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Towards a theory of everything? – Grand challenges in complexity and informatics

David G. Green and David Newth

Environmental and Information Science, Charles Sturt University
PO Box 789, Albury NSW 2640 AUSTRALIA

Email: {dgreen, dnewth}@csu.edu.au

Abstract

This account surveys some of the major developments in complexity research and proposes a number of questions and issues for future research. The topics are organized into three areas. Under *theory*, we consider self-organisation, emergence, criticality, connectivity, as well as the paradigm of natural computation. *Applications* include several areas of science and technology where complexity plays a prominent part such as development, evolution, and global information systems. Finally, under *practice*, we consider some of the issues involved in trying to develop a coherent methodology for dealing with complexity.

1. Introduction

At the beginning of the 20th Century, there was a sense in many areas of science that the key discoveries had already been made. These impressions were later shaken by discoveries that opened up vast new areas of knowledge. In contrast, we are struck at the start of the 21st Century by the enormity of what we do not know. Prominent amongst these areas of ignorance is complexity. Advances made in the final two decades of the 20th Century only serve to underscore just how much we have yet to learn about complex phenomena.

The turn of the Millennium is a suitable time to take stock of these advances, and to identify key issues that await further research. There is a long tradition of posing problems as a stimulus to future research. In 1900, David Hilbert's famous address at the International Congress of Mathematics posed 23 major research problems. These influenced 20th Century mathematics profoundly, leading to such developments as Godel's Incompleteness Theorem and theories of computation.

In more recent times, it has become fashionable to set out major problems in the form of grand challenges. This trend, which is perhaps driven more by the quest for funding than by curiosity, has been strong in the physical sciences and computing. During the 1990s, however, the biological sciences also began to identify grand challenges, notably the Human Genome Project.

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This discussion aims to set out a number of ideas and questions that we see as important to the future of complexity theory, as well as its applications to some emerging fields of research. The coverage is intended to be indicative, not exhaustive; of necessity we have had to omit many important issues, and many people would probably dispute our choices. Nor is it possible, in such a short account, to explain every issue in depth, so we have tried to provide references to relevant discussions. We organize the questions discussed here under three major headings: questions in complexity theory, applications in informatics and issues associated with the aim of developing a unified framework for describing and interpreting complexity.

2. Questions in complexity theory

We begin our discussion by examining a number of open problems in the area of complex adaptive systems.

2.1 Self-organisation and emergence

Among the very first questions in complexity theory, and still one of its central issues, is how things organise themselves. Perhaps the question that has perplexed people the most is aptly summed up by the popular phrase “the whole is greater than the sum of its parts”. That is, how do large-scale phenomena emerge from the simple components? The human body, for instance, is clearly more than a pile of cells. This issue led to the idea of “holism” (Koestler 1967) in which objects are regarded not only as discrete entities, but also as building blocks within larger structures.

Numerous mechanisms have been now identified. One is the role of connectivity in a system, which determines whether sets of objects are isolated or a fully connected system (see next section). Other authors, such as Holland (1995), have identified mechanisms involved in the appearance of new properties and behaviour.

One of the most important principles is that global phenomena can emerge out of local interactions and processes. For instance, Hogeweg and Hesper (1983) showed that the social organisation of bumblebees emerges as a natural consequence of the interaction between simple properties of bumblebee behaviour and of their environment. There is no overall design. Abstracting, the same principle underlies the self-organizing properties and patterns in computational systems, such as cellular automata (Wolfram, 1986, 1984, Wuensche 1992, 1994). Such ideas have found applications in various heuristic algorithms (eg bubble sort) and in robotics (eg. Brooks 1991).

The recognition that interactions play a crucial part in self-organisation raises the question of how different sorts of interactions produce different large-scale behaviour in assemblages of simple agents. How does a swarm of bees differ from a flock of birds or foraging ants, for example? Such questions have been a favourite theme in studies of artificial life.

