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COMPLEX ADAPTIVE SYSTEMS

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■ **Abstract** The study of complex adaptive systems, a subset of nonlinear dynamical systems, has recently become a major focus of interdisciplinary research in the social and natural sciences. Nonlinear systems are ubiquitous; as mathematician Stanislaw Ulam observed, to speak of “nonlinear science” is like calling zoology the study of “nonelephant animals” (quoted in Campbell et al. 1985, p. 374). The initial phase of research on nonlinear systems focused on deterministic chaos, but more recent studies have investigated the properties of self-organizing systems or anti-chaos. For mathematicians and physicists, the biggest surprise is that complexity lurks within extremely simple systems. For biologists, it is the idea that natural selection is not the sole source of order in the biological world. In the social sciences, it is suggested that emergence—the idea that complex global patterns with new properties can emerge from local interactions—could have a comparable impact.

To illustrate the concept of a complex adaptive system, Holland (1995) offers the example of a woman purchasing a jar of pickled herring on an ordinary day in New York City. She fully expects the herring to be there. But grocery stores do not keep large stocks of all kinds of foods to buffer fluctuations; if the daily arrivals were cut off, supplies would last no more than a week or two. How, asks Holland, do cities with millions of inhabitants avoid devastating swings between shortage and glut, year after year, without any form of centralized planning? Invoking Adam Smith’s “invisible hand” of the market does not fully satisfy Holland as a solution because it fails to explain the mechanisms that dampen fluctuations. Instead he likens the provisioning of cities to the functioning of immune systems or the interactions of species in ecosystems. Thus for food webs in rainforests to sustain biodiversity, innumerable specific flows of nutrients—equivalent to the jars of pickled herring—must persist in the absence of any form of centralized control. Similarly, an immune system also lacks centralized control and cannot settle into a permanent, fixed structure; instead it must be able to adapt to unknown invaders. Yet despite its protean nature, a person’s immune system is coherent enough to distinguish oneself from anyone else; it will attack cells from any other human. Holland suggests that immune systems, cities, and ecosystems share certain properties that make it useful to consider them as instances of a class of phenomena that he terms complex adaptive systems (CAS) (Holland 1995, pp. 4–6).

The concept of CAS is obviously at a very high level of abstraction. Moreover, it crosscuts the usual categories of anthropological thought, such as culture, nature, and society, and applies only to a rather narrow range of phenomena within them. The insights it offers are essentially mathematical and frequently involve the use of new computational tools. New theoretical ideas about CAS tend to be published initially in physics and mathematics journals; some gradually work their way into biology, the social sciences, and, on occasion, business schools and the popular press. The goal of this review is to provide an introduction to the research that I think may be of most interest to anthropologists. It has two parts: The first offers a historical overview of the broader intellectual currents shaping research on CAS; and the second surveys recent attempts to apply these ideas to anthropological questions.

INTRODUCTION: THE DIVINE TAPE PLAYER

If we could rewind an imaginary videotape of the history of life on Earth, asked biologist Stephen Jay Gould, how much of what we see around us would still be here? Gould's answer was, very little: "[T]he divine tape player holds a million scenarios, each perfectly sensible . . . the slightest early nudge contacts a different groove, and history veers into another plausible channel, diverging continually from its original pathway" (Gould 1989, pp. 320–21). As a paleontologist, Gould saw the living world in terms of phylogenetic trees, each node or species the unique result of a long chain of random evolutionary events. But, as critics of Gould have pointed out, the history of life on this planet shows many examples of convergent evolution, such as the independent evolution of eyes in many taxa, that would be very surprising if Gould were strictly correct (Depew & Weber 1995, pp. 424–27). The divine tape player does not produce exact duplicates of species, but it does generate spectacular examples of convergent evolution like anteaters and pangolins or the marsupial lions and wolves of Australia and Tasmania. At the level of molecular evolution, the phylogenetic history of these species fits Gould's model: African lions and marsupial lions shared a common mammalian ancestor millions of years ago and have been diverging ever since. But the fact that these independent pathways of evolution produced animals that are so similar in morphology and behavior suggests that Gould has captured only part of the story. It seems that random bumps and nudges may be more likely to veer into some grooves than others, producing convergence as well as divergence.

A similar paradox involving the relationship of the parts to the whole intrigued Emile Durkheim in his classic study of suicide. On the one hand, Durkheim observed, the causes of particular suicides are "almost infinite in number . . . one man kills himself in the midst of affluence, another in the lap of poverty; one was unhappy in his home, and another had just ended by divorce a marriage which was making him unhappy" (Durkheim 1979[1897], p. 303). He concluded that no matter how much a researcher knows about a collection of individuals, it is impossible to predict which of them are likely to kill themselves. Yet the number of Parisians who commit suicide each year is even more stable than the general mortality rate. A process that seems to be governed by chance when viewed at the level of the individual turns out to be strikingly predictable at the level of society as a whole.

Among students of complex systems, this phenomenon is known as "emergence." Consider a system or aggregate composed of many interacting parts. If the system is sufficiently complex, it may not be practical or perhaps even possible to know the details of each local interaction. Moreover, local interactions can produce nonlinear effects that make even simple systems impossible to solve (as Newton discovered in attempting to solve the three-body problem). But if we shift our attention from the causal forces at work on individual elements to the behavior of the system as a whole, global patterns of behavior may become apparent. However, the understanding of global patterns is purchased at a cost: The observer must usually give up the hope of understanding the workings of causation at the level of individual elements. "The statistical method," wrote physicist James Clerk Maxwell in 1890, "involves an abandonment of strict dynamical principles" (Vol. 2, p. 253). It is an interesting footnote to the history of the sciences that this discovery occurred in the social sciences and was later borrowed by physicists. "Doubtless it would be too brave," writes Porter in *The Rise of Statistical Thought*, "to argue that statistical gas theory only became possible after social statistics accustomed scientific thinkers to the possibility of stable laws of mass phenomena with no dependence on predictability of individual events. Still, the actual history of the kinetic gas theory is fully consistent with such a claim" (Porter 1986, p. 114).[1]

