BioSystems 140 (2016) 8–22

Contents lists available at ScienceDirect

BioSystems

journal homepage: www.elsevier.com/locate/biosystems

Understanding how replication processes can maintain systems away from equilibrium using Algorithmic Information Theory

Sean D. Devine

Victoria Management School, Victoria University of Wellington, PO Box 600, Wellington 6140, New Zealand

ARTICLE INFO

Article history:
Received 12 November 2013
Received in revised form
13 November 2015
Accepted 26 November 2015
Available online 23 December 2015

Keywords:
Organization in complex systems
Dynamics of evolution
Replication
Algorithmic Information Theory
Algorithmic entropy

ABSTRACT

Replication can be envisaged as a computational process that is able to generate and maintain order far-from-equilibrium. Replication processes, can self-regulate, as the drive to replicate can counter degradation processes that impact on a system. The capability of replicated structures to access high quality energy and eject disorder allows Landauer's principle, in conjunction with Algorithmic Information Theory, to quantify the entropy requirements to maintain a system far-from-equilibrium. Using Landauer's principle, where destabilising processes, operating under the second law of thermodynamics, change the information content or the algorithmic entropy of a system by ΔH bits, replication processes can access order, eject disorder, and counter the change without outside interventions. Both diversity in replicated structures, and the coupling of different replicated systems, increase the ability of the system (or systems) to self-regulate in a changing environment as adaptation processes select those structures that use resources more efficiently. At the level of the structure, as selection processes minimise the information loss, the irreversibility is minimised. While each structure that emerges can be said to be more entropically efficient, as such replicating structures proliferate, the dissipation of the system as a whole is higher than would be the case for inert or simpler structures. While a detailed application to most real systems would be difficult, the approach may well be useful in understanding incremental changes to real systems and provide broad descriptions of system behaviour.

1. Introduction

Mathematicians have developed Algorithmic Information Theory (AIT), and the associated concept of Kolmogorov or algorithmic complexity, to measure the computational resources needed to describe an object by specifying a string of characters that represent the object. Developments in mathematics have included measures of randomness (Martin-Löf, 1966; Gács, 1980); deeper insights into Gödel's theorem (Chaitin, 1974); modelling data with the ideal form of the Minimum Description Length (Vitányi and Li, 2000) and Bayesian prediction (Hutter, 2007). AIT has also been used to enquire into deep philosophical questions about the universe (Chaitin, 2004; Calude and Meyerstein, 1999; Hutter, 2010; Davies, 2003). Devine (2014a) has used AIT to show there is no need to define a fourth law of thermodynamics to explain order in the universe as postulated by the Intelligent Design community (Dembski, 2002). However, the use of AIT to study natural systems has been somewhat limited (but see Zenil et al., 2012; Ratsaby, 2008). In addition, Adami (2002) and Adami and Cerf (2000) have defined 'physical complexity' conceptually in terms of the environmental fit of a structure measured by the reduction in the length of the algorithmic description of the structure, given the information contained in its environment. For practical reasons the measure is applied using the Shannon entropy for an ensemble of structures. A comprehensive review of the mathematical background can be found in Li and Vitányi (2008), while a review tailored for scientists is available (Devine, 2014).

An important point is that the algorithmic complexity, when defined with self-delimiting coding, becomes an entropy measure called the 'algorithmic entropy'. As Section 3 outlines, while the algorithmic entropy is conceptually different from the traditional entropies, the algorithmic entropy for a typical microstate in an equilibrium configuration is effectively the same as the Shannon entropy and, allowing for units, the entropy of statistical mechanics, once allowance is made for the relatively short algorithm that may be required to define the system (Zurek, 1989a). The algorithmic entropy provides a convenient tool to track entropy changes when the states of a system change. It has a clearly defined meaning for non-equilibrium situations, while being an entropy measure that is consistent with the traditional entropies for the equilibrium macrostate that emerges when the non equilibrium system is isolated (Devine, 2009).

E-mail address: sean.devine@vuw.ac.nz

http://dx.doi.org/10.1016/j.biosystems.2015.11.008

This paper applies the tools algorithmic entropy to the emergence and maintenance of order in natural systems distant from equilibrium. The starting point of the AIT approach is that the instantaneous configuration or state of a natural system can be specified by a string of characters in an appropriate state space (see Section 3). The algorithmic entropy of a system's instantaneous configuration is the minimum number of bits of information needed to specify this string of characters. By definition, the measure is the number of bits in the shortest algorithm using self-delimiting coding which, when run on a Universal Turing Machine (UTM), halts after specifying the string representing a configuration in the natural world.

