

```
for (im = 0; im < numags; im++)
  for (ii=0;ii<6;ii++) {
rag.per[im].startnode[ii] = (int)mxnod*arnd0;
  starting node for the game
  cag.per[im].startnode[ii] = (int)mxnod*arnd0;
}
rag.per[im].strat[jm].act = (int)2*arnd0;
cag.p[im].strat[jm].act = (int)2*arnd0;
for (jm=0;jm < mxnod; jm++)
rag.per[im].strat[jm].tost[jk] = (int)mxnod*arnd0;
transitions given that node
cag.per[im].strat[jm].tost[jk] = (int)mxnod*arnd0;
}
// plays game gm
void playgame(ir,jr,gm)
int ir;
int jr;
int gm;
int ip,play1,play2,trans,som1,som2; // som1 = rag.per[ir].startnode[gm];
action, trans = new state;
som1 = rag.per[ir].startnode[gm];
som2 = cag.per[jr].startnode[gm];
for (ip =0; ip < rounds; ip++)
play1 = rag.per[ir].strat[som1].act; //agent's
first state
play2 = cag.per[jr].strat[som2].act;
trans = 2*play1 + play2;
rag.per[ir].tost[trans] = rag.per[ir].startnode[gm];
rag.per[ir].tost[trans] = rag.per[ir].startnode[gm];
som1 = rag.per[ir].strat[som1].tost[trans];
som2 = cag.per[jr].strat[som2].tost[trans];
}
```

COMPLEX ADAPTIVE SYSTEMS

AN INTRODUCTION TO

COMPUTATIONAL MODELS

OF SOCIAL LIFE

John H. Miller and Scott E. Page

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Published by Princeton University Press, 41 William Street,
Princeton, New Jersey 08540

In the United Kingdom: Princeton University Press, 3 Market Place,
Woodstock, Oxfordshire OX20 1SY

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Library of Congress Control Number: 2006933230

ISBN-13: 978-0-691-13096-5 (acid-free paper)

ISBN-10: 0-691-13096-5 (acid-free paper)

ISBN-13: 978-0-691-12702-6 (pbk.: acid-free paper)

ISBN-10: 0-691-12702-6 (pbk.: acid-free paper)

British Library Cataloging-in-Publication Data is available

This book has been composed in Sabon

Printed on acid-free paper. ∞

press.princeton.edu

Printed in the United States of America

1 3 5 7 9 10 8 6 4 2

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Preface

We have to look for routes of power our teachers never imagined, or were encouraged to avoid.

—*Thomas Pynchon, Gravity's Rainbow*

THE EMERGING TAPESTRY of complex systems research is being formed by localized individual efforts that are becoming subsumed as part of a greater pattern that holds a beauty and coherence that belies the lack of an omniscient designer. As in Navajo weaving, efforts on one area of this tapestry are beginning to meld into one another, leaving only faint “lazy lines” to mark the event. The ideas presented in this book contain various parts of this weaving; some are relatively complete, whereas others are creative investigations that may need to be removed from the warp and started anew. We suspect that, like the Navajo weavers of old, we will also introduce a few errors—though perhaps not intentionally—that will be more than sufficient to maintain our humility.

More than a decade ago, a wonderful coincidence of people, ideas, tools, and scientific entrepreneurship converged at the Santa Fe Institute. Those of us who participated in this event were blessed to partake in a burst of scientific creativity that facilitated a new wave in the sciences of complex systems. At that time, discussions about the central problems and approaches in fields such as biology, chemistry, computer science, economics, and physics made it clear that there was a common set of questions that would require a willingness to transcend the usual disciplinary boundaries if answers were to be forthcoming. Since that time, a growing community of scholars has been actively involved in developing the theory of complex adaptive social systems.

Although research in the area of complex adaptive social systems is still in its formative stages, now is a good time to take stock of these efforts. Along with documenting much of what we have learned over the past decade, we will also be a bit exploratory, both retrospectively trying to figure out why our initial intuitions about the importance of this area were justified and prospectively suggesting where the new frontiers are likely to be found.

During the past decade we have hosted an annual graduate workshop in computational modeling. In these workshops, we collaborated with a diverse set of graduate students who are interested in applying new computational modeling techniques to key problems in the social

sciences. Many of the topics presented throughout this book are the result of discussions during these workshops.

