state itself." (Lloyd & Pagels 1988, 187) According to their analysis complexity should be a measure of "how hard it is to put something together", that is, a real physical system (ibid. 189; Lloyd 2006, 192). Lloyd and Pagels proceed from the fact that there are many possible trajectories which can lead a system to a given macroscopic state in its state-space. They define the depth of a system's macroscopic state as "the amount of information required to specify the trajectory that the system has followed to its present state." (Lloyd & Pagels 1988, 190) Thermodynamic depth is then equal to the difference between the "coarse-grained entropy of the state […] and the state's fine-grained entropy." (ibid.)[5] Thermodynamic depth applies equally to organisms, non-living systems, computational devices, and other physical systems (ibid. 187): "[A] computer can generate large amounts of thermodynamic depth among its microscopic degrees of freedom." (ibid. 207) It does not therefore provide any distinction in the *kind* of complexity that distinguishes organisms from complicated mechanical devices such as computers.

These approaches were developed in order to overcome the shortcomings of the information theoretical approaches to complexity. They succeed in two critical respects. Since they have been designed to characterize real material systems they are sufficient to describe features of their physical structure. They also do not lead to any counterintuitive assessments of a system's complexity as do computational approaches because, in opposition to the information theoretical approaches, they *identify a system's complexity with the diversity of its component physical relationships*. Since they consider the regularities of a system and not merely its irregularities they reflect aspects of what might be described as the inner coherence of a system's spatiotemporal organization. We ascribe inner coherence to a system which allows an observer of a part of it to anticipate to a certain degree the state of a spatially, temporally or spatiotemporally different part of the same system. The parts of innerly coherent systems contain information, although often vague, about the whole system. Inner coherence enhances the compressibility of a system's description because it increases the ability to predict its organization from partial knowledge of it.

The inversion of the role of compressibility in the understanding of complexity which clearly occurred in the transition from the information-theoretical to these physical approaches to complexity is easy to understand if one considers that an important scientific and technical revolution took place in the time which separates both approaches – the emergence of dynamic systems theories (including chaos theory) along with major developments in non-linear mathematics and explosive advances in computing power, that made realistic simulations of complex physical processes possible. This new interdisciplinary paradigm focuses on the study of non-linear processes and particularly on that subset called "self-organized systems" (see also below). The most essential feature of self-organized systems is that they spontaneously increase their inner coherence and thus reduce their randomness to a high degree (assuming that the required external conditions are given). In other words, they tend to develop toward significant reduction of the number of their possible states, which consequently dramatically

[5] The coarse-grained entropy of a state is its thermodynamic entropy. It does not provide any information about its microscopic elements. The fine-grained entropy or Gibbs entropy takes into account all details of the state of the system's microscopic elements and displays them in the state-space. It does not provide information about the positions and momenta of all particles but about the probability distribution.

increases their predictability. In physical terms we may say that they *compress* the trajectories of their future development into small fractions of their possible state-space called "attractors." This real physical compressibility allows an external observer to create highly compressed representations of such systems. So, there is an intrinsic relation between the real compressibility of self-organized dynamic systems and the abstract compressibility of the formal descriptions of those systems. As we will describe below, physical processes that spontaneously develop toward a more compressed state pose some interesting challenges for measures of complexity which themselves are based on the concept of compression.

Despite their advances over AIC measures of complexity physical approaches still suffer from a serious limitation. Their main common characteristic is that they are designed to quantify the complexity of phenomena by measuring only the *results* of the work that produced them. They analyze a system's phenomenal regularities and/or entropy but do not attempt to assess the causal details of their underlying physical organization. To be able to identify the forms of complexity that make living and mental processes so causally distinctive as compared to non-living physical and computational processes we need to measure more than the structural or even the generative details of a physical system. We need to additionally capture the essential features of a system's causal organization, i.e. *its capacity to organize physical work to modify itself and/or other systems in response to interaction.*

