

# Complex Adaptive Systems and Complexity Theory: Inter-related Knowledge Domains

by

Rebecca Dodder and Robert Dare

ESD.83: Research Seminar in Engineering Systems  
Massachusetts Institute of Technology

October 31, 2000

## **Introduction**

This paper provides a description of two highly interrelated knowledge domains: Complex Adaptive Systems (CAS) and Complexity Theory. The initial sections provide an overview, descriptive characteristics, background and social/institutional outlines for the Complex Adaptive Systems knowledge domain. The next four sections provide descriptive material on applications of CAS thinking in the disciplines of physics, biology, economics and political science. While CAS has implications for many other disciplines, these sections illustrate how CAS thinking has found its way into ongoing theory development in a representative set of fields. The next sections of this paper describe the highly related knowledge domain of Complexity Theory, providing material on identifying and measuring complexity, and the relationship of complexity to engineering systems. The last section provides some closing thoughts on the outlook for these two closely related knowledge domains.

## **Overview of Approach to Complex Adaptive Systems**

The rise of “complex adaptive systems” (CAS) as a school of thought took hold in the mid-1980’s with the formation of the Santa Fe Institute, a New Mexico think tank formed in part by former members of the nearby Los Alamos National Laboratory. Participants at the Institute have come from such diverse disciplines as economics, physics, biology, ecology and archaeology. The Institute formed to draw from and further develop thinking over the previous twenty years in a variety of disparate fields on the issue of complexity. More information about the formation of the Santa Fe Institute is included in the background section below.

One important emphasis with CAS is on crossing of traditional disciplinary boundaries. CAS provides an alternative to the linear, reductionist thinking that has ruled scientific thought since the time of Newton. The new discipline has been distinguished by extensive use of computer simulation as a research tool.

In his book, “Complexity: the Emerging Science at the Edge of Order and Chaos”, author M. Mitchell Waldrop describes the objectives associated with the development and use of CAS concepts. Santa Fe members sought to pursue a common theoretical framework for complexity and a means of understanding the spontaneous, self-organizing dynamics of the world.

Examples of CAS are widespread in both the natural and human world. In the natural world, brains, immune systems, ecologies, cells, developing embryos, and ant colonies all fall under the category of CAS. In the human world, political parties, scientific communities and the economy are examples.

## Characteristics

CAS have several common characteristics that recur in a number of natural and human contexts. The most commonly repeated characteristics noted in the literature are as follows:

- CAS are balanced between order and anarchy, at the edge of chaos. As Waldrop (1992) describes, "...frozen systems can always do better by loosening up a bit, and turbulent systems can always do better by getting themselves a little more organized. So if a system isn't on the edge of chaos already, you'd expect learning and evolution to push it in that direction...to make the edge of chaos stable, the natural place for complex, adaptive systems to be."
- CAS are composed of a network of many agents gathering information, learning and acting in parallel in an environment produced by the interactions of these agents.
- The system co-evolves with its environment.
- Order is emergent, instead of pre-determined, always unfolding and always in transition (perpetual novelty).
- CAS tend to exist in many levels of organization in the sense that agents at one level are the building blocks for agents at the next level. An example is cells, which make up organisms, which in turn make up an ecosystem.
- Finally, CAS, by their nature, have a future that is hard to predict.

These characteristics are illustrated in the examples of CAS application to different disciplines included below.

## Background of CAS

Thinking about CAS has its roots in many different disciplines. Waldrop (1992) indicates that efforts at the Santa Fe Institute to conceptualize a "common theoretical framework for complexity" were built upon past work in the fields of neural networks, ecology, economics, artificial intelligence, chaos theory and cybernetics.

