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Modeling Complex Systems

by

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Abstract

This paper offers a brief description and summary of the characteristics of complex adaptive systems. The use of computer software such as StarLogo and NetLogo is presented as a powerful way to explore the dynamics of such systems. The author suggests that these computer programs can vitally enhance the development of the scientific mind in users within a wide range of ages and levels of experience.

Modeling Complex Systems

What is a complex system?

A relatively recent area of scientific inquiry is the exploration of the dynamics of complex systems. A defining characteristic of complex systems is their tendency to self-organize globally as a result of many local interactions. In other words, organization occurs without any central organizing structure or entity. Such self-organization has been observed in systems at scales from neurons to ecosystems.

A complex adaptive system has the following characteristics: it persists in spite of changes in the diverse individual components of which it is comprised; the *interactions* between those components are responsible for the persistence of the system; and the system itself engages in adaptation or learning (Holland, 1995, p.4). To say that a system is complex is to say that it moves between order and disorder without becoming fixed in either state. To say that such a system *adapts* is to say that it responds to information by changing.

Such systems abound. Not only the ant colony and the human body as a whole, but also various systems within the body such as the nervous system and the immune system fall into this category. These are systems that persist in spite of the continual changes of individual components, maintaining coherence and adapting in response to a phenomenal amount of information throughout the lifetime of the organism in which they function (Holland, 1995, pp. 2-3).

Adaptation and Finding Excellent Solutions

Holland (1995) argues that adaptation itself builds complexity. Kauffman (1995) agrees, saying, "A living system must first be able to strike an *internal* compromise between malleability and stability. To survive in a variable environment, it must be stable, to be sure, but not so stable that it remains forever static" (p. 73). Thus, these systems survive and thrive in an evolutionary, or more accurately, a co-evolutionary context.

Kauffman (1995) makes a case for the importance of the co-evolution of agents and their environments. As an agent changes, so does the environment, including other agents, and vice versa. Thus, agent and environment act as partners in the dance of evolution. This is easy to visualize when one thinks of the interrelationships in an ecosystem. But how does a particular agent "read" an environment of which it can only "see" a small part?

Kauffman argues that in a system in which there is a large number of underlying conflicting constraints and interconnected variables, there exists an optimum size and number of "patches" or nonoverlapping domains which, acting locally by interacting only with the nearest neighbors, maintain the system in a state of maximum fitness with regard to evolution (pp. 256-257). Each agent in the system Kauffman models has access only to information in the local vicinity. (The reality is likely more complicated than this as, at the very least, many complex systems may be seen to be small-world networks. See Strogatz, 2001 and Watts, 2003 for more about this.) At the same time, each agent may be said to have a particular evolutionary goal of which it is unaware, but for which it is suited by its evolutionary history. The ultimate goal, of course, is survival. In having achieved survival up to the present moment, the agent as a system and the larger system(s) of which the agent is a part have engaged in a particular kind of learning that is inherent in adaptation. This learning involves maximizing the system's fitness with regard to the larger environment. Complex adaptive systems exist at a wide range of scales, from neurons to social systems. Therefore, the environment in which an agent acts may be incredibly tiny or it may be vast, from the human perspective. However, it seems likely that the larger system in which an agent participates is always beyond the comprehension of the individual agent within it. According to the theory of complex adaptive systems, the scale of complex systems is of little importance, except, perhaps, in relation to the time involved in the interactions or in the life of the system as a whole (see Gell-Mann, 2003, pp. 51-52).

Here the idea of maximum fitness (Kauffman, 1995, pp. 247-264) means to be able to find *excellent* solutions to difficult problems rather than being able to find the *best* solutions. Generally speaking, finding the best solution may be impossible due to the multitude of possible solutions and the limited amount of time available for exploring them. Thus, Kauffman argues, it makes more evolutionary sense to devise strategies for finding excellent solutions at the possible expense of not finding the best or perfect ones.

Holland (1995) has worked extensively on this problem as well. He is well known for having devised the genetic algorithm and the ECHO software for computer simulation of complex adaptive systems. The agents in Holland's computer simulations behave in much the same way that Kauffman describes, finding excellent solutions in the course of interacting with other agents and with the environment.

Gell-Mann (2003) explains just how these systems are able to evolve such excellent solutions. Gell-Mann's terminology differs from Holland's in that what Holland refers to as an "adaptive agent," within a complex system, Gell-Mann refers to as a complex adaptive system in its own right. Thus, in Gell- Mann's nomenclature, a complex adaptive system may (and often does) exist within another complex adaptive system and/or it may be associated with other complex adaptive systems that aggregate to form a larger complex adaptive system, and so on (2003, p.51). Gell-Mann's description of the evolution of schemata in a complex adaptive system is elegant.

> A complex adaptive system receives a stream of data about itself and its surroundings. In that stream, it identifies particular regularities and compresses them into a concise "schema," one of many possible ones related by mutation or substitution. In the presence of further data from the stream, the schema can supply descriptions of certain aspects of the real world, predictions of events that are to happen in the real world, and prescriptions for behavior of the complex adaptive system in the real world. In all these cases, there are real world consequences: the descriptions can turn out to be more accurate or less accurate, the predictions can turn out to be more reliable or less reliable, and the prescriptions for behavior can turn out to lead to favorable or unfavorable outcomes. All these consequences then feed back to exert "selection pressures" on the competition among various schemata, so that there is a strong tendency for

more successful schemata to survive and for less successful ones to disappear or at least to be demoted in some sense. (Gell-Mann, 2003, p. 50).