Contrary to the sentiments in Pynchon's quotation, we have been blessed with some very imaginative and prescient teachers. For Miller, Ken Boulding planted the initial meme that suggested that both biological and social systems hold a deep similarity needing scientific investigation. Ted Bergstrom and Hal Varian generously indulged and guided Miller's efforts during graduate school in investigating the behavior of artificial adaptive agents in games. Bob Axelrod, John Holland, and Carl Simon were also sources of encouragement, ideas, and wisdom at that time. During the early days of the Santa Fe Institute, an outstanding group of scholars gathered together to work on complex systems, including Phil Anderson, Ken Arrow, Brian Arthur, George Cowan, Jim Crutchfield, Doyne Farmer, Walter Fontana, Murray Gell-Mann, Erica Jen, Stu Kauffman, David Lane, Blake LeBaron, Norman Packard, Richard Palmer, John Rust, and Peter Stadler, all of whom have contributed in various ways to the ideas presented here. Miller's colleagues at Carnegie Mellon University, in particular Greg Adams, Wes Cohen, Robyn Dawes, George Loewenstein, John Patty, and especially Steven Klepper, have been a continual source of ideas and encouragement, as has been Herb Simon, whose contributions to complex systems and social science will continue to inspire and craft research efforts far into the future.

For Page, his graduate adviser Stan Reiter organized a group of students to investigate research on learning, adaptation, and communication, and these discussions eventually led him to the Santa Fe Institute to learn more about complex systems. At that time, a lively and ongoing collaboration that focused on computational political economy was started among the authors and Ken Kollman. While at the California Institute of Technology, Page benefited from many discussions about mathematics, theory, complexity, and experiments, with Mike Alvarez, John Ledyard, Richard McKelvey, Charlie Plott, and Simon Wilkie. Page's current colleagues in the Center for the Study of Complex Systems at the University of Michigan, including Bob Axelrod, Jenna Bednar, Dan Brown, Michael Cohen, Jerry Davis, John Holland, Mark Newman, Mercedes Pascual, Rick Riolo, Carl Simon, and Michael Wellman, as well as his collaborator Lu Hong, have also been extremely influential.

The authors wish to thank various students and seminar participants across the world who have been kind enough to give us additional insights into these ideas. In particular, Aaron Bramson, Scott deMarchi, and Jonathan Lafky provided some detailed input. Chuck Myers at Princeton University Press has also provided wonderful encouragement and direction, and Brian MacDonald thoughtfully copyedited the manuscript.

Some of the nicest examples of interesting complex social systems have emerged in our home institutions. We are grateful to the research infrastructure of the Santa Fe Institute, Carnegie Mellon University, and the University of Michigan. In particular, we would like to thank Susan Ballati, Ronda Butler-Villa, Bob Eisenstein, Ellen Goldberg, Ginny Greninger, George Gumerman, Ginger Richardson, Andi Sutherland, Della Ulibarri, Laura Ware, Geoffrey West, and Chris Wood at the Santa Fe Institute; Michele Colon, Carole Deaunovich, Amy Patterson, Rosa Stipanovic, and Julie Wade at Carnegie Mellon University; and Mita Gibson and Howard Oishi at the University of Michigan.

PART I

Introduction

Introduction

The goal of science is to make the wonderful and complex understandable and simple—but not less wonderful.

—Herb Simon, *Sciences of the Artificial*

The process of scientific discovery is, in effect, a continual flight from wonder.

—Albert Einstein, *Autobiographical Notes*

ADAPTIVE SOCIAL SYSTEMS are composed of interacting, thoughtful (but perhaps not brilliant) agents. It would be difficult to date the exact moment that such systems first arose on our planet—perhaps it was when early single-celled organisms began to compete with one another for resources or, more likely, much earlier when chemical interactions in the primordial soup began to self-replicate. Once these adaptive social systems emerged, the planet underwent a dramatic change where, as Charles Darwin noted, “from so simple a beginning endless forms most beautiful and most wonderful have been, and are being, evolved.” Indeed, we find ourselves at the beginning of a new millennium being not only continually surprised, delighted, and confounded by the unfolding of social systems with which we are well acquainted, but also in the enviable position of creating and crafting novel adaptive social systems such as those arising in computer networks.