Late in his career, the philosopher Karl Popper argued that this shift from an atomistic and mechanistic ontology to one based on probabilities was among the most significant intellectual pirouettes in the history of science. "The world is no longer a causal machine," wrote Popper in his last book (1990). "It now can be seen as a world of propensities, as an unfolding process of realizing possibilities and of unfolding new possibilities" (Popper 1990, pp. 18–19). In physics, the application

[1]In retrospect, Durkheim's comments on the implications of this point seem remarkably prescient. The key issue is the understanding of chance. If suicides occur for many contradictory reasons, then the overall suicide rate should be governed by chance and fluctuate chaotically. As Durkheim noted, this is what would be predicted by the dominant statistical theory of his day, that of Adolphe Quételet, who held that the behavior of individuals was governed by the sum total of prior influences acting on them. Quételet's theory should accurately predict that the average man would not commit suicide, but it should also predict that the suicide rate should fluctuate randomly. To this, Durkheim responded that "Quételet's theory rests on an inaccurate observation. He thought that stability occurs only in the most general manifestations of human activity; but it is equally found in the sporadic manifestations which occur only at rare and isolated points of the social field" (Durkheim 1979[1897], p. 302). Durkheim concludes that suicides are not mere statistical outliers but the outcome of deterministic processes.

of probability theory to the gas laws and thermodynamics in the nineteenth century was followed by quantum theory in the 1920s, in which the statistical properties of ensembles were pushed down into the very structure of the physical universe. At about the same time, biologists Sewall Wright and R.A. Fisher developed models that depicted natural selection in probabilistic terms. Wright sought to understand what he called "switch-and-trigger mechanisms," which could drive evolutionary processes into new trajectories, and in the 1930s developed a model of adaptive landscapes to facilitate visualizing such patterns. In this model, genetic variation is depicted as clouds of points in a multi-dimensional landscape, often drawn in three dimensions with peaks and valleys representing high and low levels of adaptive fitness. Wright's adaptive landscapes (or fitness landscapes) were used initially to consider the effects of evolutionary forces such as inbreeding (Wright 1932) and genetic drift (Dobzhansky 1937, Mayr & Provine 1980). But recently, complexity theorists have used fitness landscapes to pose more general questions. As biologist Stuart Kauffman has written, "the fitness landscape is a powerful, basic and proper starting point to think about selection" (Kauffman 1989, p. 69).

ADAPTIVE LANDSCAPES

In the 1960s Kauffman posed a simple question: Is Darwinian natural selection, alone, responsible for the patterns of order we see in the living world? Nonliving phenomena like snowflakes exhibit spontaneous order through a process of self-organization. Might self-organizing processes also play a role in biology? To explore this question, Kauffman used computer simulations as a surrogate for Gould's "divine tape player". Although Kauffman's research was originally aimed at understanding evolution at the level of genes, his results suggest that "the range of spontaneous order is enormously greater than we had supposed" (Kauffman 1995). A brief summary of Kauffman's work on adaptive landscapes provides an introduction to some of the methods and perspectives now being used in the study of complex systems.

The original Wright-Fisher model of fitness landscapes assumes a one-to-one correspondence between individual genes and traits that affect fitness. As time goes on, a species can "climb the peak of Mount Fitness" as progressively fitter mutants appear and become dominant. But Kauffman observed that this is an oversimplification. In reality, the adaptive fitness of any particular trait is likely to be determined by several genes; these are known as epistatic connections among genes. Moreover, the fitness of an organism or species depends upon the others with which it interacts: If frogs develop sticky tongues, flies will do better with slippery feet. Thus evolution depends on many interacting (and sometimes conflicting) constraints. But rather than try to analyze the actual epistatic connections in particular instances, Kauffman posed a more general question: What is the relationship between the average connectedness of genes to the ability of organisms to evolve? (Later, Kauffman observed that one can ask analogous questions about the connectedness of firms in an economy or species in an ecosystem).

To see how Kauffman pursued this question, imagine a collection of *N* Christmas tree lights. Each bulb has one of two possible states, on or off, and is wired up to *K* other bulbs. A simple rule tells each bulb what to do. For example, let $K = 3$, meaning that each bulb is wired to 3 other bulbs.[2] From one moment to the next, each bulb decides whether to turn itself on or off in accordance with the state of these neighbors. A typical rule is majority wins, meaning that if 2 or 3 of its neighbors are on, the bulb will itself turn on; otherwise it will turn off. How will such a system behave when the electricity goes on? At first, Kauffman found that there are two possible patterns of behavior, ordered and disordered. Later, Langton (1990) pointed out that the behavior of the network at the transition point between order and chaos is different enough to be categorized as a third regime. Thus there are three regimes:

1) chaotic: If *K* is large, the bulbs keep twinkling chaotically as they switch each other on and off;
2) frozen or periodic: If *K* is small ($K = 1$), some flip on and off a few times, but most of the array of lights will soon stop twinkling;
3) Complex: If *K* is around 2, complex patterns appear, in which twinkling islands of stability develop, changing shape at their borders.

Kauffman discovered that the overall behavior of such NK networks (where *N* is the number of elements and *K* the number of connections per element) is almost entirely dependent on *K*, rather than the specific rules implemented along the epistatic pathways (like "majority wins"). Kauffman began these experiments in the days when computers were programmed with punch cards. Changing the order in which the cards were stacked would disrupt ordinary programs. But because he was interested in discovering the average behavior of NK networks, his procedure involved shuffling the cards and running the program again, to the consternation of onlookers (Flake 1998, p. 329). His principal result was that a network that is either frozen solid or chaotic cannot transmit information and thus cannot adapt. But as Langton discovered, a complex network—one that is near the "edge of chaos"—can do both (Langton 1990).

The characteristic patterns of behavior of NK networks can be visualized on a Derrida plot (Figure 1). Here we track the behavior of a network of 1600 elements (light bulbs). To set up the experiment, two versions of the network are created that are identical except for the numbers of bulbs that happen to be on or off at the start. The number of elements that differ (e.g., off or on) is called the Hamming distance between the two instances of the network. Along the X axis, the Hamming distance varies from zero (the two versions of the network are identical) to 1 (the networks are completely dissimilar: If a bulb is off in one, it is on in the other). Imagine that power is switched on and bulbs turn each other on and off in both

[2]Rules are defined by Boolean connections like "and" and "or." The "majority wins" rule used here to illustrate the concept of NK Boolean networks will not lead to chaos.