3. Cybernetics and self-organization

Cybernetically organized information processing devices, such as used in robotics, and other artificially intelligent systems designed to interact adaptively with a variable and unpredictable environment can be complex in terms of both informational and physical measures. Inorganic physico-chemical self-organized dissipative systems are also complex in all these senses. Though complex in different ways, cybernetic devices and self-organized systems exhibit a distinctive form of complexity by virtue of being interactively embedded in a physical context with which they exchange dynamical interactions and in some cases energy and materials. In this section we will deal with the controversial claim made by many physicists and computer scientists that self-organized dynamic systems and cybernetic information processing devices exemplify a form of complexity that is sufficient to characterize living and mental processes because of this openness to their environment.

Cybernetic information processing devices, like intelligent control systems and robots, interact with their environments in ways that achieve target end states irrespective of initial state, despite the effects of constant perturbations, and via diverse and unplanned causal trajectories. This end state can even be the maintenance of their functional continuation – as in the case of robots that "seek" to connect themselves to a critical resource, such as a source of electrical power to recharge their batteries. It would, however, be inaccurate to conclude that such systems generate these "aims" endogenously. Those features of their structural design, which are responsible for these convergent dynamical tendencies, must be generated extrinsically, i.e. by their designers. This is exemplified by the fact that the dynamical organization of such devices is not a functional consequence of their behaviors. The capacity of such systems to converge upon a distinctive target relationship to their environment and utilize features from that environment to achieve this result derives from influences extrinsic to all these features. Nevertheless, the openness of such systems makes them capable of far more diverse forms of behavior than most naturally occurring inorganic physical systems or mechanical devices. Consequently, they pose challenges for measures of complexity not able to encompass this dynamical openness.

Over the past half-century theorists have often invoked the logic of such open systems to shed light on the special characteristics of life and mind. This form of complex context-sensitive goal-directed system is often characterized as "teleonomic" (as coined by Colin Pittendrigh, 1958) referring to its end-directed behavior irrespective of how it is generated (and typically given a cybernetic interpretation). Although the physical structure and constructive processes necessary to characterize and generate such systems may not be of high complexity by these measures, their behaviors can have a complexity that may be extreme by these same measures. This is both because their dynamics is dependent on interacting with potentially unpredictable environmental factors and the quasi-circular causality that arises when these factors modify future interactions with that environment.

As dynamical systems theories have developed over the years to be able to more precisely describe such open systems and their circular coupling with the environment research interest has been shifting to the study of stochastically organized dissipative systems. These are thermodynamic systems that are maintained far-from-equilibrium for some period of time. Of particular interest are thermodynamic systems that are being constantly perturbed away from equilibrium and in the process of continually dissipating this disturbance develop toward highly organized dynamical configurations. These so-called self-organized systems have provided important models for exploring the difference between simple mechanistic systems and biological systems. Self-organization is a technical term. It means that the increase of a dynamic system's orderliness is the result of interactions between its elements and not the result of the imposition of this form from some extrinsic source.

A system is defined as a dynamic system if its state at any given moment can be described as a limited set of time-dependent or state variables $x_i(t) = x_1(t), x_2(t), \ldots, x_n(t)$, for which a function F can be formulated stating mathematically the connection between states at times t and $t + \delta t$. The properties of this function reflect the causal relationships at work within the system. The most abstract formula for a dynamic system must therefore be:

$$x_i(t + \delta t) = F(x_i(t), p_j, \delta t) \qquad \text{(formula 1)}$$

The letter p_j represents a set of parameters. Parameters represent those externally fixed constants which constrain the development of the state variables $x_i(t)$. Dissipative systems are dynamical systems that introduce entropy into their environment, which means that their energy "dissipates" or disperses from the system onto its environment. As a result a dissipative system will tend to approach equilibrium unless the dissipated energy, material, or disturbance of organization is replaced by other sources in the environment. All self-organizing systems are dissipative systems.

