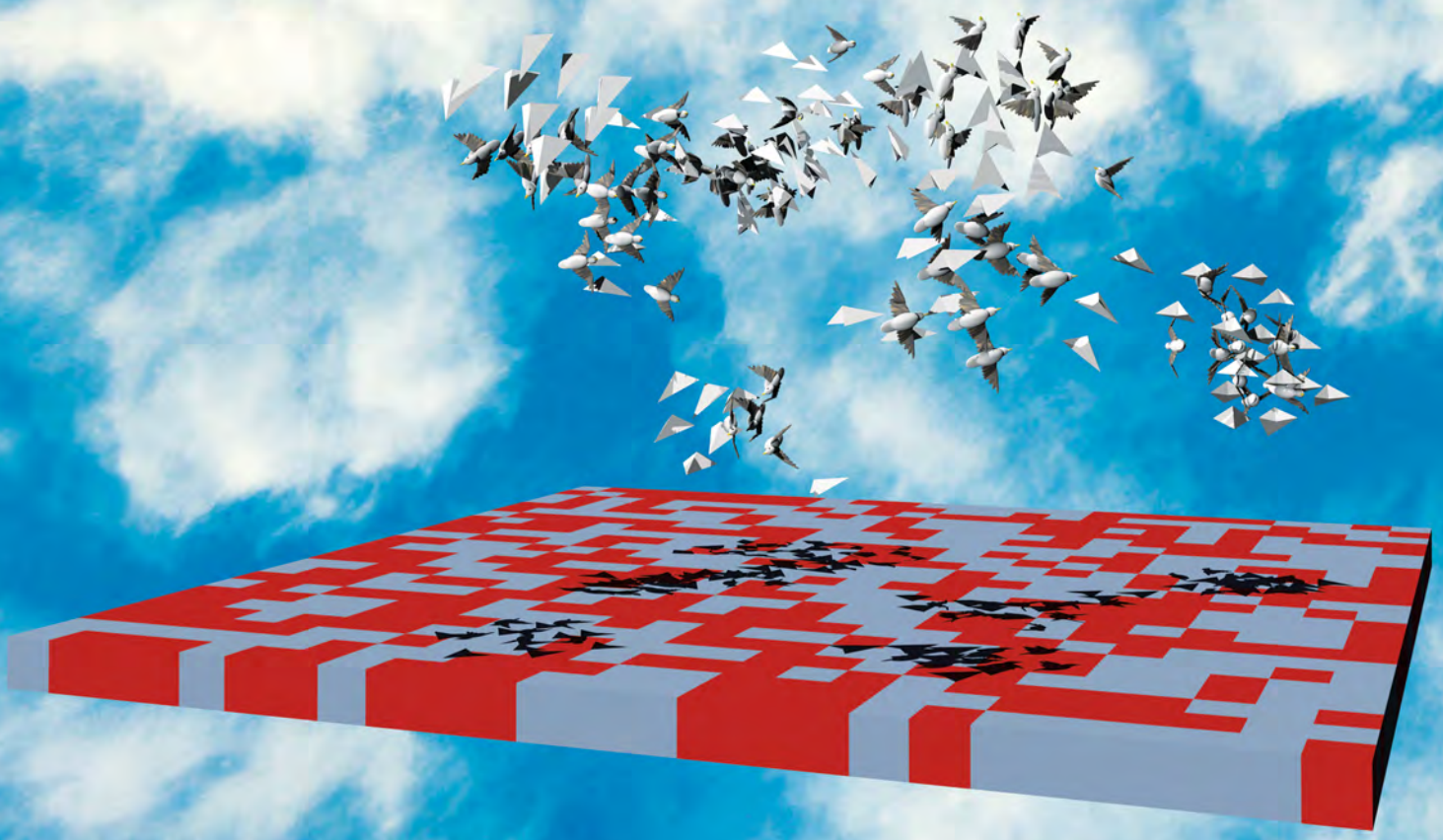
# AN INTRODUCTION TO AGENT-BASED MODELING

## MODELING NATURAL, SOCIAL, AND ENGINEERED COMPLEX SYSTEMS WITH NETLOGO



URI WILENSKY AND WILLIAM RAND

# An Introduction to Agent-Based Modeling

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Modeling Natural, Social, and Engineered Complex Systems with NetLogo

Uri Wilensky and William Rand

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# Preface

*Fortune favors the prepared mind.*

*—Louis Pasteur*

*A beginning is the time for taking the most delicate care that the balances are correct.*

*—Frank Herbert*

As the world becomes more interconnected and complex, our ability to understand it must also. Simple models no longer suffice to answer many of our questions. The advent of widespread fast computation has enabled us to work on more complex problems and to build and analyze more complex models. This has generated a new field of knowledge called "complex systems." This book is an introduction to one of the primary methodologies that has arisen from complex systems research. This methodology, called agent-based modeling, is a new way of doing science by conducting computer-based experiments.