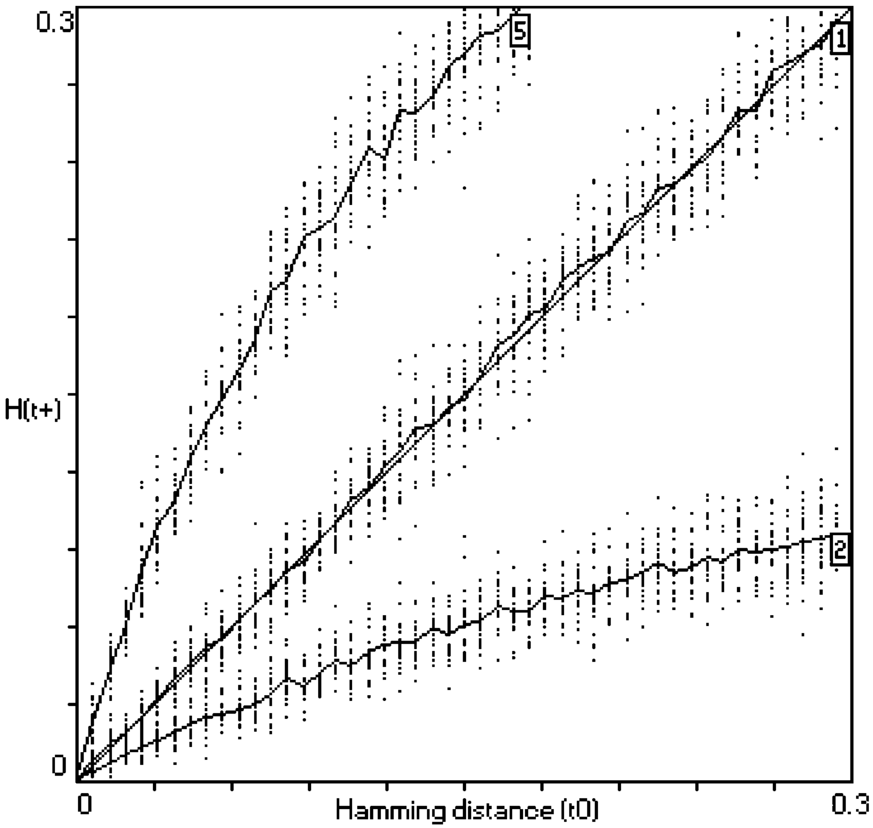

Figure 1 Derrida plot of an NK Boolean network. The Derrida plot above shows the behavior of three *NK* networks (N = 1600). The plot for each network is created as follows: Consider that the network is initialized to two initial states. The two states are identical except for *x* nodes that are changed from on to off or vice versa. The horizontal axis of the graph reflects *x*; its unit is termed the Hamming distance and indicates the number of corresponding nodes with opposite values, scaled by dividing by *N*. At the *left* of the graph the initial states are identical and are progressively more dissimilar to the *right*. Each instance of the network is then allowed to proceed forward for two time steps. The vertical axis shows the Hamming distance between the two final states that result. Several different combinations of initial states are plotted for each initial Hamming distance; each point represents one such trial, and the lines connect the averages of the results. *K* is indicated for each line. For K = 1, the Hamming distance does not change; two initial states that differ on *x* nodes lead to two final states that differ on roughly *x* nodes as well. However, if K = 2, two initial states that differ by a few nodes will tend to converge into a nearby basin of attraction so that after two time steps their initial dissimilarity is significantly decreased. Conversely, if K = 5, the system behaves chaotically so that even two fairly similar initial states will rapidly become dissimilar. This figure was created by John Murphy using A. Wuensch's Discrete Dynamics Lab; see Wuensch & Lesser 1992.

networks, resulting in a new Hamming distance that is plotted on the Y axis. In the extreme case where $K = 0$, the Hamming distance will not change; no bulb will twinkle. At the other extreme, if K is large, even a small initial difference will trigger cascades of twinkles in both networks that will cause them to diverge, and the Hamming distance will increase.

BASINS OF ATTRACTION

If the reader will bear with me, this simple example can be used to explain many of the key concepts involved in the study of complex adaptive systems. As bulbs turn each other on and off, eventually the entire array of bulbs must reach a state that it has encountered before. Once this has occurred, it will cycle back to that configuration forever. This repetitive cycle is called a state cycle or limit cycle. Sometimes more than one configuration of a network will flow into the same state cycle. Start a network with any of these initial patterns and, after passing through a sequence of states, it will settle into the same state cycle or pattern of twinkling. In the language of dynamical systems, the state cycle is called an attractor and the array of initial states that flow into it a basin of attraction. The more initial states that flow into a given attractor, the larger its basin of attraction. So one can ask questions like, how many attractors exist for a given system and how long are the state cycles? For NK networks, the number of states that are possible is 2^{N}, a hyperastronomical number for all but the smallest networks. But the number of attractors and the size of their basins varies dramatically depending on K. When $K = N$, the average length of state cycles is 2^{N}, and the number of attractors is also huge, about N/e. Such networks provide a dramatic illustration of the concept of deterministic chaos. Flip one bulb in a $K = N$ network, and the network moves out of one basin of attraction and into another. It will be a very long time indeed before it encounters a state that it has been in before (and thus completes one tour of its attractor). The network is extremely sensitive to perturbations, which instantly change its entire pattern of behavior; thus such networks cannot store information. At the other extreme, when K is small, networks exhibit stable or periodic behavior. They arrive at their tiny attractors at an exponentially fast rate and then become trapped in simple state cycles. Different sections of the network function as isolated subsections or islands. They can store information, but there is no communication between the islands. So networks with lots of connections exhibit chaotic behavior, whereas networks with very sparse connections decompose into an archipelago of isolated subsystems that either stop twinkling or follow simple repetitive patterns.