Long before the Santa Fe Institute got underway, Belgian Nobel laureate Ilya Prigogine was exploring questions about the sources of order and structure in the world. Waldrop (1992) indicates that Prigogine had been studying self-organizing structures in nature since the 1960's. He observed that atoms and molecules are exposed to energy and material flowing in from the outside, partially reversing the decay required by the second law of thermodynamics. As a result, systems are able to spontaneously organize themselves into a series of complex structures. This work resonated with many of the Santa Fe founders and represented some of the early thinking on self-organization of systems.

Many of the key figures in CAS have a strong affiliation with the Santa Fe Institute. These include institute founder and first president, George Cowan who had previously

worked on the Manhattan project and headed research at Los Alamos. Cowan was described by Waldrop (1992) as "...a fervent and determined man...to Cowan, the Santa Fe Institute was a mission...a chance for science as a whole to achieve a kind of redemption and rebirth."

Murray Gell-Mann, winner of the Nobel Prize in physics for his work on sub-atomic particles, was a fervent supporter of the formation of the institute, and has retained a strong affiliation over the years. Stuart Kauffman was a leading figure in biology, who wrote about the relevance of adaptation in addition to Darwinian selection in the evolution of species. Major works written about complexity theory by Gell-Mann ("The Quark and the Jaguar") and Kauffman ("At Home in the Universe") are described below.

John Holland's involvement at Santa Fe stems back to early workshops at the institute where he shared his thinking on key ideas on adaptation that he had been pursuing in relative obscurity for a quarter of a century. Holland's book entitled "Hidden Order" is another major work in the field.

Kenneth Arrow, a Nobel laureate in economics, was another key participant in the early days of the institute.

Soon after the Santa Fe Institute was established in 1984, the members held a series of workshops, which brought together inter-disciplinary figures at the leading edge of their respective fields. This activity jump-started many interdisciplinary connections that are still developing today. Since its formation, the Institute has taken the form of a small permanent staff and a large number of visiting fellows.

While CAS concepts have not yet achieved mainstream acceptance in the scientific community, the Santa Fe Institute remains a powerful force in developing and promoting this body of thinking.

## **Social and Institutional Outlines**

CAS is a multi-disciplinary field with participants from physics, biology, economics, archaeology, computer science and many other fields. No one field seems to dominate the thinking.

In addition to the Santa Fe Institute, which is described above, the New England Complex Systems Institute (NECSI) is another organization with a strong intellectual commitment to the study of complexity and CAS. According to its website, NECSI is "an independent educational and research institution dedicated to advancing the study of complex systems." NECSI joins faculty of New England academic institutions in an effort to collaborate "outside of institutional and departmental boundaries." Sponsors of NECSI include the National Science Foundation, Boeing, Microsoft Research, LeBaron Foundation, Group Health Cooperative, Pan Agora Asset Management, and the World Bank.

Many universities have programs or workshops associated with CAS. Chalmer's University of Technology in Sweden offers a masters degree in Complex Adaptive Systems. Iowa State University has sponsored a CAS workshop. The University of Florida, Arizona State University, and other schools have content on their websites that directly relates to CAS studies.

There are four primary journals in the field. Complexity is a multi-disciplinary journal published by John Wiley and Sons. Journal of Complexity has a strong mathematics orientation and is put out by Academic Press. Interjournal is a web-based publication sponsored by NECSI. Complexity International is put out by Charles Sturt University. Web sites for these journals are listed in the references section.

## **Applications in Physics**

One of the most famous writers on CAS is physicist Murray Gell-Mann, whose book entitled "The Quark and the Jaguar" explores the relationship between the simple and the complex. The simple refers to "underlying physical laws of matter and the universe." Gell-Mann asserts that the fundamental laws are quantum-mechanical. Therefore, since quantum mechanics "supplies only probabilities for alternative coarse-grained histories", chance must play a role in the unfolding of the universe. Gell-Mann's work on subatomic particles won him the Nobel Prize in physics.