The rise of computation has also led to an explosion in new data. The amount of new knowledge and data about our world is growing exponentially. This is true regardless of the subject area. From physics to chemistry, from biology to ecology, from political science to economics, from management science to marketing, scientists and researchers are routinely gathering data at a rate that far outstrips that of scientists in the past. As this new data is captured, we can begin to ask questions about complex systems that hitherto could not be meaningfully asked with an expectation of data-driven answers. For example, "How do multiple species interact and compete to form a stable ecosystem?" "How do political institutions affect individual decisions, especially when those individuals have the ability to manipulate political institutions?" or "How can we engineer robots that can work and interact with complex social processes?"

As these complex questions are asked, future scientists, researchers, engineers, business entrepreneurs, politicians, and practitioners will be called on to answer them. The toolkit of complex systems methods will become a necessity for these individuals, and

agent-based modeling (ABM) will play a central role in that toolkit.[1] Through this book, we will provide an introduction to ABM for anyone interested in answering questions about the complex systems that are embedded in natural, social, and engineered contexts.

Our book will draw on applications in a wide variety of fields to help illustrate the power of ABM methodology. Along the way, we will guide you through a series of hands-on examples that will help you to understand how you can use this tool in your own work. The guiding principle we used while writing this textbook (and also for NetLogo, the language we will be using) is, "Low Threshold, No Ceiling."[2] By that, we mean that there is very little prerequisite knowledge to start using the material, but at the same time there is no limit to what can be accomplished once it is mastered.

ABM is a powerful tool in helping us to understand complex systems. Our textbook, though titled "An Introduction," provides the tools necessary to enable you to build and use agent-based models to investigate your own questions.

## Who We Wrote This For

Because the field of ABM is applicable to so many domains, this textbook can be used in a wide variety of contexts. It can serve as a main text for an interdisciplinary undergraduate course on complex systems or a computer-science class on agent-based modeling. It can be used as a supplementary text in a very wide range of undergraduate classes, including any class where agent-based modeling can be profitably applied. This can be quite a broad list of content areas. The material described in this textbook has been used in natural science classes such as physics, chemistry, and biology; social science classes such as psychology, sociology, and linguistics; and engineering classes such as materials science, industrial engineering, and civil engineering. We have strived to balance the examples across content areas, in order for at least one example to hit squarely on the content area of a given course. Naturally, to achieve this goal, we must sacrifice depth in any one content area. As the field of ABM progresses, we expect that in-depth domain-specific textbooks will appear.

Though we have targeted a high-level undergraduate or entry-level graduate audience, we expect that the book will be useful to other audiences as well. The prerequisite knowledge is not great; a motivated individual learner in a wide range of academic settings could use this text. Similarly, since ABM methods may be new to many graduate students, we expect that our book could be quite useful as a supplementary text to graduate classes in a wide range of subject domains. ABM methods are increasingly used in research labs, in the business community, and in policy circles. We anticipate that professionals in these areas can benefit from the methods and examples herein. The material for this textbook

1. If ABM is used in a plural sense (ABMs) or with an article (an ABM) then ABM stands for agent-based model and not agent-based modeling.

2. In the appendix, we discuss the history of the Logo programming language from which this slogan originated. It can also be rendered as "Low Threshold, High Ceiling."

has arisen from and has been tested for over two decades of both undergraduate and graduate classes taught in Computer Science and in Learning Sciences by Uri Wilensky and additional classes taught by William Rand, as well as hundreds of workshops, seminars, and summer school courses conducted by both authors.

In the title, we specifically highlight "natural, social, and engineered complex systems." Natural systems are studied in fields such as biology and physics: complex systems that are naturally occurring. Social systems consist of individuals interacting with each other. Social systems can be natural and/or engineered. Engineered systems are those that have been designed by humans to achieve a particular goal.

There are few prerequisites for this book. We do not assume any mathematical knowledge beyond basic algebra, and we do not assume any prior programming knowledge. For chapters 6, 7, and 8, we do assume that you have a very basic knowledge of statistics—for example, that you understand what a normal distribution is. Moreover, as we discuss later, we expect you to start with a rudimentary familiarity with NetLogo, and **we suggest that you work through the first three tutorials included in the NetLogo user manual of the NetLogo software.** The NetLogo software can be downloaded from ccl.northwestern.edu/netlogo/.[3]

Working through this book will require reading and writing of computer code. This may be quite unfamiliar to some readers. Though many people believe that computer programming is too hard for them to learn, research by Constructionist educators and decades of experience has shown the authors that virtually all students can learn to program in NetLogo. We hope that you won't be scared off by all the code in the textbook, and that you will take the time to learn to read and write the code. We are very confident that you can do it and that taking the time to learn it will pay rich dividends.