While cybernetic and self-organizational systems can generate complex behaviors there is a sense in which, if analyzed with respect to fixed external parameters, they are often neither algorithmically nor physically complex in their organization. Only their non-linearity and openness makes precisely determinate behavior predictions impossible. Thus, remarkably simple nonlinear dynamical systems (such as coupled pendulums) can produce chaotic (and thus maximally complex) behaviors. The capacity of relatively simple recursive systems to produce maximally complex behaviors has been a source of considerable interest for both physicists and biologists. But while chaotic behavior is complex by the above measures it too conflicts with our intuitions about biological complexity either.

The relevance of self-organization to living complexity is widely accepted. Living systems undoubtedly depend on self-organizing chemical dynamics to generate the order they require to counteract the spontaneous increase in their entropy. So a measure of complexity that captures the complexity difference that distinguishes self-organization from chaotic dissipative systems on the one hand and isolated thermodynamic systems on the other is likely to be useful for assessing the special complexity characteristic of living organisms.

There are, however, good reasons to question the adequacy of theories based on self-organization to assess the complexity of organism dynamics. Here we emphasize only one of these reasons.[6] Systems serving as models of self-organization require gradients of energy and/or material to move them away from thermodynamic equilibrium. There is a

[6] For a more detailed explanation see Deacon & Cashman (forthcoming), and Koutroufinis (forthcoming a).

fundamental finding in thermodynamics that states that every form of physico-chemical self-organization develops toward a dynamical form that maximizes the reduction of the gradients that produce it. In other words: *Each self-organized system tends to evolve toward a dynamical form that would return the system to equilibrium in the most efficient way possible (within its boundary constraints) were the external gradients to become exhausted.* This essential property of dissipative dynamic systems is known as the principle of *maximum entropy production* (MEP).[7] Such systems develop toward a dynamical organization that more efficiently degrades the gradients which have distanced it from the state of thermodynamic equilibrium and thus maximizes the production of entropy into its environment. The order that emerges inside the system enables it to offload the destabilizing influence of an energy/material gradient more quickly and with less work than if it didn't self-organize. In other words, self-organized systems develop dynamical regularities that more efficiently destroy the very gradients that are necessary to produce these same regularities.

So self-organization is paradoxically self-undermining in this respect. The increased organization of internal dynamics is such that it leads to maximum destruction of its own supportive conditions. With the degradation of these external supportive conditions the internal regularities of self-organization breaks down. There is nothing internal to a self-organized dynamical system to maintain this order in the absence of external perturbation nor any mechanism to compensate for changes in this external support. In this respect it is not accurate to claim that self-organized systems are the sources of their own organization, and so the term 'self' is ultimately a metaphoric use in this context.[8]

4. Information, compression, and self

One reason to be suspicious of the completeness of any theory of complexity based on ideas of compressibility alone is that the concept of information is itself based on this same concept. But depending on whether the focus is on merely the potential for a medium to be used to inform or instead on the content of a particular message provided by that medium, the function of compression is opposite. Compressibility is a measure of constraint and, as is implicit in Shannon's conception of the information provided by a received message, the constraints on the informational entropy of a signal and the

[7] According to the second law of thermodynamics all physical processes produce entropy. Self-organization is characteristic of dynamical thermodynamic systems maintained far from equilibrium that not only increase global entropy but also increase the rate of entropy production in a way that compensates for any imposition of additional energy and/or material.

[8] Therefore Koutroufinis describes this kind of dynamics as "self-organization without self" (1996, forthcoming b).

reduction of uncertainty that this provides is the measure of the information thereby conveyed. All the various measures of complexity based on compression are in this respect alternative measures of a property related to Shannon entropy. It is the complexity of a physical communication medium that determines how many distinctions it can possibly convey about a particular subject of reference. However, *what* it conveys to some interpreting system depends on the latter being able to discover a pattern in this complexity; i.e. some overt or hidden regularity. So the property of being about something is itself a complex relationship of a different kind in which compression itself becomes the measure, and ultimately the complexity of forms of compression. This apparently paradoxical situation is resolved by recognizing that these may be two complementary aspects of complexity: one associated with the production of a physical medium (or signal) and one associated with interpreting its relationship to something it could be about.

