HIERARCHY, COMPLEXITY, AND AGENT-BASED MODELS

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Contents

Summary

Complexity is richness in structure or behavior that arises in many systems. Most often it emerges from interactions among many discrete agents or elements.

Complexity studies have their origins in many fields, including engineering control systems, operations research, nuclear physics, computer science, and ecology. An important paradigm is "natural computation," which interprets natural phenomena as forms of computation, and imitates nature (for example, evolution) to derive methods for solving complex problems.

One measure of complexity is the size of a program needed to represent a pattern or process. Standard methods of interpretation fail for complex systems. Instead, approaches that combine simulation and adaptation are more successful. Scenarios replace prediction and adaptive algorithms replace analytic methods of optimization and control.

Complex systems tend to be far from equilibrium. Their behavior diverges rapidly and unpredictably from an initial state. Local events can spawn large-scale patterns or processes. Systems of interacting agents are often self-organizing, with large-scale order (for example, an ant colony) emerging from a multitude of local interactions.

The deep structure of any complex system can be represented as a network, in which nodes correspond to agents and the edges correspond to interactions between the agents. Complexity reflects the combinatorial explosion of pathways linking the agents within such a network. The pathways can indicate complexity either in structure (for example, swarms of particles), or in performance (behavioral richness). Phase changes in the connectivity of random networks underlie many critical phenomena associated with complex systems.

Hierarchies are common in complex systems. They usually arise either from the organization of systems on different scales (for example, cells, organisms, and communities) or from interactions that impose order on the agents that comprise a system. Hierarchies ensure total connectivity in multi-agent systems, but limit interactions (and hence complexity) to links up or down the hierarchy.

1. Introduction

Like life and intelligence, complexity is a concept that is well known, but hard to define. Perhaps the best way of describing complexity is to say that it arises from the way things are put together. How do millions of neurons combine to make a working brain? How does an embryo grow into a complete human being?

In defining the term complexity, dictionaries often refer to systems that are composed of many parts. It is certainly true that complexity usually arises when a system consists of many interacting parts. However, the number of parts is not an absolute guide. Large systems are sometimes very simple in their structure and behavior. On the other hand, some systems with very simple structure behave in very complicated and unpredictable ways. Other definitions of complexity focus on the observer. Complexity denotes phenomena that are difficult to describe, understand, or control. However, being difficult to understand is not sufficient for something to be complex. It is only when the difficulty arises from richness in structure or behavior that a thing is considered complex. Complexity is often defined in negative fashion. Things are deemed complex by virtue of not being simple. For instance, a system is complex if it is not tractable by standard methods of analysis. Likewise, a system is complex if the behavior of individual elements cannot be understood by studying them in isolation. Finally, a system can be considered complex if it cannot be represented by a single model, but needs several different models, each representing different facets of the system, or different levels of abstraction.

Studying complexity is different from most questions in science. Scientific research normally works in reductionist fashion. To understand the whole, break it down into its parts. Processes are understood in terms of simple cause and effect. However, a common feature of complex systems is summed up in the well-known saying, “the whole is greater than the sum of its parts.” That is, features or behavior of the whole system emerge from interactions between the parts. Essential insights are missed by reducing a whole to its parts. The author Arthur Koestler popularized a special term—*holistic*—to indicate the opposite to reductionist. The term stresses the need to consider objects not only in isolation, but also in their system context and how that context affects them.

To summarize the above discussion, complexity is best described as richness and variety, either in structure, or in behavior of a system.

1.1. The Need for Complexity Studies

Complexity studies had their origin in the recognition that many apparently different systems are really manifestations of the same underlying patterns and processes. For example, the spread of a disease through a population is similar to nuclear fission. Both involve a process spreading from object to object, in which each event triggers the next event. When an atom splits it emits particles that split more atoms. When a person falls ill, he or she then infects the next person. And both of these processes also bear similarities to a host of other epidemic phenomena, such as fire spread, invasions of exotic plants, or metal fatigue. Unfortunately, the obvious differences often prevent people from recognizing that deep relationships do exist.

This problem is compounded by specialization. People usually know a lot about a single field of knowledge. They cannot see similarities if they do not know enough about the systems involved. Complexity theory, the growing body of knowledge about complex systems, is emerging out of a synthesis of ideas from many different fields.

The need to study complexity is great. There is a growing tendency, usually called globalization, for organizations and processes to grow until they become worldwide. The globalization trend means that the interactions between environment and resources, economics, and politics, are rapidly increasing.

Every action affects everything else. Effective management of the world's resources therefore requires a clear understanding of these complex interactions.

Traditional methods of studying, interpreting, and planning usually adopt a reductionist approach. Scientists try to understand a whole system by breaking it down and studying its parts. Planners try to break large problems down into smaller and smaller ones, until they become manageable. Traditional methods of analysis assume that systems are ordered, linear, ergodic, isolatable, predictable, observable, and controllable. In complex systems, these assumptions are no longer valid.

For example, traditional, reductionist science assumes that each cause has a simple effect, and vice versa. The problem of complexity is captured by the famous conundrum, "which came first, the chicken or the egg?" Such a question implicitly invites an answer in terms of simple causality. In reality, however, both the egg and the chicken are the products of a complex process.