## NetLogo and the Textbook

Many different agent-based modeling languages exist. As of this writing, NetLogo remains the most widely used. Of the others currently in use, Swarm, developed at the Santa Fe Institute, Repast, developed at Argonne National Laboratory, and MASON, developed at George Mason University, are the next most pervasive among scientists and researchers. Most ABM toolkits (including NetLogo) are open source and freely available. AnyLogic is a commercial package that has also been successful. Other software packages for building ABMs in current use include Ascape, Breve, Cormas, MASS, PS-I, and SeSam. It is also possible to write an agent-based model in any language. When building your own model in a standard non-agent-based programming language, the time to run the model may be faster, but often the time for the lifecycle of development will be considerably slower.

3. This textbook uses the desktop application version of the NetLogo software. At the time of publication of this book, a browser-based version of NetLogo will also be available. Most examples used in the book will work in the browser-based version, though some will require adaptation for that version.

We make use of NetLogo examples throughout this textbook, both to provide hands-on illustrations of the principles being discussed and also as a form of "pseudo-code."[4] However, this textbook is not a NetLogo manual. Before reading much farther, we suggest you **download the NetLogo software,** open source and available for free from **http://ccl.northwestern.edu/netlogo,** and work through the introductory material in the NetLogo manual (available through the Help menu of the NetLogo software), including the three tutorials that introduce the user to basic model development and syntax. This is a necessary prerequisite to comprehending the material in the book beyond chapter 1. The NetLogo user manual (found under the NetLogo Help menu) is the authoritative reference for NetLogo and it is regularly updated and improved. It will often be advisable to consult the manual, the interface and programming guides, the dictionary and FAQ throughout this textbook. NetLogo comes with an extensive library of models from which you can learn common code patterns. The "Code Examples" models are meant to be simple models intended to show you common code patterns. There are many online resources for help with NetLogo (see http://ccl.northwestern.edu/netlogo/resources.shtml). The NetLogo users group (reachable through the NetLogo HELP menu) is a forum where people post NetLogo questions. The community is quite responsive, and if you post a question there you will likely receive a prompt response. It is a good idea to subscribe to this group early on in working through this textbook. Another resource for asking and answering NetLogo programming questions is Stack Overflow (http://stackoverflow.com/questions/tagged/netlogo), where you will find many questions and answers about NetLogo programming.

We use the NetLogo examples in order to concretize the concepts of agent-based modeling that we present. By presenting computer code side-by-side with conceptual discussions, we hope to provide both a larger picture of the use of agent-based models as well as a specific illustration.

We have selected NetLogo as our ABM language for this text for several reasons. Before explaining the specifics, it is important to say that we believe our book will be just as useful for those using other ABM languages. Even if we had written a completely language-agnostic book, we would still have needed to include pseudo-code to illustrate our points. Since NetLogo was designed to be easily readable, we believe that NetLogo code is about as easy to read as any pseudo-code we could have used. NetLogo also has the big advantage over pseudo-code of being executable, so the user can run and test the examples. Moreover, there are a large number of agent-based models written in NetLogo in a wide variety of domains, so a literate agent-based modeler requires at least a passing understanding of NetLogo.

4. Pseudo-code is an intermediate form between text and computer code that is often used to describe computational algorithms.

We have several other significant reasons for choosing NetLogo as the language for our book. Uri Wilensky, the first author of this textbook, is also the author and developer of NetLogo and has conducted agent-based modeling research, development and teaching with NetLogo (and its precursors) for over two decades. He has taught NetLogo in his classes and in workshops for that same period. The second author has years of experience teaching NetLogo workshops and conducting agent-based modeling research with NetLogo. As such, we are intimately familiar with the language nuances and details. More important, NetLogo was designed with great attention to learnability. As we said, its core design principle is "low threshold, no ceiling."

Achieving both of these goals completely is not possible and to some degree, they trade-off against each other, but NetLogo has gone a considerable distance in achieving both. No other extant ABM language is close to NetLogo's low threshold. As such, it is an ideal language for learning ABM and is used widely in classrooms all over the world. Yet, NetLogo also achieves a high ceiling. NetLogo is in use by a large number of scientists and professionals and is regularly employed in cutting edge research (see http://ccl.northwestern.edu/netlogo/references.shtml for a partial list of research papers employing NetLogo). So after completing this text, you should be well prepared to use NetLogo in your research, teaching, and/or professional life. Learning NetLogo will make you a better ABM modeler/researcher regardless of the language that you may eventually use.