Inevitably such questions led to the question of why many systems appear to defy the second law of thermodynamics. Why does entropy not increase in living systems? And why do clouds of interstellar gas condense into stars? Such questions led Prigogine (1980) to study what he called dissipative systems, in which open flow of energy allows local order to increase, and local irregularities can grow into large-scale patterns.

Other researchers have tried to identify general features of self-organizing processes. Haken (1978) in particular, pointed out that in many emergent and self-organizing processes, phase changes (from local to global behaviour) occur at a well-defined critical value of some order parameter. For example, water freezes at a fixed temperature; nuclear chain reactions require a critical mass of fuel and lasers fire when energy input reaches a critical level. These properties are now known to be closely related to issues of connectivity (see below).

Despite all of the above advances in our knowledge of self-organisation, there is still much to learn. For instance, the issue of identification is still unclear (Holland, 1995). Sometimes, what we may see as an emergent property of a system is apparent only when an assemblage is considered in a larger context. How does this larger context influence individual objects?

On a more practical level, perhaps the question of greatest concern is how do we build artificial systems (or manage natural ones) so that the properties that emerge are the ones we want? Modern engineers and managers need to deal with many systems where we cannot design a system explicitly. Artificial learning and evolution have become accepted approaches. However there remains much to learn about these methods in highly complex and integrated systems (eg. scheduling) and in many specific applications (eg. commerce, environment).

2.2 Connectivity and chaos

Many aspects of complexity can be traced back to issues arising from connectivity. Interactions, state changes, neighbourhoods and many other phenomena all define links or connections between objects. Green (1993, 1994b) proved the following theorems.

Theorem 1

The patterns of dependencies in matrix models, dynamical systems, cellular automata, semigroups and partially ordered sets are all isomorphic to directed graphs.

Theorem 2

In any automaton or array of automata, the state space forms a directed graph.

The implication is that virtually any complex system inherits properties of graphs. The most important of these properties is that, starting from a set of isolated nodes, a phase change in connectivity occurs in any random graph as edges are added to the system (Erdos and Renyi, 1960). This feature of graphs is therefore responsible for many kinds of criticality. Green (1995) conjectures that connectivity underlies all criticality.

However to demonstrate the relationship between connectivity and criticality is not always easy. This is certainly so for the onset of chaos, in which a system undergoes an accelerating process of period doubling until chaos sets in. The precise mapping required here is not obvious. On the other hand, the similarity is so striking that one would expect one to exist.

We suspect that to find such a mapping would provide many deep insights about chaos and complexity. For instance, finding such a mapping may make it possible to derive Feigenbaum’s constant from first principles.

2.3 Criticality: edge of chaos or chaotic edge?

Several authors (eg Langton 1990) have proposed that maximum system adaptability lies on the “edge of chaos”. An alternative model (Green 1994b) suggests that systems flip-flop across a “chaotic edge” associated with a phase change in their structure or behaviour. The phase-shift works as follows:

- The system can exist in one of two states — a connected phase wherein selection predominates; and a disconnected phase, wherein variation predominates.
- Most of the time the system rests in the connected phase, where selection maintains the system in a more or less steady state.
- External stimuli may disturb the system and shift the system into disconnected phase. Whilst the system is in this phase variation has free reign.
- Following a disturbance, the system gradually cools, and crystallizes, into a new stable structure. The system is returned to the connected phase.

Figure 1 depicts the difference between these two mechanisms.