As is mentioned below, an important feature is that, as the algorithmic entropy is a function of state, only entropy differences matter and differences of algorithmic entropy are independent of the UTM used. This is a consequence of the fact that one UTM can simulate any other, and the simulation constant (the length of the string that allows one machine to simulate another) cancels for entropy differences (Chaitin, 1975; Li and Vitányi, 2008). Machine independence allows the algorithmic entropy to quantify the order embodied in a system, to capture its information content, and to provide the thermodynamic constraints that govern the emergence of local order. Furthermore, AIT provides a measure for the distance of a natural system is from equilibrium in terms of the number of information bits that must be added to the system to shift it from an ordered to an equilibrium state. Algorithmic entropy is able to offer new insights into natural world systems as it provides a tool to inquire into replication processes recognising that replication is core to many natural systems. The critical point is that the algorithmic entropy of a system of repeated structure is low (Devine, 2009) and relatively few bits are required to specify a system of repeated structures. The algorithm that specifies a system only needs to specify the structure once and then copy, or generate, repeats by a short routine. This contrast with the number of bits needed to specify a system where each structure must be independently defined. It follows that replication is a naturally ordering process that reduces the algorithmic entropy of a system in a quantifiable way. Provided resources are available, and high entropy waste can be ejected, replicated structures are more likely to emerge than similar structures produced by other natural process.

The critical understanding behind the application of AIT to the natural world is that the physical laws that drive a system from one state to another can be seen as computations on a real world Universal Turing Machine. As algorithmic entropy differences are independent of the UTM used, the algorithmic entropy derived from a programme that maps a real word computation by manipulating bits in a reference UTM in the laboratory, is the same as the equivalent number of bits derived from the real world UTM. The flow of bits or information through the two systems is the same. Section 3 points out, the length of the shortest, appropriately coded, algorithm that generates a particular string on a UTM defines H, the algorithmic entropy of this string in bits. It is when these natural computation processes, operating under physical laws, eject disorder that more ordered or low entropy structures are left behind.

Landauer's principle (Landauer, 1961) formalises the understanding of the computational processes embodied in real world computations and provides a tool to inquire into the emergence and maintenance of order in these real world systems (Bennett, 1973, 1982, 1988; Zurek, 1989b). Landauer's principle states that where one bit of information in a computational machine operating at a temperature T is erased, at least $k_B T \ln 2$ Joules must be dissipated. In a conventional computer this dissipation appears as heat passing to the non-computational parts of the system. However, where the length of the algorithmic description of the state of a system changes when ΔH bits are removed, the corresponding thermodynamic entropy change in the real world system is $k_B \ln 2 \Delta H$. Similarly, ΔH bits must be returned to the system to restore it to the initial state. There have been objections to Landauer's principle, the major one being the claim that logical reversible computations are not thermodynamically reversible. Bennett (2003) rebuts this with examples that connect logical reversibility with thermodynamic reversibility. Leff and Rex (1990), in discussing the paradox of Maxwell's demon, bring together the key arguments to resolve the issues involved. Recently, Bérut et al. (2012) have provided experimental confirmation of Landauer's principle.

The entropy changes of both living and non-living natural systems are constrained by the same laws. This allows one to apply the entropy and energy requirements of the process of replication to very simple systems and carry the initial insights over to biologically complex living systems. However in order to take this argument further, the next section explores replication processes, while the section following outlines the principles of AIT. Later Section 4 deals with some conceptual issues around the reversibility of natural laws. Section 4.3 shows the relationship between the traditional entropies and algorithmic entropy and this leads to the algorithmic formulation of the second law of thermodynamics in Section 5. Once these issues have been clarified that paper uses the AIT approach to identify the following characteristics of replicated systems.

- When order is being destroyed through degradation processes driven by the second law of thermodynamics, replication processes that access high quality energy and eject disorder, are able to restore the system to the original ordered set of configurations. In essence, replication processes use natural laws to self-regulate to maintain a system far-from-equilibrium.
- Variation in a system of replicated structures provides a natural mechanism to stabilise the system against change. In other words, variation can maintain the system in a stable configuration through adaptive evolutionary-like processes. AIT provides a reasonably convincing argument that, in many situations, those variants that persist in a changing environment are those that use resources more efficiently and have lower entropy throughputs.
- Coupled and nested replicator systems create greater stability against change by co-evolving as, from an entropy perspective, the replicated structures use resources more efficiently. This efficiency, called here 'entropic efficiency' would seem to be an important constraint on evolutionary selection processes that occur in biology. Nevertheless, while each replicated structure is efficient in this sense, the number of interdependent or nested system of replicated structures increases to ensure that overall, the high quality energy degrades more effectively than would otherwise be the case (Schneider and Kay, 1994).

2. Replication processes

Ordered structures emerge when replication processes trigger a chain reaction that creates repeats of the initial structure. Two physical examples of such a replicating system are a crystal that forms from the liquid phase and coherent photons that emerge through stimulated emission. Biological examples include an autocatalytic set, bacteria that grow in an environment of nutrients and the growth of a biological structure such as a plant. In the last example, as different genes are expressed in different parts of the plant, variations of the basic structure emerge at these points. In general, replication involves physical or biological structures that reproduce by utilizing available energy and resources and, at the same time, ejecting excess entropy as heat and waste. Freitas and Merkle (2004) have outlined different types of replication. Maturana and