## Learning Objectives

There are ten main objectives of our textbook, which roughly parallel the nine chapters and the appendix of the textbook. We will phrase these objectives in terms of questions a reader should be able to answer at the end of our textbook:

0. Why does agent-based modeling provide us with a unique and powerful insight into complex systems?
1. What is agent-based modeling and how is it used?
2. What are some simple agent-based models that we can create?
3. How do I extend an agent-based model that was created by someone else?
4. How do I create my own agent-based model?
5. What are the basic components of agent-based modeling?
6. How can I analyze the results of an agent-based model?
7. How can I tell if the implemented agent-based model corresponds to the concept of the model that I developed in words? How can I tell if the results of my agent-based model tell me anything about the real world? How can I make sure that someone else can repeat my results?

8. What are some advanced ways of including data and using output from agent-based models? What are some of the open research questions in agent-based modeling?
9. From what computational scientific roots did agent-based modeling arise?

## Features

There are four main features that are present in nearly every chapter of the book: in-line development, textboxes, explorations, and references. In-line development is what we call the approach of developing a model or an extension to a model in the main text of the book instead of asking the reader to do it later offline. It is expected for some of these chapters (2, 3, 4, 5, 6, and 7 especially) that the reader will read the textbook while sitting at their computer, entering the code from the textbook and manipulating the models as they read along. **All models developed in the textbook can be found in their entirety in the IABM Textbook folder of the NetLogo models library.** This folder is organized by chapters of the textbook. These completed models are provided as a resource, but we encourage students to follow along with the textbook, developing the models themselves before opening the models in the IABM folder. Most other models referred to in the textbook reside in the NetLogo models library, which can be accessed through the "models library" menu item from NetLogo's "file" menu. The models library is itself comprised of subfolders. The principal subfolder is "sample models," which is organized by subject, such as biology, mathematics, social science, and others. **All models used in the book and supplementary materials can be found on the website for the book, www.intro-to-abm.com, updated regularly.**

The textboxes serve to provide additional information and concepts. There are three kinds of textboxes: (1) definitional, (2) exploration, and (3) advanced concept. *Definitional* textboxes (set in blue) define words and terms critical to the discussion. *Exploration* textboxes (set in green) provide additional explorations that are relevant to the material being discussed at that point. *Advanced concept* textboxes (set in orange) highlight concepts that are beyond the scope of the book but that might be of interest to the reader.

At the end of every chapter (except chapter 0), there are explorations. An instructor may want to draw on these explorations for student homework. These explorations are roughly in order of difficulty. Some of them are quite open-ended, while others are more constrained.

At the end of the book there is a references section, the text references organized alphabetically, and the software/model references organized by chapter. To distinguish the text from the software references, the software references are italicized in the text.

## Organization

We will present the basics of ABM in nine chapters and an appendix. The nine chapters and the appendix can be thought of as three sections: (1) What ABMs are, (2) How to

build ABMs, and (3) How to utilize ABMs to answer complex questions. The first two chapters (0 and 1) and the appendix describe why ABMs are interesting and useful (chapter 0), what they are (chapter 1), and where they came from (the appendix). Together this material defines and describes the field of ABM. The next four chapters (2, 3, 4, and 5) cover how to create simple ABMs (chapter 2), extend an ABM (chapter 3), and build your own ABM (chapter 4), identifying the basic components of an ABM are (chapter 5). These four chapters form a unit on the methods for building ABMs. The final three chapters describe how to analyze ABMs (chapter 6), how to verify, validate, and replicate ABMs (chapter 7), and how to use advanced features of ABMS including using external data sources (chapter 8). Together, these cover the experimental methodology of ABMs.

We believe that all of these chapters are important for someone who is interested in gaining a comprehensive knowledge of ABM. However, if you have a particular interest, there may be a subset of chapters that is more appealing. For people who are interested in what can be done with ABM but who do not need a hands-on knowledge of how to construct ABM, we recommend reading chapter 0 (for an overview of why to use ABM), chapter 1 (for a discussion of how an ABM can be used), the appendix (for an overview of the computational origins of ABM), chapter 7 (to understand how to analyze ABMs), and chapter 8 (to learn about advanced uses of ABM). For readers who simply want a practical hands-on introduction to building ABM, we recommend reading chapter 0 (for an understanding of why to use ABM), chapter 1 (to learn how to pose questions suitable for ABM), chapter 2 (to learn how to create simple ABMs), chapter 3 (to learn how to extend another user's ABM), and chapter 4 (for an introduction to designing and authoring an ABM). These readers might then move on to chapter 5 (for a discussion of the basic ABM components). For other readers, the more detailed chapter overview below may help you choose the chapters that are the most appropriate for you.