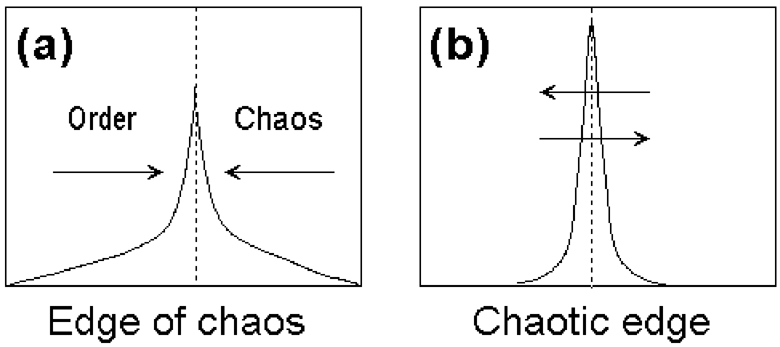

Figure 1. Contrasting the edge of chaos model of system adaptation with the phase change model of the chaotic edge. The x-axis represents a connectivity "order" parameter appropriate to the system concerned. The spike represents a critical point where a phase change occurs. (a) In the edge-of-chaos model, complex systems evolve to lie near or at the critical point, between chaotic and ordered. (b) In the phase shift model, external stimuli flips the system across the chaotic edge into a phase where variation predominates. The system then gradually cools, crystallizing into new structure or behavior as it does.

Some of the issues here are to identify systems that behave according to these models. For example the fossil record supports the chaotic edge model.

2.4 Does nature know best?

The "biology as computation" paradigm has proved to be a rich source of novel computational ideas and methods that are based on natural processes. However, genetic algorithms, neural networks and other methods are really parodies of the original processes on which they are modelled. Artificial neural networks, for instance, rapidly converge to particular behaviour, whereas living neural systems are prone to respond chaotically (Freeman 1992). Freeman suggests that chaos may be an important source of novelty in nature.

We have argued that mimicking biological systems more closely is a fruitful way to develop new computational algorithms (Green 1994a; Green 1995; Kirley et al., 1998). However, the biological paradigm goes further still. Optimization methods are usually preoccupied with finding the very best solution possible. On the other hand, living organisms usually seek only *adequate* solutions. A foraging animal, for instance, does not need to find every scrap of food in its territory, just enough to live on. Genetic algorithms and other biologically inspired methods for search and optimization adopt a biological approach implicitly. However, the full requirements, and implications of, "adequacy" remain to be explored. For instance, do NP-complete problems (ie. ones in which the number of steps for an exact solution grows faster than polynomial time) become tractable if we are content to accept “good solutions” rather than perfect ones (Cook 2000). Likewise, biology teaches us that perfect solutions are not always desirable. Many natural systems require adaptation to the variance, rather than the mean of a system. For example, many of the plant species in Australia have adapted to the variability of rainfall. These ideas have immediate implications in problems such as dynamic scheduling (Kirley and Green 2000).

2.5 Diversity in complex dynamic systems

Much has still to be learned about the behaviour of complex dynamic systems. Many phenomena can be represented as large arrays of interacting variables, such as, plant and animal populations in an ecosystem, stock prices in an economy, or current through a complex switching network. Although many aspects of such systems are well known (eg feedback, chaos), much remains unknown about their large-scale dynamics.

In ecosystems for instance, ecologists have long observed that increasing complexity (measured by species diversity) seemed to accompany stability. However May (1973) showed that the reverse holds true in general for complex dynamics. Randomly assembled dynamic systems generally collapse because positive feedback loops tear them apart. The exact mechanism is still unclear. We suspect, but this has yet to be shown, that an evolutionary process occurs in which a process of random additions and collapses yields systems that are both complex and viable (Green 1993; Green et al. 2000).

2.6 Emergent structure and behaviour

Some questions about general properties of large assemblages have potentially deep implications, especially when they raise issues about the very ways in which we perceive and study systems. Here are two examples of such questions.

The first concerns tree structures. Why are tree structures so abundant in complex systems? They are common in both natural systems (eg. taxonomic hierarchies, trophic pyramids) and in human organisations (eg. military units and ranks, corporate structure). Do they arise out of some fundamental process, or are these perceived structures artifacts of human observers and biases? There are some grounds for supposing that trees form naturally in many situations - any graph without cycles is a tree. They also provide an efficient form of total connectivity, which is one need they satisfy in the human organisations listed above.