Thus, a complex adaptive system: 1) interacts with the environment, 2) creates *schemata*, which are compressed and generalized regularities experienced in those interactions, 3) behaves in ways consistent with these schemata, and 4) incorporates feedback from the environment to modify and adapt its schemata for greater success. When Gell-Mann talks about "identifying" and "predicting" he is not necessarily referring to conscious events. For example, in the case of slime mold, which has no brain, the process is a purely biochemical one (Johnson, 2001, pp. 11-17).

Self-Organization in Complex Systems

The process by which a complex system achieves maximum fitness results in *self-organization* by the system, that is, agents acting locally, unaware of the extent of the larger system of which they are a part, generate larger patterns which result in the organization of the system as a whole. This concept can be seen at work in ant and termite colonies, beehives, market economies, and can even be modeled on one's home computer using free software such as StarLogo ("Starlogo", 2004) or NetLogo (Wilensky, 1999, 2004). The idea that an ant colony is a system that organizes itself without any leader is intriguing. Each individual ant, acting with limited information, contributes to the emergence of an organized whole. This new way of looking at organization as an emergent property of complex systems calls into question some fundamental assumptions about organization in general, and about learning in particular.

Not every system is a complex adaptive system; certain conditions must be met in order for a system to self-organize. First of all, the system must include a large number of agents. Constructing a simple model in StarLogo and adjusting the number of agents involved will readily demonstrate this principle. In addition, the agents must interact in a nonlinear fashion. As Kelso (1995) explains:

> If there aren't enough components or they are prevented from interacting, you won't see patterns emerge or evolve. The nature of the interactions must be nonlinear. This constitutes a major break with Sir Isaac Newton, who said in Definitions II of the Principia: "The motion of the whole is the sum of the motion of all the parts." For us, the motion of the whole is not only greater than, but *different* than the sum of the motions of the parts, due to nonlinear interactions among the parts or between the parts and the environment. (p. 16)

Complex Adaptive Systems Summarized

From this discussion, the following characteristics of complex adaptive systems can be extracted:

1. Complex adaptive systems involve agents whose local, non-linear interactions result in self-organization by the system as a whole.

2. Complex adaptive systems exist in a mixed condition between order and chaos that enables them to achieve stability and flexibility simultaneously.
3. The agents in a complex adaptive system thrive by devising excellent solutions to difficult problems, rather than by finding best or perfect solutions.
4. Complex adaptive systems find excellent solutions by creating schemata based on regularities identified as successful, behaving in ways consistent with these schemata, and incorporating feedback to adapt the schemata for greater success.

Modeling Complex Systems

One way to examine what may be happening in self-organizing complex systems is through the use of computer simulations. Two free software programs, StarLogo ("Starlogo", 2004) and NetLogo (Wilensky, 1999, 2004), offer users opportunities to witness self-organization in action by modeling the dynamics of complex systems. The Logo language, which is the foundation of these modeling systems, was developed by Seymour Papert at MIT in order to teach children the basics of computer programming. As such, it is user-friendly and easy to learn. The novice can explore models that are included in the model libraries, manipulating the variables through sliders and simple commands. Those with greater interest or more experience can create models of their own. Because of their accessibility and ease of use, these software programs can be found in labs and classrooms all over the world.

The three main components of the modeling environment are turtles, patches, and the observer. The individual agents in the system are called turtles, although they can represent any kind of agent from a molecule to a person. The environment in which the turtles operate is divided into patches. Patch size and movement by turtles within and between patches is determined by the program designer. Patches are not necessarily passive but may be, and typically are, active components of the system. Commands may apply either to turtles or to patches. The third component, the observer, can issue commands that affect both patches and turtles. The observer also conducts maintenance and documentation of the turtle world. In NetLogo 2.1, documentation functions such as graphing are built into the interface.

Variables within a model may be set up as sliders, and in many models the sliders can be manipulated while the model is running. This feature allows the user to alter variables and search for excellent solutions within the constraints identified by the model designer. For example, a simple model of an ecosystem might include agents identified as *predators*, other agents called *prey* and patches with *food* for the prey in varying amounts. The interactions between the two different kinds of agents, as well as between the agents and the patches, can be defined by simple commands that identify when *predators* eat *prey*, when *prey* eat *food*, under what conditions new agents are "born" and "die," and so on. If such a model is designed with sliders to control the numer of *predators* and *prey*, as well as the proportion of *food* available, the user can experiment to try to determine how a change in one part of the system affects the system as a whole and how a system might adapt in order to survive or thrive.

The beauty of these modeling tools with regard to building the scientific mind is that they provide the user with a dynamic visual and interactive medium through which to explore the concepts of complex systems. They are simple enough to be used by students in middle or high school, while at the same time they have the potential sophistication required of graduate level research. As such, the use of these free modeling tools opens up the world of complex systems to a broad audience, including those without advanced understanding of science and mathematics. The medium itself can describe and explain, through color, pattern and motion, concepts that previously might have been incomprehensible.

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