### Chapters 0 and 1 and the Appendix: What Are ABMs?

In Chapter 0, we discuss the motivations for using ABM. We note the ubiquity of emergence in the world and review the literature that shows how difficult it has been for people to understand emergent phenomena. We also explore how ABM can help us to make sense of phenomena that are nondeterministic and/or have distributed mechanisms and control. Agent-based modeling is powerful because its basic ontology is parallel to the ontology of the world around us. As a result, we can define and describe complex systems using ABMs in quite naturalistic ways. We do not have to define in advance the emergent, global properties; instead, we can observe these properties as they arise from a simulation of multiple distributed interacting agents. This enables us to provide very different descriptions of the world around us, and to understand complex processes in fundamentally new ways. Even for phenomena that we may understand well such as basic physics, chemistry and biology, ABM provides a "restructuration" (Wilensky & Papert, 2005, 2010) of these

disciplines, making them easier to understand for novices and enabling experts to develop new insights.

In chapter 1, we begin with a description of ant behavior and discuss how an ABM of an ant colony could be created. The practice of ABM is the use of multiple interacting, heterogeneous agents to create models of complex systems. ABM enables us to create models straight from empirical observations of behavior. We can build mechanisms that we conjecture might explain the behavior and examine how these mechanisms interact. On the basis of this examination, we can at least ascertain if our models are sufficiently generative that they *could* account for the phenomenon being observed. Using a model of ant behavior, we show how scientists might examine several different mechanisms and use models in concert with empirical observations to ascertain which of these mechanisms could explain the behavior observed.

The appendix describes the historical development of the research, people, and ideas that resulted in the creation of the field of agent-based modeling from a computational perspective. ABM, unlike some other discipline-specific methods, did not arise out of any one particular domain or field. Instead, it arose contemporaneously in many different fields, some of which were aware of each other and some of which were not. The history of ABM, like many of the applications of ABM, can itself be told in terms of complex systems with many distributed actors and nonlinear interactions that occurred. An understanding of the origins of ABM and the historical development of canonical ABM models is helpful in deciding whether an ABM approach will be productive and in selecting a design for an ABM of a target phenomenon.

Together, this material covers why ABM is useful, what it is, and who developed it. The two chapters plus the appendix provide the fundamental motivation, concepts and history of ABM.

### Chapters 2, 3, 4, and 5: How to Build ABMs

In chapter 2, we develop some very simple ABMs that have powerful features. We begin with Life Simple, which is a version of the game of Life. This model illustrates how very simple rules can create interesting and emergent patterns. We then move on to Heroes and Cowards, a model that illustrates how just changing one rule can dramatically alter the results of a model. Finally, we conclude with the Simple Economy model, which demonstrates how very simple ABMs can help us think through real-world problems.

In chapter 3, we go through the process of taking an ABM that someone else has constructed and modifying it. These modifications could be as simple as adding new visual characteristics to clarify a particularly interesting set of agents or interactions in the model, or to look at a completely new phenomenon using the previous model as a basis for the new design. We will use these extensions to illustrate four characteristics of agent-based modeling: (1) simple rules can be used to generate complex phenomena, (2) randomness in individual behavior can result in deterministic global behavior, (3)

complex patterns can "self-organize" without a central leader, and (4) the same phenomenon can be modeled in many different ways, depending on which aspect of it you want to emphasize.

Chapter 4 takes us to the next step of starting to develop models from scratch. We develop a model, named Wolf Sheep Simple, in five distinct stages. The model that we develop illustrates many of the basic concepts that go into ABM creation and design, and it includes many core features of ABMs, such as different agent types, environmental and agent interactions, and competition for resources. Central to this chapter is the delineation and elaboration of the key design principle of ABM.

In chapter 5, we zoom out to take a look at the broader picture, cataloguing and describing the constituent parts of an ABM. After classifying these components into the five categories of Agents, Environments, Interactions, User Interface/Observer, and Schedule, we examine each of these component classes in turn. Within each of these classes, we discuss common issues that should be considered before and while building an agent-based model. For example, what kind of topology should the environment have? Or what properties and actions do the agents in the model have? It can be quite useful to make a plan for each component class and their interactions at an early point in the design plan, and to revisit that plan throughout the design process.

Together, these four chapters provide an in-depth treatment of how to construct agent-based models and provide the basic tools needed to design, construct, and select the components that will go into a model. After reading these four chapters, you should have sufficient knowledge to design and construct basic agent-based models.

### Chapters 6, 7, and 8: How to Analyze and Use ABMs

One feature of many ABMs is that they create large amounts of data. Chapter 6 discusses how to examine these data to find meaningful relationships and conduct analyses that are useful for understanding the behavior of the model. We discuss how to explore and describe model results using statistics, graphs, and geographic and network methods. We also discuss the importance of multiple model runs and how to sweep a parameter space to determine the range of behaviors exhibited by a model.