A closely related idea is *modularity*. In many systems, sets of elements form self-contained modules that each interact with the outside as a single object. Dividing an army into a hierarchy of modules - platoons, companies, batallions and so forth - simplifies the flow of command and control. Likewise, the object-oriented approach to programming simplifies the problem of creating large, complex applications. There is increasing evidence that modularisation is a common process in nature. For instance, recent studies suggest that the genome is modular, with different sets of genes affecting different phenotypic characters (Wagner and Altenberg, 1996, Ancel & Fontana, 1999).

A more general question we could ask is whether specific conditions lead to particular kinds of structure (eg. trees, cycles etc), organisation and behaviour.

As an example of behavioural issues, an interesting conjecture (originally ascribed to ecologist Bruce Patten, 1975) is whether the large-scale dynamics of ecosystems are essentially linear. Natural selection, Patten (1975) proposed, tends to either eliminate non-linear processes or else nullify their effects. He based his hypothesis on the experiences of engineers, who find that linear systems are reliable and desirable, whereas systems with non-linear behaviour are not. Modellers too find that linear models seem to approximate ecosystem behaviour more easily than non-linear ones. Patten argued that four aspects of ecosystem makeup contribute both to produce linear behaviour and to preserve it:

1. Ecosystem behaviour tends to be regular and reliable because the complexity of ecosystem behaviour causes many different processes to superimpose their behaviours upon one another.
2. Biotic limiting factors force linear control on otherwise non-linear behaviour.
3. Many ecosystem processes act as perturbations about equilibrium states.
4. Ecosystems are rich in feedback interactions, which dampen non-linearities.

These ideas raise an important general question: is the linear behaviour observed in complex systems real? Or does it reflect the way we model them? It can be impossible to decide, from the data alone, what sort of model best describes a process. Unless they are guided by a theory that demands a particular sort of model, scientists analyzing data tend to look for the simplest equation that fits their observations; the simplest model is usually a straight line. This tendency to use linear models is increased because the range of observations is often limited. Short segments of most continuous functions look like straight lines - the shorter the interval, the better the approximation. We often exploit this fact in interpolation. Similarly, scientists observing nature rarely see a process operate over its whole range; sometimes the range of observations is quite restricted. Finally, the last point is important because feedback, and external constraints, act to keep a process within a limited range of values, so that the process tends to look linear.

3. Applications in informatics

Above we looked at questions concerning general properties of complexity. Equally important are questions associated with complexity in specific contexts.

3.1 Detailed organisation of embryo development

The mapping of the human genome is only the beginning of the story. Together with the cellular environment in which they are housed, the genes form a complex system that controls the processes of development and maintenance. Kauffman's (1991) model of boolean switching networks is still the best abstract model of genetic control. The challenge now is to translate it into a concrete model for the real genome.

3.2 From genomes to geography

One of the biggest challenges in biology is to understand the complex relationships between genotype, phenotype, and ecological interactions. Although much is known about form and function, the complex manner in which growth changes to produce phenotypic adaptations and variations is largely unknown. Lsystem models of plant growth (Prusinkiewicz 1996) are now sophisticated enough to allow studies into these matters. Moreover, by placing full growth models into simulated landscapes, they raise the possibility of gaining insights into the complex and subtle relationships between environment and adaptation.

3.3 A general theory of evolution?

In recent studies (Green 1994b, 1995; Green et al. 2000), we have shown that the processes governing species evolution in a landscape are similar in nature to a wide range of critical phenomena. Landscapes exhibit two phases - a *connected phase*, in which selection predominates; and a *disconnected phase*, in which variation predominates. Disturbances such as fires and cometary impacts flip the landscape from connected to disconnected phases. This process leads to both the isolation of populations necessary for speciation to occur and to the explosive spread of new species. We argue that the underlying process involved - accumulating adaptations via repeated phase changes - is common in many natural and artificial processes. For instance, many optimization algorithms (eg. simulated annealing (Kirkpatrick et al. 1983)) exploit phase changes in the connectivity of the solution landscape to mediate between global and local search. Such analogies raise the prospect of identifying general processes that govern adaptive processes in many different kinds of systems.