Dynamical systems which actually organize themselves must contain information about how their internal dynamics fits or does not fit with the local environment, and must have some way to utilize this information for their own self-persistence. This clearly applies to organisms. In contrast to inorganic self-organized systems, the exchange of energy and matter between organisms and their environment does *not* follow the principle of maximal entropy production. Instead, organismic systems develop toward a *minimization* of entropy production with respect to the work they perform to resist internal entropy increase.[9] Organisms adapted to their environment act in ways that tend to preserve the useful matter and energy at their disposal. This is trivially exemplified by the way that past organisms have sequestered the energy captured in hydrocarbon bonds; energy that supplies modern industry's maximization of entropy production.[10] Also, in clear contrast to inorganic self-organized systems, organisms autonomously locate and use sources of energy and matter which are distributed unevenly in their environment. This capacity clearly warrants describing them as interpreting systems, even if just in a minimal non-mentalistic form. Thus, organisms are the only complex systems for which physical differences contained in their environment have referential and normative value.

The centrality of the referential and normative features of information to life is linked to the way living dynamics differs from and is more complex than non-organic self-organizing dynamics. Thus the dynamical organization that constitutes a living system inverts three defining features of self-organization. First, organisms do not maximize entropy production but rather tend to more efficiently organize entropy

[9] See: Falkner & Falkner (forthcoming), Martyushev & Seleznev 40.

[10] Paradoxically, by taking advantage of this resource provided by billions of years of living dynamics, human industrialization has shifted the entropy production of the ecosystem back toward the maximization logic of a simple self-organized system; i.e. toward an increasingly rapid self-undermining pattern.

production with respect to the work they do to persist and reproduce. Second, their dynamical organization is not self-undermining, even though it incorporates features of self-organization. Third, organism dynamics is specifically self-beneficial (thus inverting the logic of self-organization) and depends on system-internal rather than system external determinants of its organization. These attributes are not merely the result of increased structural or dynamical complexity, they are not merely cybernetic, and they cannot be a consequence of simply additively combining self-organized processes. In this respect there is an increase in some form of complexity from self-organized to living systems that is not captured by any of the notions of complexity so far considered.

Perhaps the most fundamental difference to emerge with life that each of these distinguishing attributes reflects is the appearance of an unambiguous "self." Self in this sense is a dynamical process organized in such a way that it minimizes the probability that its organization will be lost. Inevitably, the conditions conducive to generating this distinctive dynamical configuration are far less probable than those producing self-organized dynamics alone. More importantly, since the fundamental behavioral tendency of living systems is to maintain these rare supportive conditions, by generating those that are least likely to arise spontaneously, there is a coupling of antecedent and consequent states that makes their intrinsic dynamical organization the generator of these same highly improbably and complex preconditions. This curious quasi-circularity linking living dynamics to the production of its own preconditions is why neither structural nor generative concept of complexity offer an adequate measure of the complexity difference that characterizes life.

Therefore, organisms are more complex than cybernetically organized systems because their behavior directly contributes to their own self-maintenance and physical self-creation. They are also more complex than what can be characterized as self-organized systems because they develop dynamical properties that minimize (rather than maximize) the probability of their own dissolution. For these reason we require a new concept of complexity which emphasizes those characteristics of organism dynamics that make them unique among complex systems.