However, when $K = 2$, very different dynamics occur; these networks are in between the chaotic and stable/periodic regimes. Both the number of attractors and their average length are equal to the square root of N, a small number even when N is large. Thus when $K = 2$, a network of 1600 light bulbs will settle down and cycle through the square root of 1600 states, a mere 40. Initialize a new $K = 2$ network, and it will soon find itself headed for one of a few relatively stable configurations. The network as a whole does not decompose, nor does it become chaotic. But the most interesting property of $K = 2$ networks is their response to perturbation. Flip one bulb in a $K = 2$ network, and in most cases only a few neighbors will twinkle. But occasionally a perturbation will induce large changes, perhaps moving the network into a new basin of attraction. This explains the Derrida plot for $K = 2$: Most networks are located in just a few large basins of attraction, so networks tend to converge toward one of a relatively few attractors, and the Hamming distance decreases.

These results have dramatic implications for the ability of networks to evolve. To see this, imagine that the *N* elements are genes and that each one contributes something to the fitness of the whole network. To ensure that the model is very general, let fitnesses be assigned randomly to all the "genes" or elements in the array. When $K = 0$ (meaning that the fitness of each gene or element does not depend on any others), the fitness landscape shows a single Mount Fuji peak. Start anywhere in this landscape, and you can always find a neighbor one step away with a higher fitness. But as *K* grows larger there are more and more conflicting constraints. As the complexity of the network increases, selection is progressively less able to alter its properties. When $K = N$, each gene's fitness contribution depends on all the other genes in the array. This means that the differences in fitness between genes is very small, and the adaptive landscape looks like a lot of tiny hills. As Kauffman observes, "in sufficiently complex systems, selection cannot avoid the order exhibited by most members of the ensemble. Therefore, such order is present not because of selection but despite it" (Kauffman 1993, p. 16).

Complex Systems and the Edge of Chaos

Kauffman emphasized the role of selection in bringing living systems to the edge of chaos, a controversial point to which we shall return. But physicist Per Bak and his colleagues have shown that nonliving systems can also exhibit self-organizing properties that may take them to the edge of chaos (Bak & Chen 1991, Bak 1997). Bak's examples include phenomena like earthquakes, which are unlike biological systems because no process of adaptation is involved; these are known as complex systems rather than complex adaptive systems. Bak's best-known example is a sandpile. If you patiently trickle grains of sand onto a flat surface, at first the sand will simply pile up; but eventually the pile will reach a critical state. At that point, Bak found that the size of the avalanches triggered by dropping another grain of sand follows a power law distribution: The size of avalanches is inversely proportional to their frequency (in other words, there will be many little avalanches, a few medium-sized ones, and on rare occasions a large one). Such a sandpile is at the "edge of chaos," analogous to a $K = 2$ Boolean network (to picture this, it may help to imagine that a $K = 0$ pile would be flat, whereas a $K = N$ pile could be a tall and precarious column with a diameter of one grain). Other researchers have found additional pathways that lead to the edge of chaos. The first research on this topic was carried out by Langton, who wrote a dissertation (1991) entitled "Computation at the Edge of Chaos." Langton studied the behavior of cellular automata (CA), a mathematical concept invented by John von Neumann. More recently, mathematician Stephen Wolfram carried out exhaustive computer simulations in an attempt to clarify the dynamics of complex behavior in cellular automata (Wolfram 2002). A simple two-dimensional cellular automata begins with a line of different-colored cells on a grid or lattice. Each cell checks its own color and that of its immediate neighbors and decides on the basis of a rule whether to turn color in the next line of the grid. It is equivalent to a two-dimensional NK model where the *K* inputs are restricted to the cell's closest neighbors on the lattice. Wolfram noticed the existence of four classes of behavior in CA: (I) fixed, (II) periodic, (III) chaotic, and (IV) complex. Langton became interested in the relationship between these classes and developed a measure, the lambda parameter, that relates the nature of the rules to the overall behavior of the cellular automata (Figure 2). Tuning the lambda parameter leads through Wolfram's classes in the order I-II-IV-III; thus the complex regime (class IV) lies between the periodic and chaotic regimes. This led Langton to propose that class IV behaviors could be associated with a phase transition between order and chaos: the edge of chaos (Langton 1990).

The methods used to study complexity in cellular automata differ from those used to investigate NK models. The study of CA usually involves following a single rule on its journey to its attractor, whereas investigating NK networks requires taking statistics on their average patterns of behavior. It is interesting that each of these independent lines of research—Bak's sandpiles, Kauffman's NK Boolean nets, and Wolfram's Class IV cellular automata—provide intuitive examples of complex behavior near the phase transition between ordered and chaotic regimes (Langton's edge of chaos), but so far there is no satisfactory mathematical definition of complexity.

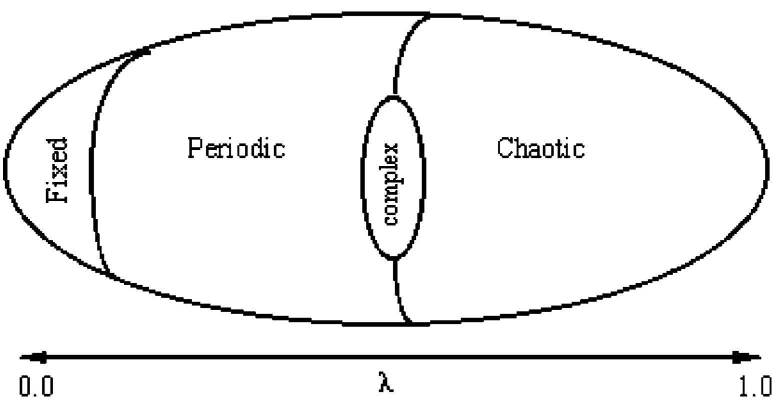

Figure 2 Langton's classification of cellular automata. The behavior of cellular automata depends on the rules that govern their evolution in time. Some rules will map a cell into a quiescent state. Lambda is the fraction of rules that map to non-quiescent states. Langton found that tuning lambda shows that complex behavior (Wolfram's Class IV CA) emerges between classes II and III, at the edge of chaos. See Langton 1990.