3.4 Global information system

Global communications networks have revolutionized the way we communicate, do business, store and process data. The most popular Internet technology is the World Wide Web (WWW). Whilst it provides a uniform interface to display information, it also has a number of limitations, especially the need for better indexing tools.

With advances in other technologies, such as data warehousing, a host of new practical problems arise:

1. How to store large volumes of data in standard format?
2. How to transport such data effectively?
3. How to make such a system self-maintaining?
4. How to organize the data and information (ie. effective metadata, indexing mechanisms)?
5. How to effectively process the stored data?
6. How to coordinate and distribute processing?

As an example, the **top500.org** records that the world’s most powerful supercomputer has 9632 processors. This is nowhere near the capacity of the entire Internet, which has some 20+ million processors. Projects such as SETI@Home (Sullivan et. al. 1997, Muir 1998) have shown that massively distributed processing over the internet is possible, with over 2 million computer systems being utilized to search for extraterrestrial communications.

Standards such as HTTP, Z39.50, XML, and agent based technologies offer partial solutions to many of the above problems, but the overall key is to unify all the above ideas into a single information system. There is an obvious need for unified global information systems in certain areas, such as geography and biodiversity (to name just two). Although major technical challenges need to be overcome to meet this goal, a far greater challenge is to overcome the human issues involved (eg. Green, 1994c). For instance, although there is international agreement about a Clearinghouse Mechanism for environmental information, few countries yet have procedures for implementing data sharing internally. Also, agreements on global standards have been slow to emerge, and very little legacy data conforms anyway. In contrast, data sharing is well advanced in some fields, such as biotechnology, and shows what can be achieved.

4. Towards a unified framework

In this section we describe a number of questions concerned with foundation theory that need to be addressed.

4.1 Retuning Turing

A number of classic models of automata have been used to study computation (Feynman 1996). These models include finite state machines, linear bound automata and the Turing Machine (Hopcroft and Ullman 1969). Each is capable of solving different classes of problems. However they have limited application when modelling systems such as those described in Section 2.1.

The paradigm of natural computation interprets all manner of processes as forms of computation (Bossomaier and Green 2000). Despite the central role that computation plays in complexity theory, no coherent body of computational theory exists for describing and interpreting complex phenomena. In this section we set out one possible approach for developing a general framework. This framework, based on ideas in Green (1996), addresses computational issues as well.

One of the first questions is whether we should reconsider the theoretical foundations of computing itself. Any of the usual definitions of computation, such as formal automata or universal Turing machines, all base computation in a single processor. Formally this may be the case, but it does not provide any scope for understanding the complex interactions and issues involved in parallel computation. At present, there are many pieces of theory, covering such diverse aspects as parallel computers (eg. Fox and Coddington, 2000), object-oriented modelling and information networks.

4.2 Universal measurement

Traditional science has implicit biases that tend to promote a reductionist approach to problems. One of these biases is the restriction of the term “measurement” to numerical data. This forces scientists, before they even begin to analyze phenomena, to look for ways to reduce a situation to numerical variables that can be measured. But complex structures cannot be captured as numbers, nor can many important properties and behaviours.

To overcome the above problem, Green (1996) proposed extending the definition of measurement to any procedure for data collection that satisfied four criteria:

- values are expressed within a well-defined *formal language*;
- relationships between different values are defined by a *model*;
- a set of *standards* defines the meaning of terms and constants in the language;
- values are obtained by following a well-defined *formal procedure*.

Under this new definition, behavioural strings entered in an event recorder and deriving DNA sequences become measurement. The point is that at present we tend to treat such data as raw material from which to derive numerical measures (eg percent similarity between DNA sequences) with which to do the real study. By calling them measurements in themselves, we are saying that these are data to work on directly (eg by computing consensus sequences). One immediate implication is that many aspects of pattern recognition could be reinterpreted in terms of measurement.