What it takes to move from an adaptive system to a *complex* adaptive system is an open question and one that can engender endless debate. At the most basic level, the field of complex systems challenges the notion that by perfectly understanding the behavior of each component part of a system we will then understand the system as a whole. One *and* one may well make two, but to really understand two we must know both about the nature of “one” and the meaning of “and.”

The hope is that we can build a *science of complexity* (an obvious misnomer, given the quest for simplicity that drives the scientific enterprise, though alternative names are equally egregious). Rather than venturing further on the well-trodden but largely untracked morass that attempts to define complex systems, for the moment we will rely on Supreme Court Justice Stewart’s words in his concurring decision on a case dealing with obscenity (*Jacobellis v. Ohio*, 1964): “I shall not today attempt further

The science of complex systems is a rapidly evolving area, in terms of both domains and methods. The interest in this area, as well as its rapid subsequent diffusion, has been rather remarkable (especially in a field like economics, where, as Paul Samuelson (1999, xi) once remarked, “science advances funeral by funeral”). We intend for this book both to summarize some key past contributions as well as to lay out an agenda for the future. Any such agenda will require the efforts of many scientists, and we hope to provide sufficient insights and practical guidance so that others can productively join in this research effort.

The tools and ideas emerging from complex systems research complement existing approaches, and they should allow us to build much better theories about the world when they are carefully integrated with existing techniques. Some of the discussions in this book surround basic issues in good scientific modeling. Having a good understanding of these issues is certainly a prerequisite for anyone interested in pursuing work in this area, and unfortunately explicit discussions of modeling are rarely encountered by most scholars.

The book’s central theme, “The Interest in Between,” has two meanings. The first relates to the level and techniques we use to illustrate the core material in complex adaptive social systems. The second concerns the scientific space that this area occupies.

Complex systems has become both a darling of the popular press and a rapidly advancing scientific field. Unfortunately, this creates a gap between popular accounts that rely on amorphous metaphors and cutting-edge research that requires a technical background. Here we hope to provide a point of entry that lies between metaphor and technicalities. Our work focuses on simple examples that are accessible, yet also contain much deeper foundational insights. This approach is analogous to learning game theory by studying the Prisoner’s Dilemma or the Centipede game. While game theory rests on a very abstract and technical foundation—fixed points, hemicontinuous correspondences, and the like—most of the core insights are contained in the analysis of these simple games. In a similar spirit, here we rely on simple models and examples to convey the key ideas. These illustrations will exist in between metaphor and abstract mathematics, in between the flowery language that has taken hold in the press and concrete computations. We view this “in-between” as a good point of entry into the material and hope that it gives readers the ability and interest to dig deeper into the field as they see fit.

We have strived to make this book accessible to both academics and the sophisticated lay reader. Whether you are a graduate student or faculty member in the social sciences trying to understand better what complex systems is about and how it could be used, an engineer hoping to improve

your models of processes by using social agents, or someone interested in business, economics, or politics who wants a deeper understanding of the causes and implications of complexity, you should find this book useful and approachable.

Ultimately the study of complex systems illuminates the interest in between the usual scientific boundaries.

It is the interest in between various fields, like biology and economics and physics and computer science. Problems like organization, adaptation, and robustness transcend all of these fields. For example, issues of organization arise when biologists think about how cells form, economists study the origins of firms, physicists look at how atoms align, and computer scientists form networks of machines.

It is the interest in between the usual extremes we use in modeling. We want to study models with a few agents, rather than those with only one or two or infinitely many. We want to understand agents that are neither extremely brilliant nor extremely stupid, but rather live somewhere in the middle.

It is the interest in between stasis and utter chaos. The world tends not to be completely frozen or random, but rather it exists in between these two states. We want to know when and why productive systems emerge and how they can persist.

It is the interest in between control and anarchy. We find robust patterns of organization and activity in systems that have no central control or authority. We have corporations—or, for that matter, human bodies and beehives—that maintain a recognizable form and activity over long periods of time, even though their constituent parts exist on time scales that are orders of magnitude less long lived.