In chapter 7, we examine three key concepts in modeling: verification, validation, and replication. Verification is the process of comparing an implemented model to its associated conceptual model and investigating whether the implemented model is faithful to the conceptual model. By verifying a model, we show that the model implementer has comprehended the intended micro-level rules and mechanisms and has correctly implemented them in the model code. This is true even if the model author may have intended different emergent behavior or predicted different emergent results from those that arise in the implemented model. Validation is a comparison of an implemented model to the real world, to see if the results of the implemented model give us insight into the corresponding real world phenomenon. Validation enables us to use the model to make statements about the

real world. Replication is the reproduction of a model result published by one scientist or model developer by another scientist or model developer. Replication is a central process in the creation of scientific knowledge, and replication procedures for agent-based models are explained. Overall, this chapter discusses how implemented ABMs relate to both other models and the real world.

In chapter 8, we address advanced topics with regard to agent-based modeling and how the methods that we have described in the first eight chapters can be further refined. We focus on ways to incorporate data into ABMs from advanced sources such as social network analysis, geographic information systems, and real-time sensors. We also discuss how to make ABMs more powerful, by incorporating techniques such as machine learning, system dynamics modeling, and participatory simulation. We conclude this chapter with a discussion of future challenges for ABM.

In these last three chapters we discuss how to analyze ABMs, how to verify and validate the results of ABMs, and how to use advanced techniques in ABM. These are the important practices of ABM after creating your model and for examining models authored by others.

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In addition, we received valuable feedback from a number of internal and external reviewers over the course of the writing of this textbook. Chief among them are the teaching assistants for Wilensky's agent-based modeling class at Northwestern University, in which these materials were tested over several years: Forrest Stonedahl, Josh Unterman, David Weintrop, Aleata Hubbard, Bryan Head, Arthur Hjorth, and Winston Chang carefully reviewed the materials, observed the students using the materials, and gave extensive helpful comments for improving the text, the model code, and the explorations. Many other members of the Northwestern Center for Connected Learning and Computer-Based Modeling also gave very helpful feedback, including Seth Tisue, Corey Brady, Spiro Maroulis, Sharona Levy, and Nicolas Payette. Dor Abrahamson, Paulo Blikstein, Damon Centola, Paul Deeds, Rob Froemke, Ed Hazzard, Eamon Mckenzie, Melanie Mitchell, Michael Novak, Ken Reisman, Eric Russell, Pratim Sengupta, Michael Stieff, Forrest Stonedahl, Stacey Vahey, Aditi Wagh, Michelle Wilkerson-Jerde, and Christine Yang contributed illuminating examples. Forrest Stonedahl, Corey Brady, Bryan Head, David Weintrop, Nicolas Payette, and Arthur Hjorth suggested useful explorations for the chapters that have enriched student experience. Wilensky's students at Tufts University, Ken Reisman, Ed Hazzard, Rob Froemke, Eamon McKenzie, Stacey Vahey, and Damon Centola, shared their abundant enthusiasm, generated interesting applications, and furthered the educational uses. Northwestern's dean of engineering, Julio Ottino, was always supportive and encouraging, and confident in the importance of an ABM textbook.

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Many of the materials in this textbook had previously been used in Wilensky's agent-based modeling class in the Computer Science Department at Northwestern University. Early versions of the textbook were used as the basis for a summer workshop taught by Rand as part of the Summer CommuniCy (under the leadership of Klaus Liepelt) at Mittweida University in Germany, and in various classes at the University of Michigan and University of Maryland. We have also piloted these materials in hundreds of NetLogo workshops in the United States and abroad. We would like to thank the students who have been involved in these classes over the years for their feedback and support.

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# 0 Why Agent-Based Modeling?

*Some look at things that are, and ask why? I dream of things that never were and ask why not?*

*— John F. Kennedy*

*I think the next century will be the century of complexity.*

*—Stephen Hawking*

*We shape our tools and then our tools shape us.*

*—Marshall McLuhan*

This book is an introduction to the methodology of agent-based modeling (ABM) and how it can help us more deeply understand the natural and social worlds and engineer solutions to societal problems. Before we discuss why agent-based modeling is important, we briefly describe what agent-based modeling is. An *agent* is an autonomous computational individual or object with particular properties and actions. *Agent-based modeling* is a form of computational modeling whereby a phenomenon is modeled in terms of agents and their interactions. We will describe ABM more comprehensively in chapter 1. As you will see in this textbook, ABM is a methodology that can be promiscuously applied—there are few, if any, content areas where ABM is not applicable. It can enable us to explore, make sense of, and analyze phenomena and scenarios across a wide variety of contexts and content domains. In the past two decades, scientists have increasingly used agent-based modeling methods to conduct their research.

The main argument of this introductory chapter is that ABM is a transformative representational technology that enables us to better understand familiar topics, and at younger ages; make sense of and analyze hitherto unexplored topics; and enable a democratization of access to computational tools for making sense of complexity and change. As such, we believe that developing ABM literacy is a powerful professional and life skill for students, and we should strive for universal ABM literacy for all, from young students to professionals.