A more controversial issue is Kauffman's suggestion that a selective metadynamics may drive complex adaptive systems toward the edge of chaos. Kauffman has demonstrated how this process could occur with computer simulations, but the idea is not easily reconciled with standard models of multilevel selection in evolutionary biology (for a clear statement of this problem, see Levin 2003). Still, from a mathematical standpoint it is clear that systems that find themselves in this region of their state space are advantageously situated for adaptation. As Langton showed, the ability of networks to both store and transmit information is optimized at the edge of chaos. Moreover, as Kauffman observed, this is where the adaptive landscape is most favorable for gains in fitness. At present, physicists (rather than biologists) remain at the forefront of research on the edge of chaos. Two recent examples are noteworthy: One group of physicists found that the rate of entropy increases at the edge of chaos (Latora et al. 2000), whereas de Oliveira confirmed that "the eternal search for new forms, better than the current one, is imperative for evolutionary dynamic systems" and is optimized at the edge of chaos (de Oliveria 2001, p. 1). On the other hand, Mitchell & Crutchfield (1993) report experiments with cellular automata that call into question Langton's suggestion that the ability of cellular automata to perform computational tasks is optimized when lambda values are closest to the edge of chaos.

Although questions remain, the theoretical analysis of complex systems has already produced some intriguing results. Kauffman calls the study of complex adaptive systems "antichaos," because it is concerned with the spontaneous appearance of order in dynamical systems. For mathematicians and physicists, the biggest surprise is that complexity lurks within extremely simple systems. For biologists, it is the idea that natural selection is not the sole source of order in the biological world. As for the social sciences, I suggest that emergence—the idea that complex global patterns with new properties may emerge from local interactions—may someday have a comparable impact. Because space is limited, here I conclude this introduction to the theory of complex systems and turn to some applications of these ideas in the social and behavioral sciences.

THE CRITIQUE OF EQUILIBRIUM THEORY IN ECOLOGY AND ECONOMICS

In a recent article (1999) in the *Annual Review of Anthropology* on "New Ecology and the Social Sciences," Scoones describes the emergence of a "new ecology" beginning in the 1970s. The turning point was May's 1976 paper in *Nature* on "Simple Mathematical Models with Very Complicated Dynamics," which showed that "simple nonlinear systems do not necessarily possess simple dynamical properties" (p. 459). Subsequently, the mathematical foundations of ecology began to shift away from the study of equilibrium (the balance of nature), using simple differential equations, to the study of nonequilibrium theory, with the techniques of nonlinear analysis (Ferriere & Fox 1995, Levin 1999). Scoones suggests that these ideas have so far had little impact on the social sciences and urges "a fuller engagement with the issues raised by the new ecological thinking" (Scoones 1999, p. 496).

May's paper is now seen as a milestone in the first phase of nonlinear analysis, the discovery of chaos. Most of the ecological research discussed by Scoones is also concerned with chaotic dynamics and nonequilibrium systems (it should be noted, however, that a good deal of contemporary research in ecology makes little use of nonlinear methods). More recently, the study of spontaneous order and self-organizing properties in ecosystems has become a major new theme of research. As Levin (2003, p. 3) observes in a recent review article on the mathematics of complex adaptive systems, studying antichaos "involves understanding how cooperation, coalitions and networks of interaction emerge from individual behaviors and feed back to influence those behaviors." Although nonlinear approaches have spread to many areas of ecological research, the aspects that may be of greatest interest to anthropologists have to do with the emergent properties of social and behavioral systems. Here one often encounters broad theoretical pronouncements, such as Schank's contention that "most animal social systems are self-organizing" (Schank 1998, p. 1). But specific applications of nonlinear models to animal behavior have also begun to appear. For example, Bonabeau has investigated the foraging behavior of various species of ants and concludes that they are "a clear example of adaptation to the edge of chaos" (Bonabeau 1997, p. 29). The ants use multiple systems for communication and for recruiting foragers to newly discovered food sources. Species at the edge of chaos, like *Tetramorium caespitum*, can adaptively switch to newly discovered food sources if they are of higher quality, whereas other species do not take advantage of the higher-quality food until the first source is exhausted. Bonabeau's mathematical model shows how the global decision-making processes of the ants emerge from the local interactions between individual foragers (Bonabeau 1997).

Complexity theory is also beginning to have a similar impact on economics: a shift from equilibrium models constructed with differential equations to nonlinear dynamics, as researchers recognize that economies, like ecosystems, may never settle down into an equilibrium. A clear and readable account of this change in perspective is provided by Arthur in his article (1999) on "Complexity and the Economy." Arthur argues that "complexity economics is not a temporary adjunct to static economic theory, but theory at a more general, out-of-equilibrium level. The approach is making itself felt in every area of economics: game theory, the theory of money and finance, learning in the economy, economic history, the evolution of trading networks, the stability of the economy, and political economy" (Arthur 1999, p. 109; see also Arthur et al. 1997). Kauffman draws explicit parallels between biological and economic systems: "[T]he modern corporation is a collectively self-sustaining structure of roles and obligations that 'lives' in an economic world, exchanges signals and stuffs, and survives or dies in ways at least loosely analogous to those of *E. coli* . . . . Both *E. coli* and IBM coevolve in their respective worlds" (Kauffman 1995, p. 300). Economists have followed up on this idea by investigating the "web structure" of economies, as, for example, in

Kauffman and Scheinkman's analysis of the relationship between the diversity of sectors and rate of economic growth in cities (Kauffman 1995, p. 295).

Today the study of nonequilibrium economics is well under way, for example, in the simulation of stock markets both real and imaginary. The study of the global properties of these economies has been accompanied by research on the behavior of economic actors. Economist Sam Bowles and his colleagues have begun to work with anthropologists to investigate, as an empirical question, how social actors make decisions in game-theoretical or economic contexts (Bowles & Gintis 2002). Based on these results, they propose to supplement *Homo economicus* with a larger and more diverse "family of man." Research in economics on complexity thus proceeds at two levels: the characteristics of individual social actors and the global dynamics of economies or societies. This research draws heavily on mathematical models of nonlinear systems; investigators keep an eye out for power-law distributions of events (such as the growth of firms or the frequency of stock market events) that may signal a system near the edge of chaos (Scheinkman & Woodford 1994).