The complex includes "the rich fabric of the world that we perceive directly and of which we are a part." He sites a range of Earthly complex systems "from the prebiotic chemical reactions that first produced living things, through biological evolution and the cultural evolution of humanity, all the way to computers equipped with appropriate hardware or software and to possible future developments treated in science fiction, such as composite human beings formed by wiring people's brains together."

Gell-Mann describes the role of chance as having a fundamental role in the description of nature. In his view, "each alternative history of the universe depends on the results of an inconceivably large number of accidents." Self-organization occurs through a combination of such "frozen accidents" and the fundamental laws.

Gell-Mann describes the behavior of CAS, saying that they take in "coarse grained" information about the universe, find "perceived regularities" and ignore the remaining information as being random. The regularities lead to formation of schema, which provide a description of the world and allow the CAS to prescribe behavior for themselves. This sequence leads to the emergent behavior observed from complex adaptive systems.

## Applications in Biology

Stuart Kauffman, another influential thinker associated with the Santa Fe Institute, wrote a book entitled “At Home in the Universe” to explain his perspectives on complexity in the field of biology. Kauffman finds that a combination of natural selection and self-organization leads to matter organizing itself into complex structures in spite of the forces of entropy. From a philosophical standpoint, this distinction elevates human existence from “unaccountably improbable accidents” as would be implied by the random mutations of natural selection. Instead, Kauffman argues, “...selection has always acted on systems that exhibit spontaneous order. If I am right, this underlying order, further honed by selection, augurs a new place for us – expected, rather than vastly improbable, at home in the universe in a newly understood way.”

Kauffman discusses the second law of thermodynamics, which has as a consequence the disappearance of order from equilibrium systems. This law leads to “our current sense that an incoherent collapse of order is the natural state of things.” Yet Kauffman goes on to cite the abundant evidence of order in our world, from microscopic cells, to the plenitude of species unleashed in the Cambrian era, to “our postmodern technological era, in which the exploding rate of innovation brings the time horizon of future shock ever closer.”

One of Kauffman’s central questions is whether there are any general laws that govern this range of complex activity. Even if one postulates the existence of some absolute law or laws, Kauffman describes two barriers to achieving predictive powers. The first is quantum mechanics and its indeterminism at the sub-atomic level, which translates to “macroscopic consequences” such as the mutation of DNA. The second problem, from chaos theory, concerns the “butterfly effect” in which “a legendary butterfly flapping its wings in Rio changes the weather in Chicago.” This analogy highlights the sensitivity of complex systems to miniscule changes in initial conditions. Taken together, these considerations preclude the possibility of predicting long-term behavior of such systems.

Given these constraints, Kauffman’s hope is “to characterize classes of properties of systems that...are typical or generic and do not depend on the details.” To illustrate the potential benefits, he notes that the periodic motion of a pendulum depends on its properties of length and mass. This example implies that it is possible to form theories of system behavior that are insensitive to a full set of descriptive details. The search for such system properties is becoming “a fundamental research strategy.”

Kauffman also explores the implications of self-organization of complex systems, which provide a sort of “order for free.” His hope is to determine an intersection between the phenomena of natural selection and self-organization that may yield universal laws.

## **Applications in Economics**

Economists have played an important role in bringing together many of the ideas that would come to be defined as Complexity. In 1987, at one of the early multidisciplinary conferences of the Santa Fe Institute, ten theoretical economists and ten physicists, biologists, and computer scientists took on the theme, “The Economy as an Evolving Complex System.” The conference was designed to stimulate the cross-fertilization of ideas and analytical methods in order to deal with what economist Brian Arthur identified as the six “difficult” features of real-life economic systems:

1. Dispersed interactions
2. No global controller
3. Cross-cutting hierarchical organization
4. Continual adaptation
5. Perpetual novelty
6. Out-of-equilibrium dynamics

What emerged from that conference was the “complexity perspective” on economics and economic modeling. The early research that developed from this new perspective explored concepts such as positive feedback, lock-in and the impact of historical “accident” when path dependence is an importance factor in the subsequent development of economic systems. The economists who were exploring complexity also began to recognize that there is a difference between the individual economic agents and the aggregate economic system that emerges from their interactions. Furthermore, the interactions of these heterogeneous agents lead them to self-organize into network-based structures that may never settle into equilibrium.