It is the interest in between the continuous and the discrete. The behavior of systems as we transition between the continuous and discrete is often surprising. Many systems do not smoothly move between these two realms, but instead exhibit quite different patterns of behavior, even though from the outside they seem so “close.”

It is the interest in between the usual details of the world. We need to find those features of the world where the details do not matter, where large equivalence classes of structure, action, and so on lead to a deep sameness of being.

The science of complex systems and its ability to explore the interest in between is especially relevant for some of the most pressing issues of our modern world. Many of the opportunities and challenges before us—globalization, sustainability, combating terrorism, preventing epidemics, and so on—are complex. Each of these domains consists of a set of diverse actors who dynamically interact with one another awash in a sea of feedbacks. To understand, and ultimately to harness, such complexity

will require a sustained and imaginative effort on the part of researchers across the sciences.

Kenneth Boulding summarized science as consisting of “testable and partially tested fantasies about the real world.” The science of complex systems is not a new way of doing science but rather one in which new fantasies can be indulged.

Complexity in Social Worlds

I adore simple pleasures. They are the last refuge of the complex.

—Oscar Wilde, *The Picture of Dorian Gray*

When a distinguished but elderly scientist states that something is possible, he is almost certainly right. When he states that something is impossible, he is very probably wrong.

—Arthur C. Clarke, *Report on Planet Three*

WE ARE SURROUNDED by complicated social worlds. These worlds are composed of multitudes of incommensurate elements, which often make them hard to navigate and, ultimately, difficult to understand. We would, however, like to make a distinction between complicated worlds and complex ones. In a complicated world, the various elements that make up the system maintain a degree of independence from one another. Thus, removing one such element (which reduces the level of complication) does not fundamentally alter the system's behavior apart from that which directly resulted from the piece that was removed. Complexity arises when the dependencies among the elements become important. In such a system, removing one such element destroys system behavior to an extent that goes well beyond what is embodied by the particular element that is removed.

Complexity is a deep property of a system, whereas complication is not. A complex system dies when an element is removed, but complicated ones continue to live on, albeit slightly compromised. Removing a seat from a car makes it less complicated; removing the timing belt makes it less complex (and useless). Complicated worlds are reducible, whereas complex ones are not.

While complex systems can be fragile, they can also exhibit an unusual degree of robustness to less radical changes in their component parts. The behavior of many complex systems emerges from the activities of lower-level components. Typically, this emergence is the result of a very powerful organizing force that can overcome a variety of changes to the lower-level components. In a garden, if we eliminate an insect the vacated niche will often be filled by another species and the ecosystem will

continue to function; in a market, we can introduce new kinds of traders and remove old traders, yet the system typically maintains its ability to set sensible prices. Of course, if we are too extreme in such changes, say, by eliminating a keystone species in the garden or all but one seller in the market, then the system's behavior as we know it collapses.

When a scientist faces a complicated world, traditional tools that rely on reducing the system to its atomic elements allow us to gain insight. Unfortunately, using these same tools to understand complex worlds fails, because it becomes impossible to reduce the system without killing it. The ability to collect and pin to a board all of the insects that live in the garden does little to lend insight into the ecosystem contained therein.

The innate features of many social systems tend to produce complexity. Social agents, whether they are bees or people or robots, find themselves enmeshed in a web of connections with one another and, through a variety of adaptive processes, they must successfully navigate through their world. Social agents interact with one another via connections. These connections can be relatively simple and stable, such as those that bind together a family, or complicated and ever changing, such as those that link traders in a marketplace. Social agents are also capable of change via thoughtful, but not necessarily brilliant, deliberations about the worlds they inhabit. Social agents must continually make choices, either by direct cognition or a reliance on stored (but not immutable) heuristics, about their actions. These themes of connections and change are ever present in all social worlds.

The remarkable thing about social worlds is how quickly such connections and change can lead to complexity. Social agents must predict and react to the actions and predictions of other agents. The various connections inherent in social systems exacerbate these actions as agents become closely coupled to one another. The result of such a system is that agent interactions become highly nonlinear, the system becomes difficult to decompose, and complexity ensues.