COOPERATION AND THE "TRAGEDY OF THE COMMONS"

"Common to all studies on complexity," writes Arthur, "are systems with multiple elements adapting or reacting to the patterns these elements create" (Arthur 1999, p. 107). However, what if the elements are not cells or light bulbs but agents capable of reacting with new strategies or foresight to the patterns they have helped to create? As Arthur observes, this adds a layer of complication not experienced in the natural sciences, and much of the current research by social scientists on complex adaptive systems is concerned with precisely this question. One consequence has been to breathe new life into the field of game theory. Like many anthropologists, as a graduate student I had little interest in game theory because it seemed to embody implausible assumptions about human nature, what Marshall Sahlins calls the common average social science wisdom. But the complexity approach has led to a major shift in perspective, from static models of rational choice to the evolution of strategies over time, and from local interactions to their global effects. Perhaps the most active area of research in this field is concerned with the broad subject of social cooperation, which spans topics ranging from the evolution of cooperation in social animals to the human management of natural resources. Here I briefly trace the outlines of this shift from static to dynamic models of the emergence of cooperation.

The obvious place to begin is with Axelrod's famous study of the emergence of cooperation between groups of front-line soldiers who faced each other across the trenches of France in World War One (Axelrod 1984). Axelrod wondered how cooperation could develop between groups of men who could not converse and were in fact trying to kill each other. His approach was to try to identify the strategic choices each group faced in dealing with their opponents across No Man's Land.

Thus a vigorous assault at an unexpected time might lead to a victory, with many enemy dead. But the same option was also available to the enemy. Alternatively, if each group only pretended to attack and made their artillery fire completely predictable, their opponents would have time to take cover. If both sides adopted this strategy, neither side would suffer casualties. In terms of the available options, although a successful attack was deemed the best outcome, to be a victim of such an attack was clearly the worst, while “live and let live” falls somewhere in between. But for a “live and let live” strategy to work, each side must trust the other. Yet such informal truces broke out repeatedly along the trenches and became a major headache for the high command on both sides.

Axelrod suggested that the underlying dynamics of the “live and let live” system could be represented as a game. The advantage to such formalization is that it becomes possible to compare the wartime case with other unlikely instances of spontaneous cooperation to see if similar processes are involved. The particular game is called the Prisoner’s Dilemma. As the story goes, two prisoners are each given the choice of giving evidence against the other and so reducing their own sentence. The dilemma arises because if neither defects on the other, the police can convict them both only on a lesser charge. But if one defects (by giving evidence to the police), he goes free, whereas the other goes to jail for a long time. If both defect, both will receive the maximum penalty. These choices and their respective payoffs may be represented in a table (Table 1). Here the rewards are scaled from zero (the worst) to 5 (the best). Mathematician Karl Sigmund suggests that the game becomes more interesting if we think of these payoffs as gold bars, not “measly little numbers” (Sigmund 1993). In Table 1, the numbers in the boxes refer to the payoffs: The first number is the payoff for Player 1 and the second for Player 2. So if Player 1 cooperates and so does Player 2, the payoff for each is 3, as shown in the top left box. But if Player 1 cooperates and Player 2 defects (top right box), Player 1 receives the “sucker’s payoff” of zero, whereas the unscrupulous Player 2 reaps the maximum reward: 5 gold bars (or a ticket out of jail in the original anecdote).

The problem is that the optimal strategies for each player create the worst possible joint outcome. Thus, if the other player defects, you are better off defecting (you get one bar instead of none). If the other player cooperates, you are still better off defecting (you get five bars, he gets none). So, cold logic dictates that the best strategy is always to defect. But since the same logic holds for the other player, the outcome is mutual defection, and everyone loses. The chief advantage to defining the problem in this way (as a simple game) is that it can help to reveal the essence of the problem. Indeed one can see that Garrett Hardin’s “tragedy of the commons”

TABLE 1 The Prisoner’s Dilemma

	Player 2: Cooperate	**Player 2: Defect**
Player 1: Cooperate	3,3	0,5
Player 1: Defect	5,0	1,1

is another instance of exactly the same game (Hardin 1968, 1998). All fishermen would be better off if they exercised voluntary restraint and did not take too many fish. But in such a situation, an unscrupulous fisherman who decides to take more fish will reap greater rewards than the "suckers" who take only their share, unless there is a common property management system in place (see Agrawal 2003, this volume).

Axelrod suggested that the tragedy of mutual defection can be avoided only if players understand themselves to be in a situation where continuing cooperation can pay off, because the circumstances of the game will recur. In other words, it is worthwhile to cooperate with me today provided I am in a position to repay you by cooperating tomorrow. In the trenches of World War I, Axelrod relates an anecdote in which the artillery from the German side opened up at an unexpected time and killed some British soldiers, thus violating the implicit agreement. Some Germans came out under a flag of truce to apologize and promise that the mistake would not happen again. Subsequent studies emphasized the wide applicability of the Prisoner's Dilemma. For example, sociologists compared the behavior of drivers in large cities versus small towns and villages. Shaking one's fist at other drivers, honking the horn, and other acts of rudeness are more frequent in big city traffic, perhaps because drivers in cities can assume that they are anonymous. Similarly, evolutionary biologists have suggested that cooperation (reciprocal altruism) occurs only among social species that are capable of recognizing other individuals and remembering whether they cooperated on previous occasions. Examples include vampire bats, dolphins, elephants, primates and most especially humans (summarized in Sigmund 1993). Humans turn out to be remarkably good at predicting whether others will cooperate. This was shown in an ingenious experiment: Economist R.H. Frank found that if a group of strangers are asked to play the Prisoner's Dilemma game, their ability to predict who will cooperate (and who will not) improves dramatically if they are given just 30 min to socialize with the other players before the game begins (Frank 1988).

In the original game, rational choice leads to ruin. But if the game continues over time, intuitively it seems possible for cooperation to emerge, as these examples suggest. Axelrod and other researchers accordingly reformulated the game to allow simulated agents to play a series of games with one another, treating their strategies and their memory of the behavior of other players as variables (Axelrod 1997). Because the success of particular strategies is frequency-dependent, the entire game can be treated as a dynamical system evolving over time, with global characteristics that emerge from the local interactions of players and strategies. Under these circumstances, Axelrod found that cooperation would emerge under a wide range of conditions.

Subsequently, physicist Kristian Lindgren embedded game-playing agents on a lattice, adding greater flexibility by making memory length an evolutionary variable. Over tens of thousands of generations, he observed the emergence of spatial patterns that resemble evolutionary processes and that help to clarify preconditions for the emergence of cooperation and competition (Lindgren 1994).