Thus, the Santa Fe approach represented a profound break with many of the assumptions of the standard neoclassical paradigm by moving away from an equilibrium-based view of the economy, which tended to assume away the six features identified above. The new paradigm that took its place was that of the economy as an adaptive nonlinear network, which necessitated the development of new economic tools for theoretical and empirical modeling. The multidisciplinary interaction fostered the application of tools from other sciences – nonlinear dynamics, statistical mechanics, and neural nets – to economic theory. These tools have appeared in applications to problems in financial systems, economic geography, theories of innovation, and international trading networks.

## **Applications in Political Science**

A similar conceptual and analytical shift has occurred in other social sciences, particularly political science, influenced in part by the changing paradigm of economic systems. As in economics, the ideas of complexity represent a break from the traditional paradigm of rational actors, by focusing on the evolution of behavior and strategies that are often based on limited local information, and may not allow for foresight and optimization of strategies.

Much of complexity-related work in the political and social sciences has employed the tools of agent-based models and modeling of “artificial societies” to probe underlying behaviors and motivations and derive results as to their emergent properties. The political scientist, Robert Axelrod, one of the earlier proponents of applying computer simulation to the investigation of social science problems, applied agent-based models to game theory to model the complex and unanticipated behavior that can emerge from simple iterated games such as the Prisoner’s Dilemma. *The Complexity of Cooperation* (Axelrod, 1997) provides an overview of the types of problems that can be analyzed from a perspective of cooperation and competition in an agent-based model – social norms, political alignment, standards, and the dissemination of culture.

Joshua Epstein and Robert Axtell (1996) take an even more holistic view of complex systems as being open and highly interconnected.

The broad aim of this research is *to begin the development of a more unified social science, one that embeds evolutionary processes in a computational environment....*Artificial society-type models may change the way we think about *explanation* in the social sciences.

In *Growing Artificial Societies*, Epstein and Axtell explore what they refer to as bottom-up or generative social science. In this view, simulation techniques can provide a type of “social science laboratory” that allows social scientists to move beyond the problems that arise from models based on assumptions of homogeneity and aggregation. Through their “Sugarscape” model, they explore many of the basic emergent phenomena in human societies such as trade, reproduction, conflict, and disease.

## Identifying Complexity

As seen from the above examples of applications, the focus of the Santa Fe approach has been upon Complex Adaptive Systems, in which complex and patterned output arises from simple, fundamental principles, but requires many actors and multiple interactions over time to produce the emergent complexity. Yet, this characterization represents only a sample of the myriad of different facets of complexity<sup>1</sup>. None of the definitions or approaches that appear in the complexity literature seems to be mutually exclusive, but this could lead to some degree of ambiguity and an inclination to identify systems as “complex” in a somewhat haphazard manner. Notwithstanding the wide variety of factors that make a system complex, the characterizations of a system’s “complexity” tend to group roughly into the following categories<sup>2</sup>:

---

<sup>1</sup> For an early survey identifying different types of complexity in the systems sciences, John Casti (1979) provides an interesting and extensive overview of the “three C’s” in systems theory – complexity, connectivity and catastrophe. Casti draws examples from Systems Analysis, General Systems Theory, Cybernetics, Information Theory, Dynamic System Theory, and Computer Science, and provides excellent references to these as well as other systems sciences.

<sup>2</sup> Please note that the categories are the interpretation of the author.