The complexity of contemporary issues creates a need for interdisciplinary approaches to resolve them. Global environment forums repeatedly identify international economic reform as a major issue, for instance. This need runs counter to a growing trend towards specialization that is evident in every area of knowledge. This trend towards specialization appears to be driven by two factors: the reductionist paradigm mentioned above, and a rapid growth in the sheer volume and detail of knowledge during the twentieth century.

A trend towards ever-narrower specialization dominated the twentieth century. It was driven partly by the reductionist paradigm, and partly by the sheer volume of knowledge, which made expertise across a broad range of fields impossible.

However, by the beginning of the new millennium, the pace of increase in knowledge and information had become so fast, and the need for interdisciplinary approaches to problems so great, that they call for different skills. People now tend to be temporary experts.

They have deep knowledge, cutting across a wide range of fields, about the particular problem that they are currently working on.

2. The Nature of Complexity

2.1. The Network Model

To understand complexity requires models that are capable of representing the richness of large interacting systems. There are many such models; most are concerned with complexity in particular contexts. Graphs and networks capture the essence of complexity at its deepest level.

2.1.1. Graphs

In mathematics, a graph is a structure built from two kinds of components—*vertices* and *edges*—that link pairs of vertices. Graphs are usually drawn as dots (representing the vertices) joined by lines (representing the edges). A graph may contain isolated vertices, which have no edges attached to them. Edges never appear alone; they must always join two vertices.

The graph model is an abstract way of representing objects and relationships in the real world. For instance, if the vertices denote stars, then the interactions might be gravitational attractions between them. If the vertices denote people, then the edges might denote kinship ties, or neighbors, or command structures in an organization. If the vertices denote neurons in the brain, then the edges might denote neighboring neurons. If the vertices denote towns, then the edges might denote roads joining them.

The graph model is all-pervasive. It is present in all systems and processes. It is even built into human language, with nouns denoting objects and verbs indicating relationships. A proof of the graph model's universality is indirect. The models used to represent systems always assume an underlying abstract structure, and graphs are inherent in all of them. For instance, in an equation such as $y = f(x)$, the variables x and y can be considered vertices, and the function f defines an edge in the graph. Likewise, graphical structures are embedded in every other kind of model.

The universal nature of graphs extends to behavior as well. Suppose that a computational model can simulate a system. Then, in the process of computing behavior, the model passes through a series of states. For instance, in a game of chess, each state would correspond to a position of pieces on the board and a game would be a sequence of states defined by the players' moves. The set of all possible states of the game is called its *state space*. In general, each possible state of a system defines a vertex in an underlying graph, and transitions between states define edges in the graph. The actual behavior of the system can be seen as a pathway through the graph of all possible states that the system could take.

A consequence of the universality of graphs is that features of graphs manifest themselves in system structure and behavior. For instance, a path is a sequence of vertices A, B, C, etc. that are linked pairwise by edges AB, BC, etc. A cycle is a closed path (see Figure 1). That is, the edges form a closed loop. Vertices A, B, and C form a cycle if the graph contains the edges AB, BC, and CA. A set of vertices is connected if there is a path joining every pair of vertices in the set. A tree is a connected graph that contains no cycles.

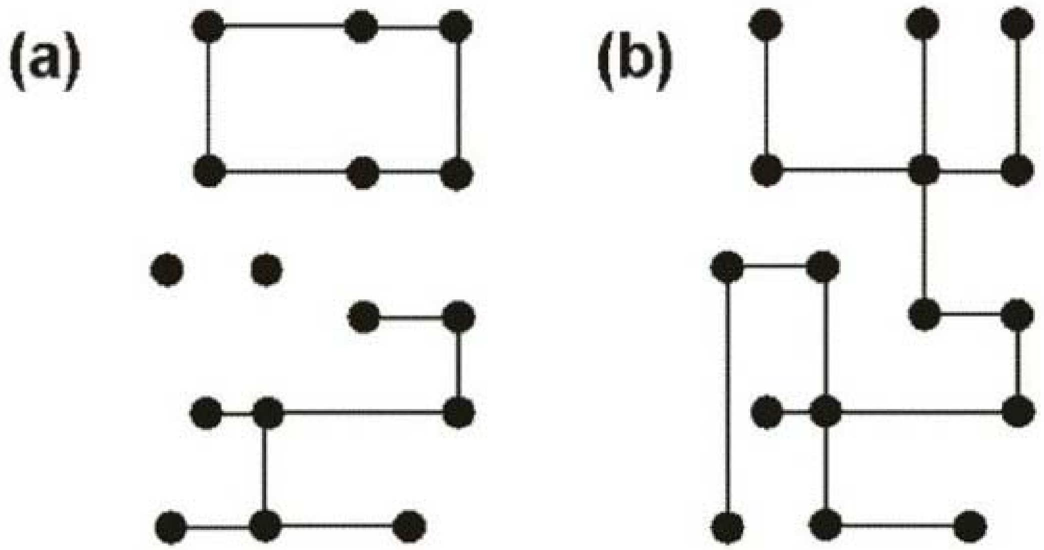

Figure 1. Examples of simple graphical structure. (a) A partially connected graph, which includes two isolated nodes (centre) as well as a cycle (top) and a tree (bottom). (b) The same nodes lined to form a fully connected graph.