4.3 Algebraic theory of complexity

The idea of measurement for complexity leads naturally to the idea of variables and hence to algebraic relationships between these variables. Several questions immediately arise.

First, what are natural units of measurement for expressing organisation and other complex relationships? We argue that several bases already exist and are in common use (Green, 1996). The theorems presented earlier show that graphs are as fundamental to complexity as numbers are to simple systems. Unlike numbers, we do not have a simple system for naming particular graphs. On the other hand various notational systems, such as the Universal Modelling Language (UML), do exist for modelling systems of objects and relationships.

Many other possible systems of units also exist, such as strings for representing behaviour and other sequential phenomena. We suggest that generic approaches need to be developed, each aimed at particular classes of phenomena.

What is the value of representing systems algebraically? We suggest that there are several advantages. First, it helps to emphasize deep relationships, and insights, between different phenomena. Secondly, it simplifies the modelling process. Every simulation model, for instance, rests on some underlying abstract structure (eg a network, a grid), and formalism helps, not only to streamline the modelling process, but also to study processes in the abstract. Theoretical studies of cellular automata and boolean networks, for instance, have certainly provided insights about many systems.

The other great advantage of traditional algebra is that particular methodologies have been developed around it for analyzing and understanding systems. We next look briefly at this idea.

4.4 Computational complexity

One agenda for the scheme we propose above would be to integrate complexity and computing under a common theoretical framework.

We can interpret *pattern* as the result of a computational *process*. The process consists of a *program*, which provides the ordered or repeating elements in a pattern, plus *data*, which provides the random elements. This idea underlies efforts to define both algorithmic complexity (eg. Chaitin, Kolmogorov) and information and entropy (eg. Papentin, 1980; Brooks and Wiley, 1986). For instance, in Papentin’s scheme, the length of the shortest program is a measure of the “organized complexity” in a system, and the data measures the information content. Most definitions of this kind hinge on the notion of the shortest program. However, this idea is unworkable in practice because in general we cannot prove that a particular program is the shortest. As an alternative we propose that complexity be measured in context. For instance, for a given string of symbols, different parsing schemes are likely to produce different descriptions. We propose that complexity be measured relative to such schemes.

These ideas extend into many areas of computing. Most data compression algorithms, for instance, retain a fixed program and reduce a file to the data needed to regenerate the original pattern. An alternative, based on some of the above ideas, would be to decompose a pattern by passing it through a number of filters, each of which retains part of the information required to regenerate it. The compressed item is then some input data plus a map of its pathway through a set of filters.

Schemes such as the above are not necessarily more efficient or concise than others, but have the benefit that they would make clear the relationships between different patterns. For instance, partially parsing superficially different amino acid sequences according to various physical properties immediately makes identical structural features jump out (Green 1996).

5. Conclusion

In this account we have tried to outline what we see as some of the major developments and directions in complexity at the present time. We have also outlined a number of questions that we feel will yield fruitful results and will have important implications. Although we have tried to provide some overview and interpretation of the field, we must stress that this is not meant to be a review, but rather an exposition of seminal ideas.

The need for a greater understanding of complexity has never been greater. With globalization rampant in economics (Friedman 2000) and culture (Saul 1997), the human race is rapidly approaching its “limits to growth”. Any major activity impinges on people and places everywhere. Raise the price of soybeans and vast tracts of rainforest come under threat. Try to save a unique wildflower and a giant corporation could go bankrupt. Introduce a new communications medium and the fabric of society begins to break down.

Given such vast consequences, it is crucial to understand how to deal with the complex interactions that are an increasingly common aspect of the modern world. This is perhaps the greatest of all practical grand challenges for research on complexity in the new Millennium. Ultimately, our very survival may depend on it.

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