- *Static complexity* refers to the structural aspects of a system's complexity. This includes notions of hierarchy, connectivity, detail, intricacy, variety, and levels/strength of interactions; most easily visualized as a network with complex patterns of links and nodes. Static complexity is to a certain extent context dependent, since the structural complexity would appear much differently on the micro versus macro-level scale, and would change as one redefines the scope and boundaries of the system.
- *Dynamic complexity* encompasses the ideas of complexity related to behavior, processes of cause and effect, feedback, fluctuations and stability, cycles and time scales. The focus on Complex Adaptive Systems is closely identified with this notion of changes in behavior over time, which relates to an important aspect of dynamic complexity: *evolving complexity*. Yet, this evolutionary aspect to the dynamic complexity can result from both the adaptation of the systems, as well as adaptation of the individual agents in the system. In fact, the complexity of a system may evolve without any adaptation by the individual agents.
- *Informational complexity* represents a somewhat more abstract notion (linked to the measurement of complexity), which can be thought of as the complexity involved in describing or evaluating a complex system. It can reflect both the *static complexity*, e.g. the intricacy of a network, as well as the *dynamic complexity*, e.g. the complexity of the processes involved in the creation of a system. From the engineering perspective, one also considers the *evaluative complexity*, which could be a form of information complexity needed to describe and evaluate the function, performance and "success" of a system.

## Measuring Complexity

Beyond the identification of complexity in a system, is the more difficult question of measuring complexity. The fundamental question – *how complex is a system?* – raised by scientists and engineers in all of the systems sciences, is brought explicitly to the forefront by complexity. The issue of measurement is a critical component to advancing the understanding of and ability to work with complex systems. First, it creates a common yardstick to draw more accurate comparisons between the complexity of a wide variety of systems ranging from the human immune system to the international financial system to a transportation network. Second, it creates the possibility for evaluating, predicting, modifying, controlling, or even designing a complex system. Finally, establishing a measure of complexity would enable one to follow the evolution of complexity in a system over time, in order to follow its path of increasing or decreasing complexity.

In developing methods to measure complexity, there have been contributions from a diverse set of fields including Thermodynamics, Information Theory, Statistical Mechanics, Control Theory, Applied Mathematics, and Operations Research. The approaches to the measurement of complexity have tended to couple two complementary aspects: *knowledge* and *ignorance* of the system. With respect to the latter, the degree of

entropy or *ignorance* provides one measure of complexity by determining the disorder of the system, which in turns establishes a measure of our ignorance about a system. With respect to the *knowledge* of a systems, “one apparently crucial element in any reasonable measure of complexity is the information processed or exchanged by the system under study” (Lloyd, 1990). Shannon’s information theory uses this quantity of information as an indicator of complexity. Another widely explored measure is the Algorithmic Information Content (AIC), which relates complexity to the minimum amount of information needed to describe the system, as measured by the shortest computer program that can generate that system.

The idea of measuring complexity with a combination of measures of *knowledge* and *ignorance* is intuitively appealing, since it reflects the concept of a complex system as residing somewhere in the realm between a deterministic and rule-bound state of *order* and a random and anarchic state of *chaos*. However, measuring either one or the other illuminates some of the subtleties in complexity. For example, while the AIC approximates the magnitude of complexity as the amount of information, it cannot differentiate complexity and *intricacy* from pure randomness. Because there is a high degree of AIC in creating a purely random state, this randomness is misjudged as complexity. However, a random system should actually be considered “simple” since random states are easy to assemble. Simple systems are also those which are completely deterministic or easily specified.

An ideal measure of complexity combines how much information is required to describe a system’s regularities, as well as the magnitude of the irregularities – i.e. what is the combination of deterministic and chaotic behavior that gives rise to the complexity of the system? As noted earlier, scientists in a diverse set of fields continue to work toward establishing this measure of complexity.