5. Dynamical depth

In an effort to clearly distinguish living dynamics from nonliving dynamics Deacon (2012) identifies three modes of system dynamics that are distinguished by their hierarchic (i.e. nested) dependencies and their reversals of spontaneous global dynamical tendencies to reach different kinds of stable end-states (or attractors) if they are provided with the required time to do so. They are also distinguished by differences in the ways they eliminate, introduce, or preserve constraints. These dynamical modes include *homeodynamics* (e.g. equilibrating processes such as in close-to-equilibrium thermodynamic systems), *morphodynamics* (e.g. non-chaotic dissipating processes such as in so-called self-organizing systems), and *teleodynamics* (e.g. living evolving processes such as in organisms). These dynamical modes define three levels of what we will call *dynamical depth*, as distinguished from the various complexity measures discussed above.

At base are thermodynamic processes, which are defined by their spontaneous tendency to *eliminate constraints*, and thus increase entropy. The natural end-state of an isolated thermodynamic system, i.e. of a multi-particle system which is energetically and materially closed, like a gas in a fixed size container, is the state of the system's maximum *possible* entropy, which is also the state of zero entropy production or thermodynamic equilibrium. Chemical reactions in an isolated system also tend to exhaust their potential to react in the process of reaching the chemical and thermodynamic equilibrium i.e. the end-state in which the concentrations of the reactants and products do not change.[11]

Mechanical (e.g. clockwork) systems also belong to the lowest level of dynamical depth because they tend to reach their maximal possible entropy by always working towards the exhaustion of their mechanic gradient (e.g. potential energy of a spring or the weights of a pendulum clock). In this way they eliminate the one source of constraint available to change. But simple mechanical devices like clocks do not generate any new constraints. The watchmaker puts the gears together and allows them to have only one degree of freedom, which is their rotational angle. Mechanical clocks could only generate new constraints if they were able to reposition their own gears in other ways by virtue of their own internal movements. Finally, we also class among the lowest level of dynamical depth all current forms of computational devices so far constructed or conceptualized. It is easy to understand this conclusion if one considers that, in principle, all operations of electronic computers can also be implemented by mechanical devices.

A second "deeper" level of dynamical depth is produced by self-organization. As noted above, self-organization arises in the special case where an extrinsically imposed energetic and/or material gradient introduces constraints into a partially open system at a rate that exceeds the rate at which that system can spontaneously dissipate them. As a result the countervailing processes of extrinsic constraint introduction and intrinsic constraint elimination tend to do work that organizes system dynamics in a way that matches the rate of constraint dissipation to the rate of constraint imposition. Thus new intrinsically organized constraints in the form of symmetrically distributed dynamic

[11] This kind of chemical end-states obey to the law of Guldberg and Waage or law of mass action.

processes develop over time and facilitate this balancing of input and output. Deacon (2012) terms such processes *morphodynamic* processes because of the way that they internally generate these regularities; i.e. forms. A critical feature that distinguishes morphodynamic processes from merely thermodynamic processes is that morphodynamic processes generate new constraints locally, represented by the time-dependent or state variables $x_i(t)$ in formula l, in order to dissipate the global constraints, represented by the parameters p_j in the same formula, being imposed on them. Morphodynamic processes will tend to spontaneously regenerate these internally generated local dynamical constraints (and thus regularities) in response to being perturbed by extrinsic influences that drive them away from equilibrium. So long as the supportive externally imposed gradients persist within certain limits these regularities will persist, even though these internal regularities tend to degrade these supportive conditions. Since the internally generated constraints (variables $x_i(t)$) in a morphodynamic process persist because of their efficiency at degrading the externally imposed constraints (parameters p_j) it is not possible for them to also act in any way that is self-preserving. They cannot limit the rate of degradation of this external gradient and still persist. In other words, although the form that the internal constraints takes is dependent on system-intrinsic properties and is in this sense autonomously determined so long as supportive extrinsic conditions persist, this special correspondence between internal variables and external parameters is entirely accidental and independent of system dynamics.