This textbook is a foray in the direction of such ABM literacy, aimed at undergraduate and graduate students in virtually any domain of study. To achieve universal ABM literacy, we foresee a need for many complementary such textbooks and materials aimed at a wide variety of people, topics, and social niches.

ABM is a species of computation, growing up alongside the maturation of computer technology. The advent of powerful computation has brought about dramatic change in many areas of life, including significant changes in the practice and content of science. As access to powerful computation increases (and its cost deceases), scientists are able to perform calculations and simulations that simply were not possible in the past. The increase in computational power and connectivity has also enabled the collection and analysis of very large data sets. These data sets often include data at micro-scale levels, enabling us to extract more insight as to how individuals in society behave, animals in an ecosystem survive, or elements of an engineered system affect each other. The combination of large data, cheap computation, and high connectivity allows agent-based models to be constructed with millions of individual agents whose properties and behaviors have been validated. Moreover, computational representations are dynamic and executable, allowing for greater interactivity between the user and representation. Perhaps, even more important, agent-based representations have particular advantages in that they are easy for people to understand.

Agent-based representations are easier to understand than mathematical representations of the same phenomenon. This is because agent-based models are constructed out of individual objects and simple rules for their movement of behavior, as opposed to equational models that are constructed from mathematical symbols. In our natural discourse, we commonly describe our experience in terms of the interactions of individuals, as opposed to in terms of the rates of change of aggregates as in differential equations. In thinking about individual agents, we can make sense of them by projecting our bodily experience onto the agents. Thus, the language and concepts we use in agent-based modeling is much closer to natural language and our natural thinking.

But, to a great extent, these dramatic changes in representation and in the practice of science have not resulted in significant change in the world of education. There are many reasons for the slow pace of change in "technology transfer" to the education system. One obstacle is the lack of widespread understanding of the benefits of such a transfer. In this chapter, we develop a conceptualization of this enterprise in historical and epistemological terms that we hope will situate ABM with respect to other representational advances and increase understanding of the benefits of widespread adoption.

As a first step to presenting this conceptualization, we look back historically at changes to representational tools and practices used in science and the significant benefits they had for both scientists and learners. The example that we have found most useful in presenting our idea is the shift from Roman to Hindu-Arabic numerals in arithmetic. We believe it is important to study more systematically changes of this kind, to examine the history of

science in search of cases with similar consequences for the dramatic advancement of science. By studying this transformation, we can better understand how other transformations, such as the development of ABM, can be accelerated to cultivate new insights and understandings of the world around us. We begin by looking more closely at the Roman to Hindu-Arabic numeracy transition through a thought experiment developed by Wilensky and Papert (2010).

## A Thought Experiment

Imagine a country (let's call it Foo) where people represented numbers as the Romans did, using symbols such as MCMXLVIII. Fooian scientists worked laboriously to quantify and more accurately calculate basic science such as planetary motion and dynamical forces. Businesspeople had great difficulties with their financial calculations, tradespeople struggled with their measurements, and consumers labored to assess their purchases. Educational researchers and policymakers in this imaginary country were very concerned with the difficulty of learning to handle numbers, and they worked hard to make these skills accessible to more of their citizens. They engaged in a number of different approaches. Some researchers studied the misconceptions and mistakes typically made by children. They might have discovered that some children believed that since CX is ten more than one hundred, then CIX must be ten more than CI. Others constructed and studied computer programs that allowed students to practice numerical operations. Still others developed physical representations—wooden blocks marked with the symbols C, X, V, and I—to help students learn. Members of the Fooian ministry of education called for more rigorous testing on Roman arithmetic. Yet another group tried to elucidate the problem by framing it in evolutionary terms, speculating that perhaps humans were not wired to do multiplication and division, or that such tasks were only feasible for a small subset of highly trained experts.

It is not hard to imagine, in our thought experiment, that many of these approaches brought about substantial improvements in numeracy. But let us now imagine that, at some point, the scientists of this country invented Hindu-Arabic numerals. This invention then opened up a new way to handle and think about numbers. Resulting gains toward a functional numeracy due to this representational shift would likely far outstrip any of the benefits that would have accrued from any of the improved techniques for working with the Roman numeral system. Before, the knowledge gap in arithmetic was immense; only a small number of trained people could do multiplication. After, multiplication became part of what we can expect everyone to learn.