## **Complexity and Engineering Systems**

Turning away from the more abstract concepts of measuring complexity in a system, we now examine the prospects for application of Complexity to problems in engineering systems. First, it should be noted that due to an infinite number of possible initial conditions and “accidental” perturbations along the way that can generate non-linear and often nearly chaotic effects, accurate prediction and control of the outcome and performance of complex systems would be a daunting task. Notwithstanding, it may be possible that the real value of modeling complex systems comes less from any predictive properties and more from the ability to provide insights regarding the dynamic and structural characteristics of systems. The tools and models of the complexity sciences also allow observations of the system not only at the end point, but also at points where the systems undergoes transitions. Therefore, complexity may provide insights as to points of control at critical stages in the process of emergence. These would be the “lever points” in a system, for interventions related both to policy and engineering.

Dynamic computer-based models represent the critical factor in the application of complexity theory to engineering systems. In this sense, these models can be described

as a “flight simulator” for the investigation of these complex systems, as it allows for “real time” feedback revealing the changing state of the systems as one provides inputs or sets controls on the system at different stages. Yet, the extent to which this approach to engineering would be widely accepted remains to be seen, and depends upon the future development, refinement and testing of these computer-based models, as viable tools to investigate specific engineering systems.

Much of the work in Complexity has developed around the natural and social sciences, as a method for understanding complex systems in the physical and human realm. Notwithstanding, the transition to Complexity in engineering will be an important although difficult step, as the science moves from understanding a system, to interfering in that system. As stated by MIT Professor Seth Lloyd, who organized the Complexity in Engineering Conference in November 1999:

“Cars, computers, and even toasters are more complex than they were ten years ago. But greater complexity brings both benefits and new problems...The purpose of the conference is to determine the implications this ‘complexification’ has for society, and to develop techniques and strategies for engineering complex but reliable systems” (MIT News, November 8, 1999).

## **Outlook for Complexity**

It would be impossible to catalogue the astounding diversity of the types of questions and range of systems being explored by scientists engaged in Complexity. However, these research activities tend to fall under certain categories:

- *Recognizing Patterns of Complexity* - To what extent can we draw comparisons across systems? How do we improve our analytical methods for recognizing and describing the patterns in these systems, in terms of both their structure and dynamic behavior? Why do some networks or systems persist, despite the continual changeover in the components of the systems? To what extent can we separate a common set of “systems” features or properties that are not context dependent?
- *Measuring Complexity* - As described more fully above, how do we compare the complexity of a rain forest ecosystem with that of a human culture? Furthermore, can we develop a measure of complexity that is not sensitive to the context?
- *Modeling Complexity* - The issue of modeling encompasses two important endeavors. First, how can computer-based modeling be developed further? What are the limitations of these tools? Second, in studying complexity and phenomena such as emergence, how does one create a “model” without resorting to either extreme of reduction (dissecting and studying the parts in isolation) or abstraction (describing the emergent patterns and macro-structures without much of the detail). A model cannot

contain *all* of the details and complexity of the real life system, but how can one ensure that the model has captured the critical aspects?

Complexity Theory has fostered a unique dialogue across a broad range of disciplinary boundaries, especially between the natural and the social sciences, resulting in an exchange of concepts and methodologies. Indeed, it seems to be this sense of an underlying commonality in the patterns and emergent behavior in complex adaptive systems that enables this bridging of disciplines. Consequently, as complexity theory develops, it has also provoked thought as to the existence of “universal laws of complexity”. Yet, the diversity and constantly evolving nature of complex systems seems to place a limit to the amount of generalizable “laws” that can be derived through complexity. As summarized by Goldenfeld and Kadanoff (1999):

“Up to now, physicists looked for fundamental laws true for all times and all places. But each complex system is different; apparently there are no general laws of complexity. Instead, one must reach for “lessons” that might, with insight and understanding, be learned in one system and applied to another.”

Complexity may not lead to a unification of the sciences, but it has established a forum for interaction, as well as a language, terminology and set of methods for describing and analyzing complex systems. In addition to the journals dedicated specifically to the study of Complexity and Complex Adaptive Systems, articles have increasingly appeared in a substantial number of the traditional disciplinary journals such as the American Economic Review, American Political Science Review, and Physical Review. This provides some indication that the ideas have increasingly gained acceptance in disciplinary circles, although there continues to be some skepticism as to how far complexity science can progress in providing answers to the burgeoning set of questions and issues it has generated.