More recently, mathematician Karl Sigmund has developed simulations of games in which players remember encounters they have observed; here cooperation develops very quickly (Sigmund 1993, Nowak & Sigmund 1998). Such simulation results have inspired behavioral ecologists to reexamine biological systems. For example Milinski has studied stickleback fish, which enjoy "a well-earned reputation for keeping abreast of the latest trends in animal behavior." According to Milinski, cooperation in "predator inspection" by the sticklebacks follows the dynamics of the iterated Prisoner's Dilemma (cited in Sigmund 1993, p. 201). The results of these simulations have also been used to model problems in political science and economics (Axelrod 1997).

But cooperation is by no means the only emergent property investigated by social simulations. Philosopher Brian Skyrms has studied the evolution of the social contract by modeling it as a problem in the evolution of dynamical systems. His most ambitious models tackle such large questions as the evolution of justice, linguistic meaning, and logical inference. Skyrms finds that "the typical case is one in which there is not a unique preordained result, but rather a profusion of possible equilibrium outcomes. The theory predicts what anthropologists have always known—that many alternative styles of social life are possible" (1996, p. 81). But this may be a bit too modest. With respect to the evolution of meaning, for example, Skyrms shows that evolutionary processes provide a plausible answer to the fundamental question, "How do the arbitrary symbols of language become associated with the elements of reality they denote?" (Skyrms 1996, p. 81).

COMPLEX SYSTEMS IN ANTHROPOLOGY

There have been several notable studies by anthropologists investigating nonlinear dynamics, such as Park's investigation of the relationship between chaos in flood-recession agriculture and the emergence of social classes (Park 1992). But adaptive agent models have been the main point of entry of complex systems theory into anthropology, beginning with Gumerman's pioneering collaboration with physicist Murray Gell-Mann (Gumerman & Gell-Mann 1994). Gumerman became interested in Axtell and Epstein's Sugarscape, a simulation model developed to study how sociocultural phenomena like trade, warfare, and class structures can arise from simple interactions of adaptive agents. Epstein & Axtell wrote a book about their Sugarscape simulations that provides an excellent overview of research on artificial societies (Epstein & Axtell 1996; for my own critique of this field see Lansing 2002). In Sugarscape, the environment is very simple, consisting of the agents themselves plus some idealized resources, like sugar and spice. Gumerman and his collaborators wondered if more realistic environments could be simulated, with heterogeneous agents and landscapes defined by real archaeological data, observing that "while potentially powerful, agent-based models in archaeology remain unverified until they are evaluated against real-world cases. The degree of fit between a model and real-world situation allows the model's validity to be assessed" (Dean et al. 2000, p. 180). They further observe that the explanatory power of mathematical models may be greatest when they fail because such failures may expose where the researcher's underlying conceptual model or explanation is flawed.

Gumerman & Dean (Dean et al. 2000) worked with Epstein and Axtell to apply the techniques developed for Sugarscape to create an agent-based model of the Anasazi society of Long House Valley in northeastern Arizona from 1800 B.C. to A.D. 1300. Here, the simple lattice environment of Sugarscape is replaced by paleoenvironmental data on a 96-km^2 physical landscape. The environment of "Artificial Anasazi" is populated with human households so that spatiotemporal patterns of settlement formation and household production can be simulated and compared with the archaeological record. A similar approach was developed by Kohler (Kohler & Gumerman 2000) to model human settlements in Mesa Verde circa A.D. 900–1300. Such models enable their creators to test their intuitions about the complex nonlinear processes involved in human-environmental interactions. As Kohler observes, "agent-based approaches admit an important role for history and contingency (and) can also, in principle, accommodate models that invoke heterogeneity among agents, or which drive social change through shifting coalitions of agents, argued by many (e.g., Brumfiel 1992) to be a critical social dynamic" (Kohler & Gumerman 2000, p. 14).

One of the strengths of this type of simulation modeling is that it enables researchers to subject trial explanations for sociocultural phenomena to a rigorous test. Of course this has always been the main justification for mathematical models; what is new about the adaptive agent approach is their ability to capture nonlinear effects that would otherwise be out of reach. But in my view, a more important development is the revelation, foreshadowed by theoretical work on complex adaptive systems, that social institutions can emerge from the bottom up as a result of feedback processes linking social actors to their environments (as Kohler & Gumerman observe in their recent volume). Such institutions might look very different from those that social scientists normally study; they might even be invisible.

Recently my colleagues and I have suggested that the water temple networks with which Balinese farmers manage their centuries-old irrigation systems and rice terraces are a real-world example of a complex adaptive system, whose dynamics resemble those of Lovelock's Daisyworld (Lovelock 1992, Lansing et al. 1998, Lenton & Lovelock 2000). For decades, both social scientists and engineers have marveled at the success of the Balinese in managing complex irrigation systems involving hundreds of villages. But the question of how this was achieved remained mysterious. We developed a simple game-theory formulation of the choices that Balinese farmers face when they make decisions about cooperation in water management, and we verified that this game captured the farmer's views in questionnaires administered to farmers from 15 different irrigation societies. A simulation model of 200 communities was constructed to explore the effects on rice terrace ecology at the watershed scale. We found that even though local communities "do not consciously attempt to create an optimal pattern of staggered cropping schedules for entire watersheds . . . the actual patterns [we] have observed in the field bear a very close resemblance to computer simulations of optimal solutions" (Lansing 2000, p. 313). In subsequent experiments, we pursued the kinds of questions Kauffman posed in *The Origins of Order*, such as the relationship between the structure of connections between farming communities (subaks) and the ability of the entire collection of subaks to self-organize (Lansing et al. 1998).

In the Balinese case, global control of terrace ecology emerges as local actors strike a balance between two opposing constraints: water stress from inadequate irrigation flow and damage from rice pests such as rats and insects. In our computer model, the solution involves finding the right scale of reproductive synchrony, a solution that emerges from innumerable local interactions. This system was deliberately disrupted by agricultural planners during the Green Revolution in the 1970s. For planners unfamiliar with the notion of self-organizing systems, the relationship between watershed-scale synchrony, pest control, and irrigation management was obscure. Our simulation models helped to clarify the functional role of water temples, and, partly as a consequence, the Asian Development Bank dropped its opposition to the bottom-up control methods of the subaks, noting that "the cost of the lack of appreciation of the merits of the traditional regime has been high" (Lansing 1991, pp. 124–25).