2.1 THE STANDING OVATION PROBLEM

To begin our exploration of complex adaptive social systems we consider a very simple social phenomenon: standing ovations (Schelling, 1978; Miller and Page, 2004). Standing ovations, in which waves of audience members stand to acknowledge a particularly moving performance, appear to arise spontaneously.¹ Although in the grand scheme of things

¹There are circumstances, such as the annual State of the Union address before the U.S. Congress, where such behavior is a bit more orchestrated.

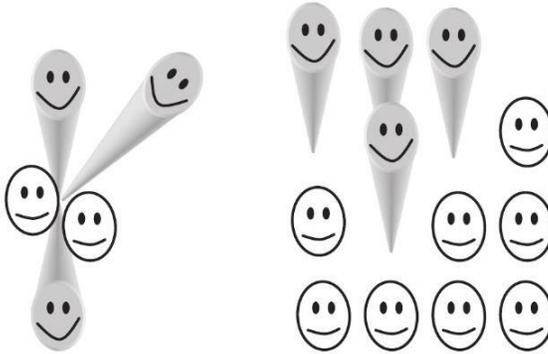


Figure 2.1. Two views of modeling the standing ovation. In its simplest form, the model requires that everyone shares the same seat in the auditorium (*left*), while the more elaborate model (*right*) allows space, friendship connections, and physical factors like vision to play a vital role in the system. While the simple model might rely on traditional tools like formal mathematics and statistics, the more elaborate model may require new techniques like computational models using agent-based objects to be fully realized.

The dynamics of the model also becomes more complicated. In the original model, we had an initial decision to stand, followed by a second decision based on how many people stood initially. After this second decision, the model reached an equilibrium where either the original group remained standing or everyone was up on their feet. The new model embodies a much more elaborate (and likely realistic) dynamics. In general, it will not be the case that the model attains an equilibrium after the first two rounds of updating. Typically, the first round of standing will induce others to stand, and this action will cause others to react; in this way, the system will display cascades of behavior that may not settle down anytime soon.

These two modeling approaches illuminate the world in very different ways. In the first model either fewer than α percent stand or everyone does; in the second it is possible to have any percentage of people left standing. In the first model the outcome is determined after two periods; in the second cascades of behavior wash over the auditorium and often reverberate for many periods. In the first model everyone's influence is equal; in the second influence depends on friendships and even seat location. Oddly, the people in the front have the most visual influence on others yet also have the least visual information, whereas those in the back with the most information have the least influence (think of the former as celebrities and the latter as academics).

The second model provides a number of new analytic possibilities. Do performances that attract more groups lead to more ovations? How does changing the design of the theater by, say, adding balconies, influence ovations? If you want to start an ovation, where should you place your skills? If people are seated based on their preferences for the performance, say, left or right side of the aisle or more expensive seats up front, do you see different patterns of ovations?

Although standing ovations per se are not the most pressing of social problems, they are related to a large class of important behaviors that is tied to social contagion. In these worlds, people get tied to, and are influenced by, other people. Thus, to understand the dynamics of a disease epidemic, we need to know not only how the disease spreads when one person contacts another but also the patterns that determine who contacts whom over time. Such contagion phenomena drive a variety of important social processes, ranging from crime to academic performance to involvement in terrorist organizations.

2.2 WHAT'S THE BUZZ?

Heterogeneity is often a key driving force in social worlds. In the Standing Ovation problem, the heterogeneity that arose from where people sat and with whom they associated resulted in a model rich in behavioral possibilities. If heterogeneity is a key feature of complex systems, then traditional social science tools—with their emphases on average behavior being representative of the whole—may be incomplete or even misleading.

In many social scenarios, differences nicely cancel one another out. For example, consider tracking the behavior of a swarm of bees. If you observe any one bee in the swarm its behavior is pretty erratic, making an exact prediction of that bee's next location nearly impossible; however, keep your eye on the center of the swarm—the average—and you can detect a fairly predictable pattern. In such worlds, assuming behavior embodied by a single representative bee who averages out the flight paths of all of the bees within the swarm both simplifies and improves our ability to predict the future.

2.2.1 *Stay Cool*

While differences can cancel out, making the average a good predictor of the whole, this is not always the case. In complex systems we often see differences interacting with one another, resulting in behavior that deviates remarkably from the average.