In summary, Complexity Theory and Complex Adaptive Systems has begun to develop an understanding of physical and social systems that is an alternative to a more linear and reductionist mode of thinking. Much (if not most) of this advancement has been due to the extensive use of computer-based modeling, such as agent-based simulations, which has expanded the set of tools used to explore complex system behavior. Although the models of complexity can allow scientists and engineers to portray the behavior and understand the structure of a system, there may be limitations as to the actual predictive power of these models. Consequently, this may create resistance to the use of models in a more applied setting.

Although Complexity Theory is still an “emerging” systems science, the concepts and tools continue to develop rapidly. Those individuals involved in the development of the science of complexity are optimistic as to its ability to provide new insights into the fundamental questions facing science and humanity. As stated by John Holland (1998),

“whatever answers we come upon will profoundly affect our view of ourselves and our world.”

## References

### Journals

Complexity, J. Wiley and Sons. (<http://journals.wiley.com/complexity>)

Journal of Complexity, Academic press. (<http://www.idealibrary.com/links/toc/jcom>)

InterJournal, New England Complex Systems Institute. (<http://www.interjournal.org>)

Complexity International, Charles Sturt University. (<http://www.csu.edu.au/ci>)

### Books

Arthur, W.B., Durlauf, S.N. and D.A. Lane, eds. (1997). *The Economy as an Evolving Complex System II*, Proceedings Volume XXVII, Santa Fe Studies in the Sciences of Complexity. Reading, MA: Addison-Wesley.

Axelrod, R. (1997). *The Complexity of Cooperation*. Princeton, NJ: Princeton University Press.

Casti, J. (1979). *Connectivity, Complexity, and Catastrophe in Large-Scale Systems*. New York, NY: Wiley.

Epstein, J.M. and R. Axtell (1996). *Growing Artificial Societies: Social Science from the Bottom Up*. Cambridge, MA: MIT Press.

Gell-Mann, Murray (1994). *The Quark and the Jaguar: Adventures in the Simple and the Complex*. New York: W. H. Freeman and Company.

Holland, J.H. *Emergence: From Chaos to Order*. Reading, MA: Perseus Books.

Holland, John (1995). *Hidden Order: How Adaptation Builds Complexity*. Reading, MA: Addison-Wesley Publishing Company.

Kauffman, Stuart (1995). *At Home in the Universe*. New York: Oxford University Press.

Prigogine, I. (1984). *Order Out of Chaos*. New York, NY: Bantam Books.

Waldrop, M. Mitchell (1992). *Complexity: the Emerging Science at the Edge of Order and Chaos*. New York: Touchstone.

## Articles

Gell-Mann, Murray and Lloyd, Seth. "Information Measures, Effective Complexity, and Total Information." Complexity, September/October 1996.

Lloyd, Seth. "The Calculus of Intricacy: Can the Complexity of a Forest be Compared with that of Finnegans Wake?" The Sciences, Sept/Oct 1990.

Lloyd, S. (1990). "Valuable Information" In W.H. Zurek, (ed.) *Complexity, Entropy and the Physics of Information: SFI Studies in the Science of Complexity, Volume VIII*. Addison-Wesley.

## Working Paper

Sussman, J. (2000) "Ideas on Complexity in Systems – Twenty Views" Engineering Systems Division Working Paper.

## Websites

- <http://www.brint.com/systems.htm> - collection of articles and links
- [www.necsi.org](http://www.necsi.org) - New England Complex Systems Institute home page
- <http://www3.interscience.wiley.com> - complexity (journal)
- <http://www.idealibrary.com/links/toc/jcom> - journal of complexity
- <http://www.calresco.org> - collection of papers and links on complexity