An intriguing parallel to the Balinese example has recently been proposed by ecologist Lisa Curran (1999). Forty years ago Borneo was covered with the world's oldest and most diverse tropical forests. Curran observes that during the El Niño Southern Oscillation (ENSO), the dominant canopy timber trees (*Dipterocarpaceae*) of the lowland forests synchronize seed production and seedling recruitment. As in the Balinese case, reproductive success involves countless local-level trade-offs, in this case between competition among seedlings versus predator satiation. The outcome of these trade-offs is global-scale synchronized reproductive cycles. But forest management policies have failed to take into account this vast self-organizing system (Curran et al. 1999). As Curran explains, "With increasing forest conversion and fragmentation, ENSO, the great forest regenerator, has become a destructive regional phenomenon, triggering droughts and wildfires with increasing frequency and intensity, disrupting dipterocarp fruiting, wildlife and rural livelihoods" (p. 2188). As a consequence, the lowland tropical forests of Borneo are threatened with imminent ecological collapse (L.M. Curran, personal communication).

These examples serve to highlight two points emphasized by Holland. The first point is that recognizing complex adaptive systems involves a shift in perception; thus the most fruitful strategy may be "to make cross-disciplinary comparisons in hopes of extracting common characteristics." Holland's second point is to echo the warning sounded by many ecologists: "We, as humans, have become so numerous that we perforce extensively modify ecological interactions, with only vague ideas of longer-range effects" (Holland 1995, pp. 4, 6). Ecologists are beginning to try to quantify these effects; for example, Field recently calculated the fraction of the earth's total biological productivity that is appropriated by *Homo sapiens* at nearly 40% and rising fast (Field 2001). Understanding this phenomenon is an intrinsically interdisciplinary problem, as Holland emphasizes; yet so far it has received far less attention from anthropologists than ecologists (Levin 1999, Solé & Manrubia 1995, Holling 2001, Lenton & Lovelock 2000).

CRITIQUES, REVIEWS, AND RESOURCES

There have been several recent critiques of the field of artificial societies. Thus Smith wrote in the *New York Review of Books* that he has "a general feeling of unease when contemplating complex systems dynamics. Its devotees are practising fact-free science. A fact for them is, at best, the outcome of a computer simulation; it is rarely a fact about the world" (Smith 1995, p. 30). Science writer John Horgan cautions that "as the philosopher Karl Popper pointed out, prediction is our best means of distinguishing science from pseudo-science . . . . The history of 20th-century science should also give complexologists pause. Complexity is simply the latest in a long line of highly mathematical 'theories of almost everything' that have gripped the imaginations of scientists in this century" (Horgan 1995, p. 104). (Here, Horgan appears to be mostly concerned with the very general theories of emergence developed by Stuart Kauffman and Per Bak, among others.)

A broader critique was recently published by an anthropologist, Stefan Helmreich, who offers an ethnographic account of the researchers working at the Santa Fe Institute in the mid-1990s. In *Silicon Second Nature* (1998), Helmreich argues that artificial-societies models reflect the unconscious cultural assumptions and social prejudices of their creators: "Because Artificial Life scientists tend to see themselves as masculine gods of their cyberspace creations, as digital Darwins exploring frontiers filled with primitive creatures, their programs reflect prevalent representations of gender, kinship, and race and repeat origin stories most familiar from mythical and religious narratives" (p. 95). For example, Helmreich describes Holland's genetic algorithms as reflecting a "heterosexual" bias: "There are a number of ways we might understand the exchange of bits between strings, but the metaphor of productive heterosex is gleefully emphasized by most authors" (p. 146). Thus for Helmreich, simulation models are like Rorschach tests, revealing the researcher's cultural background and psychological idiosyncrasies. All statements, especially theoretical pronouncements, are taken not as statements about the world but as evidence about the author's beliefs and mode of thought. "That many Artificial Life practitioners are white men who grew up reading cowboy science fiction," observes Helmreich, "is not trivial" (p. 95). Simulation models may also be dangerous (as Helmreich suggests with reference to my own work), urging that "the use and abuse of computer simulations bears watching—especially in situations where there is a notable power differential between those putting together the simulation and those whose lives are the subjects and objects of these simulations" (Helmreich 1999; for my response, see Lansing 2000 and Lansing et al. 2001).

Readers interested in an overview of the field cannot do better than Kohler & Gumerman's (2000) volume, which contains review essays by archaeologists Kohler and Henry Wright, as well as "Modeling Sociality: the View from Europe" by sociologist Nigel Gilbert (2000). There are a large number of popular accounts of research on chaos and complexity; my favorites are Gleick's (1987) *Chaos* and Waldrop's (1992) *Complexity* (though both are rather out of date). More substantial overviews include Langton 1994, Flake 1998, Hofbauer & Sigmund 1988, Depew & Weber 1995, Lansing 2002, and Kauffman 1993. A useful weekly digest of publications pertaining to complexity is available at http://www.comdig.org, and the working papers of the Santa Fe Institute are available for the asking at http://www.santafe.edu. Simulation of cellular automata, random Boolean networks, and Derrida plots can be accomplished using free software created by Andrew Wuensch and is available at http://www.santafe.edu/~wuensch/ddlab.html. Anthropologists may also be interested in mathematical models of "small-world" networks (Watts 1999, Watts & Strogatz 1998), which investigate the topological properties of social and ecological networks.

CONCLUSION

This chapter is already too long, so I will conclude with a single observation. So far, only a handful of anthropologists have taken an interest in complex systems. Yet much contemporary research on complex adaptive systems is concerned with questions that have traditionally formed the subject matter of anthropology. As the distinguished mathematical biologist Simon Levin observed in a review of current research, "there is fundamental interest in the evolution of social norms, or of language, and how such group properties emerge from and feed back to influence individual behavior . . . . [T]he potential payoffs are enormous and the mathematical challenges irresistably seductive" (2003, p. 10). There seems little doubt that such questions will be pursued, if not by anthropologists then by our colleagues.

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