Finally, and most critical for this analysis, are what Deacon (2012) terms teleodynamic processes. Analogous to the generation of morphodynamic processes from balanced but opposed constraint-eliminating (e.g. entropy increasing) processes, teleodynamic processes emerge from precisely complementary, interdependent morphodynamic processes. This complementary relationship is such that the supportive boundary conditions for each component morphodynamic process are generated by one or more of the other self-organized processes in the system. As a result the otherwise highly improbable boundary conditions that make the component self-organizing processes possible can become nearly inevitable. Such a combination of boundary constraints would otherwise be astronomically improbable to occur spontaneously. This complementarity and interdependence constitutes a yet higher order form of constraint on the constraint-generation of the component morphodynamic processes. The internal generation of these higher order constraints thereby increases the probability that these same component morphodynamic processes will persist despite changes in extrinsic conditions. The result is a tendency to behave in a way that makes this distinctive form of self-reconstituting dynamics highly likely to persist, reform if disrupted, and even become reproduced in independent systems. Deacon (2006, 2012) describes a molecular model system called and autogen (or autocell) which precisely exemplifies an empirically testable form of this distinctive dynamical organization and its unique systemic attributes.

The probability of the co-appearance of such reciprocally fine-tuned morphodynamic processes such that they produce a teleodynamic process is many orders of magnitude less probable than the spontaneous appearance of any one of the component morphodynamic process alone. Likewise the probability that thermodynamic conditions will spontaneously converge to produce either component morphodynamic process is many orders of magnitude less probable than the spontaneous appearance of either of the component thermodynamic processes alone. Thus one characteristic attribute of dynamical depth is that the probability of spontaneous appearance declines by many orders of magnitude with each level of increasing depth.

The progressive internalization of constraint generation with increasing levels of dynamical depth exemplifies another defining attribute: an increase in what can be described as *organizational autonomy*. Thus the organization of homeodynamic (e.g. thermodynamic) processes is entirely dependent upon extrinsically imposed conditions, whereas the organization of morphodynamic (e.g. self-organized) processes is additionally a function of the ways that the components of the medium in question tend to interact. As a result morphodynamic processes generate intrinsic constraints whose forms are independent of the form of the extrinsic constraints that drive the system to generate them. Teleodynamic systems demonstrate an even greater degree of organizational autonomy and are the only systems that can be described as "self"-organized in a non-metaphoric sense of *self*. There are several reasons to ascribe selfhood to teleodynamic systems:

1) The end-directedness of a teleodynamic systems is more than an "attractor" in the sense that a morphodynamic processs has an attractor. A morphodynamic system's attractor reflects the constraint on dynamical possibilities that is a *reaction* to externally imposed environmental influences, whereas the end-directedness of a teleodynamically organized system is generated internally. The higher order constraint of morphodynamic interdependency which determines teleodynamic individuation reinforces and regenerates itself in response to changing environmental conditions. Teleodynamic end-directedness can as a result be considered as a second order attractor, i.e. as one that generates the conditions which it requires. In this sense teleodynamic systems are *self-attractive*.
2) Teleodynamic systems are organized in a way that preserves and re-generates their own essential constraints. In this respect, there is an inner coherence to their dynamics that is lacking in morphodynamic systems which are intrinsically self-undermining. Consequently a teleodynamic system interacts with its environment in a way that sustains supportive relationships with its environment and compensates for

unsupportive or destructive relationships, e.g. by repairing or reproducing itself (Deacon 2012). A teleodynamic system can therefore be said to implicitly include a *self-representation* that persists despite a partial loss of system coherence, and with respect to which coherent organization can be re-achieved. This property is closely related to what Koutroufinis calls *autognostic*, i.e. self-knowing, entities (1996, forthcoming b).