A directed graph is a graph in which the edges have a direction. So if A and B are vertices, then the edge AB is different from the edge BA. Directed graphs can contain edges that link vertices to themselves, for example, AA. Paths and cycles in a directed graph have a direction, which is defined by the order implied by the edges that form them. In a directed graph, a tree may have a root, which is a vertex with edges leading from it and none to it.

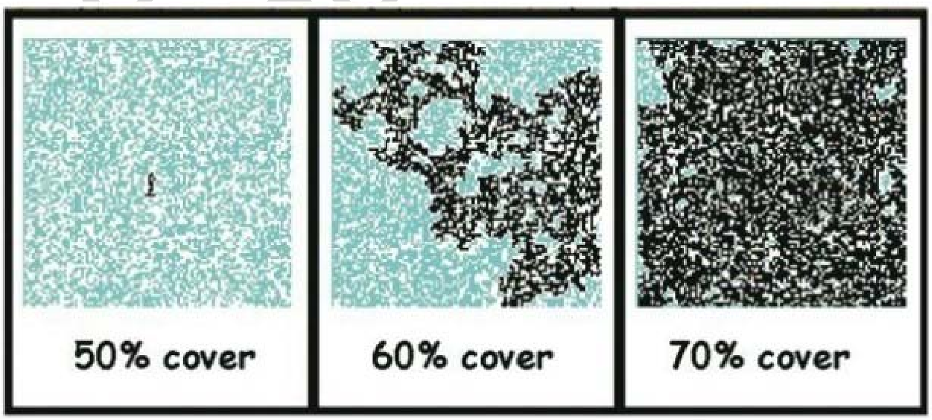

Plate 5.11-1. An example of a phase change in the connectivity of a grid representing a landscape. The shaded cells all share some property and are randomly distributed with the density indicated. The black region indicates a single patch of connected cells. Here

the term connectivity means that some process (for example, seed dispersal in a forest) defines a set of neighboring cells at each location. Note that a small increase in the percentage of shaded cells leads to a phase change in connectivity of the entire region. Source: Green et al. (2001).

Perhaps the most important property of graphs is the phase change from disconnected to connected (Plate 5.11–1). Adding edges at random to a set of isolated vertices forms a graph. During this process, the largest connected sets are at first just pairs of vertices. However, when the number of edges reaches a certain, critical density (this occurs when the number of edges equals half the number of vertices), then the connected set rapidly join to make the entire graph connected. Because graphical structure underlies the organization and behavior of all systems, the above phase change in connectivity is the ultimate cause that underlies many physical phenomena, especially criticality (see section 3.3).

2.1.2. Networks

The network model extends the idea of a graph. A network is a directed graph in which the vertices (and or edges) have attributes associated with them. Network models are often applied to systems involving some kind of flow, such as traffic along streets, electricity through wires, nutrients through an ecosystem, information across the Internet, or control through a command structure. Network models of complexity appear in many different guises. A Boolean network (BN) is a network in which the vertices have two possible states 0 and 1 (or OFF and ON), and the edges denote neighbors that influence one another. Its current state and the pattern of states in its neighbors determine changes in the state of a cell.

A cellular automaton (CA) is a network in which the vertices (called cells in this context) have states and are arranged in a grid pattern (see section 4.4). A CA in which there are just two states for each cell is a special case of a Boolean network. The neighborhood of a cell normally consists of some pattern of cells immediately adjacent to it. CA models can apply to many physical systems, such as flows or epidemic spread, which involve processes in a line, plane, or volume. Ising's spin glass model is a random network in which the cells include a state called spin. Spin glasses have been used to study the process of spin alignment to form coherent media, such as glass. Phillip Anderson's work on broken ergodicity—transitions between coherent and incoherent configurations of spin states—influenced the development of theories about disordered materials in solid-state physics.

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Biographical Sketch

Professor David G. Green completed two degrees in pure mathematics before undertaking a Ph.D. on the forest history of Nova Scotia. In his research career he has applied computers to such diverse real world problems as starfish, bushfires, DNA, and social networks. He played a leading role in setting up Australia's Environmental Resources Information Network (ERIN) in the early 1990s. In 1992 he established Australia's first World Wide Web service, and his work has influenced the development of on-line information systems for biodiversity and environmental management. Since 1994 he has been Professor of Information Technology in the School of Environmental and Information Technology at Charles Sturt University. His research on complexity has included work on the crucial role of connectivity and spatial processes in landscape ecology. His research on evolutionary computation and artificial life has stressed the many valuable lessons to be learned from living systems. He is editor of the research journal *Complexity International* and the author of over 150 research papers. He has also written several books on complexity, including *Patterns in the Sand* (1998), *Complex Systems* (2000), and *Complexity in Landscape Ecology* (2001).