To see why, we can return to our bees. Genetic diversity in bees produces a collective benefit that plays a critical function in maintaining hive temperature (Fischer, 2004). For honey bees to reproduce and grow, they must maintain the temperature of their hive in a fairly narrow range via some unusual behavioral mechanisms. When the hive gets too cold, bees huddle together, buzz their wings, and heat it up. When the hive gets too hot, bees spread out, fan their wings, and cool things down.

Each individual bee's temperature thresholds for huddling and fanning are tied to a genetically linked trait. Thus, genetically similar bees all feel a chill at the same temperature and begin to huddle; similarly, they also overheat at the same temperature and spread out and fan in response.

Hives that lack genetic diversity in this trait experience unusually large fluctuations in internal temperatures. In these hives, when the temperature passes the cold threshold, all the bees become too cold at the same time and huddle together. This causes a rapid rise in temperature and soon the hive overheats, causing all the bees to scatter in an over ambitious attempt to bring down the temperature. Like a house with a primitive thermostat, the hive experiences large fluctuations of temperature as it continually over- and undershoots its ideals.

Hives with genetic diversity produce much more stable internal temperatures. As the temperature drops, only a few bees react and huddle together, slowly bringing up the temperature. If the temperature continues to fall, a few more bees join into the mass to help out. A similar effect happens when the hive begins to overheat. This moderate and escalating response prevents wild swings in temperature. Thus, the genetic diversity of the bees leads to relatively stable temperatures that ultimately improve the health of the hive.

In this example, considering the average behavior of the bees is very misleading. The hive that lacked genetic diversity—essentially a hive of averages—behaves in a very different way than the diverse hive. Here, average behavior leads to wide temperature fluctuations whereas heterogeneous behavior leads to stability. To understand this phenomenon, we need to view the hive as a complex adaptive system and not as a collection of individual bees whose differences cancel out one another.

2.2.2 *Attack of the Killer Bees*

We next wish to consider a model of bees attacking a threat to the hive.³ Some bees go through a maturation stage in which they guard the

³This is a simplified version of models of human rioting constructed by Grannoveter (1978) and Lohmann (1993). Unlike the previous example, the direct applicability to bees is more speculative on our part.

entrances to the hive for a short period of time. When a threat is sensed, the guard bees initiate a defensive response (from flight, to oriented flight, to stinging) and also release chemical pheromones into the air that serve to recruit other bees into the defense.

To model such behavior, assume that there are one hundred bees numbered 1 through 100. We assume that each bee has a response threshold, R_i , that gives the number of pheromones required to be in the air before bee i joins the fray (and also releases its pheromone). Thus, a bee with $R_i = 5$ will join in once five other bees have done so. Finally, we assume that when a threat to the hive first emerges, R bees initiate the defensive response (to avoid some unnecessary complications, let these bees be separate from the one hundred bees we are watching). Note that defensive behavior is decentralized in a beehive: it is initiated by the sentry activities of the individual guard bees and perpetuated by each of the remaining bees based only on local pheromone sensing.

We consider two cases. In the first case, we have a homogeneous hive with $R_i = 50.5$ for all i . In the second case, we allow for heterogeneity and let $R_i = i$ for all i . Thus, in this latter case each bee has a different response threshold ranging from one to one hundred. Given these two worlds, what will happen?

In the homogeneous case, we know that a full-scale attack occurs if and only if $R > 50$. That is, if more than fifty bees are in the initial wave, then all of the remaining one hundred will join in; otherwise the remaining bees stay put. In the heterogeneous case, a full-scale attack ensues for any $R \geq 1$. This latter result is easy to see, because once at least one bee attacks, then the bee with threshold equal to one will join the fray, and this will trigger the bee with the next highest threshold to join in, and so on.

Again, notice how average behavior is misleading. The average threshold of the heterogeneous hive is identical to that of the homogeneous hive, yet the behaviors of the two hives could not be more different. It is relatively difficult to get the homogeneous hive to react, while the heterogeneous one is on a hair trigger. Without explicitly incorporating the diversity of thresholds, it is difficult to make any kind of accurate prediction of how a given hive will behave.

2.2.3 *Averaging Out Average Behavior*

Note that the two systems we have explored, regulating temperature and providing defense, have very different behaviors linked to heterogeneity. In the temperature system, heterogeneity leads to stability. That is, increased heterogeneity improves the ability of the system to stabilize