3) Because they are self-representing and self-attractive, and not just dynamically coherent (like systems with first order attraction), teleodynamic systems can be considered *self-compressing systems*. In other words, the system's own (physical) compression mechanism, i.e. its self-attractive physical organization, effectively embodies a representation capable of reconstituting both its complex physical organization and a representation of the complexity of its environment. Since it is a representational compression of a physical compression process generated by this very process itself, it might be considered as a new type of compression: Teleodynamic organization consists essentially in an indecomposable interpenetration of semiotic (self-representation) and physical (self-attraction) features which condition each other. For this reason teleodynamic complexity is not able to be represented by scientific models using any simple compression relationship like the systems of coupled non-linear differential equations so commonly employed in systems-biology. It is in this respect not reducible to any of the above-described forms of complexity. It is a specific and new form of complexity.

4) The self-coherence of teleodynamic organization generates a distinct compression of environmental complexity (i.e. a representation) that is specifically relevant to self-maintenance and self-creation. It autonomously regulates its internal dynamics and relations to this self-relevant. Teleodynamic systems thus have an *Umwelt* and not just "surroundings" as do merely reactive morphodynamic systems.

What we term *dynamical depth* then, is this hierarchic complexity and irreducibility of constraint-generating dynamics, such as distinguishes teleodynamics from morphodynamics and morphodynamics from thermodynamics. Each of these transitions is characterized by the generation of intrinsic constraints at different recursive levels of complexity and with increasing autonomy from extrinsically imposed constraints. Since constraints are a prerequisite for producing physical work, the increasing autonomy of constraint generation with dynamical depth also corresponds to an increasing diversity of the capacity to resist and counter spontaneous tendencies to change, as well as to originate self-beneficial interventions in the dynamics of the environment. Thus the complexity of the possible interactions between a dynamical system and its environment also increases with dynamical depth.

The concept of dynamical depth is orthogonal to all measures of complexity that we have discussed above. Because of its connectedness to the three distinctive nested forms of emergent dynamics, dynamical depth also has a non-continuous nature. It can be measured only with integer values. The transitions from thermo- to morpho- and from morpho- to teleodynamics always occur abruptly, roughly comparable with the 1st order phase transitions in physics. The three levels of dynamical depth refer to three fundamentally different discontinuous kinds of systemic organization; between them there are no intermediate stages. This discontinuity is exemplified by the distinct inversions of certain dynamical system tendencies at these transitions. Thus for example, isolated thermodynamic systems tend to develop to a point where there is no further entropy production (equilibrium), morphodynamic systems tend to develop toward a point of maximum entropy production, and teleodynamic systems tend to develop toward minimizing the amount of entropy production necessary to remain far-from-equilibrium (see for example, Falkner and Falkner, forthcoming).

6. Conclusions

Throughout this discussion we have discovered that again and again the concept of compression is critical to the definition and assessment of complexity. The concept of compression is intimately related to the concepts of constraint and representation. A physical system that is more constrained in its structure or dynamics than another can be represented in a more compressed form. The compression of descriptions is defined by the re-presentation of differences exhibited in one medium by fewer differences in another, such that the compressed version can be decompressed to regenerate the uncompressed version. In computational and information theoretic terms compressibility is a way of representing redundancy or constraint in the structure of a signal. Thus, more compressible equals less complex and less compressible equals more complex. Compression can also be thought of in physical generative terms. Rules or algorithms able to generate a set of values that constitutes a given output can also be compared. An algorithm or set of rules or instructions that approaches in length the representation of what it describes is more complex than one that is much shorter in comparison. Although generative decompression is assessed diachronically it too can be re-presented in terms of synchronic differences in a representing medium, and thus is reducible to a denumerable value. Thus complexity ultimately measures a feature of representational correspondence—a mapping relationship. This should not be surprising since compression is in effect a measure of constraint, and as Shannon's original analysis demonstrated the measure of information of a received message is proportional to the constraint exhibited in that sign/signal medium compared to its possible prior Shannon entropy. The degree of compressibility is then a measure of how much information a given medium can provide about a given phenomenon. This fits with our intuitive sense of the power of representation, since the more compressed a representation, the more information it seems to provide about what is represented, and a simple description that provides no compression but merely recounts every detail effectively lacks all explanatory power.

Our survey of ways of defining complexity has necessarily left out many variant definitions and methods of assessing complexity in order to focus on some quite general paradigmatic approaches to the concept. We have roughly divided these paradigms into three distinct approaches:

1. Analyses that focus on the incompressibility of representations, such as alphanumeric character strings. They are better applicable to random sign sequences and to (non-constrained) systems at the state of their maximal possible entropy like simple thermodynamic systems and mechanical devices.
2. Analyses that focus on the number of computational operations or the extent of thermodynamic work necessary to generate or specify the structure of a given representation of a physical system. These appear to better conform to our intuitions about complex inorganic near-equilibrium physical systems.
3. Analyses that focus on the compressibility of the dynamical capacity to generate compressed relationships themselves. We argue that living and semiotic processes require this additional orthogonal assessment of complexity.

We have shown that the first two, though different by virtue of whether their emphasis is on a descriptive or generative analysis of the phenomena they consider or on the ontological status of their subject of analysis (e.g. character strings versus physical structures), can both be reduced to a definite linear parametric value. In contrast the third measure of complexity, which we have called dynamical depth, *is itself complex* in that it is a measure of complexity that itself exhibits a discontinuous, quantized, form of incompressibility. In other words, in the case where non-linear dynamical relationships that produce dynamical compression of the state space of their behaviors (rather than chaos), complexity analysis is effectively analyzing the compressibility of a compression process.

Thus, self-organized (morphodynamic) processes, by virtue of compressing their own dynamical complexity, exhibit what is in effect a second order form of complexity, since the compressibility of our (abstract) representation of such a system must itself represent its (physical) tendency to compress. But most importantly, living and mental (teleodynamic) processes, are third order forms of complexity. Our abstract description of teleodynamic systems has to represent something that represents itself and its environment. Such a description attempts to compress a self-representing and self-compressing system and not just a compressed one, as it is the case for morphodynamics.

The selfhood of teleodynamic systems sets limits to the compressibility of our representations of those systems. Representations of teleodynamics which fail to capture this limitation lose the ability to represent it as self-representing semiotic and self-compressing physical process. So, by virtue of compressing their own capacity to compress their dynamical complexity, teleodynamic systems are in effect complexity-measuring processes themselves, and thus third order forms of complexity that are irreducible to either second or first order forms.

This relationship between complexity, compression, constraint, and explanation/representation/description is what makes the concept of dynamical depth a critical missing link in the chain of concepts required to build a complete theory of information, i.e. a theory of information that includes both its referential and normative functions. More importantly, it shows why the very concept of information cannot be fully defined without understanding the irreducible complexity of teleodynamics. A teleodynamic process is by definition a compression process in both a physical and semiotic sense. A teleodynamic system not only compresses its own dynamics, but in so doing it provides a compression (i.e. its own compressed representation) of those features of its environment that are of relevance to this internal dynamic. In other words, this compressed representation of environmental constraints with respect to the maintenance of system-internal constraints effectively creates what Jakob von Uexküll termed an *Unwelt*. In contrast, simple thermodynamic and morphodynamic systems have only (externally set) surroundings and no Umwelt.

Finally, precisely identifying the nature of the incompressibility of our representations of living (and by implication, mental) dynamics—and thus their distinctive and orthogonal forms of complexity—provides a new way to understand the challenge that biology and psychology poses to reductionistic analysis. The incompressibility of a process that itself performs compression of its own and its environment's physical complexity is thus a necessary logical consequence of this nested relationship, and the basis for the apparent discontinuity between merely physical as compared semiotic-normative processes. Dynamical depth may in this way serve as a precise index of what has come to be called emergence, and a way to identify transitions that exemplify strong irreducibility. Moreover, it demonstrates that this is an ontologically fundamental discontinuity and not merely an analytic artifact.

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