The sort of transformation exemplified here has no name in the standard scientific or educational discourse. A first step is to name the sort of innovation associated with the shift from Roman to Hindu-Arabic representations of number. It is not sufficient, for example, to say that we have a new approach to learning and working with numbers. Even

in this simple case, things fundamentally change. The algorithms that are taught after this transformation are different. People's mental representation will alter, as will their sense of systematicity in the field. Psychologically important landmark values (i.e., V vs. 0) will be different. Even social embedding, such as "who can do what," changes (e.g., scribes or special human calculators for the emperor vs. modern carpenters or business people doing their own calculations). In our terminology, we will say that we have a new structuration of a discipline (Wilensky & Papert, 2010; Wilensky et al., 2005). We will proceed to flesh out this term through concrete examples. But, for now, we introduce a preliminary formal definition: By *structuration* we mean the encoding of the knowledge in a domain as a function of the representational infrastructure used to express the knowledge. A change from one structuration of a domain to another resulting from such a change in representational infrastructure we call a *restructuration*.

There have been many examples of restructurations in human history. Of course, our thought experiment is based on a historical reality. Before the transition from the use of Roman to Hindu Arabic numerals in Europe around the turn of the first millennium, most Europeans were able to use Roman numerals fluently. However, because Roman numerals were not very well suited to large numbers and to multiplication and division of such numbers, people went to special "experts" to perform multiplication and division for them. European mathematicians first started employing Hindu-Arabic numerals at the end of the tenth century, quickly realizing its advantages in working with large numbers. In 1202, the mathematician Fibonacci wrote a text outlining the Hindu-Arabic system that resulted in gradual adoption by scientists. Still, "universal" adoption of Hindu-Arabic numerals in Europe was not achieved until the sixteenth century—a restructuration that took more than half a millennium! Why did it take so long for a representational infrastructure quickly recognized as superior to gain widespread adoption? The case of Italian shopkeepers may help explain this quandary. Medieval Italian shopkeepers kept two sets of books for their accounting: one set, in which they did their real calculations, was kept in Hindu-Arabic; the other set, which was presented to the inspecting authorities, was kept in Roman, since a Roman representation was required by the government. The shopkeepers had to laboriously translate the first set into the second. That they deemed such translation worthwhile is a testimony to the value of the restructuration. The fact that the authorities did not officially recognize the Hindu-Arabic books was a major obstacle to the structuration's more rapid spread. We call this resistance to the spread of structurations "structurational inertia" (Wilensky & Papert, 2010). Just as an object's inertia keeps it from changing its motion, so structurational inertia keeps structurations from changing, impeding the spread of restructuration.

Our Roman-to-Arabic numeracy example is just one of many that we could have chosen. In his book *Changing Minds* (2001), DiSessa describes the historical restructuration of simple kinematics from a text-based to an algebraic representation. He illustrates this restructuration through a story of the seventeenth-century scientist Galileo. In his book

*Dialogues Concerning Two New Sciences* (1638), Galileo struggles to handle a problem involving the relationship between distance, time and velocity. He laboriously describes four theorems relating these three quantities. The reader is invited to peruse and decipher these theorems. The surprising realization is that all four of these theorems are in fact variations of the single equation $D=VT$, or distance equals velocity times time. How could it be that Galileo, inventor of the telescope, and one of the great "fathers of modern science," struggled so mightily with an equation with which most middle-schoolers are facile? The explanation is both simple and profound: Galileo did not have algebraic representation. He had to write these theorems in Italian, and natural language is not a well-suited medium for conveying these kinds of mathematical relationships. Thus, the restructuration of kinematics from the representational system of natural language to that of algebra transformed what was a complex and difficult idea for as powerful an intellect as Galileo's into a form that is within the intellectual grasp of every competent secondary student.

The development of Arabic numerals and the transformation of kinematics via algebra were empowering and democratizing, enabling significant progress in science and widening the range of people who could make sense of previously formidable topics and skills. The vista opened to the imagination is dramatic: If the problems with which we struggle today could be so transformed, think of the new domains we could enter and conquer. If algebra could make accessible to students what was hard for Galileo, what domains that are hard for us today to understand could we restructurate to make more accessible?

## Complex Systems and Emergence

What might be the analogy today? What areas are widely thought to be difficult for people to comprehend and potentially ripe for restructuration? One such area is complex systems. Its very name suggests that it is a difficult area for comprehension.

What we perceive as difficult has cognitive dimensions, but difficulty is also greatly affected by our current needs. As commerce developed in the Middle Ages, there arose an increasing need for arithmetic with large numbers, so the difficulty of doing it with Roman numerals became more salient. As science developed the need to account more precisely for heavenly bodies, the difficulty of describing their motions became more transparent. In the current day, the world we live in has become increasingly complex, in part because, in earlier periods of history, we did not have to pay as much attention to complex interactions; we could get by with understanding simple systems and local effects. Yet, as technology and science have advanced, we have become more affected by complex interactions. We are now aware that changes to the rain forest in Brazil can have dramatic effects on the climate of faraway countries; that unwise financial decisions in one country can have significant economic impact on the rest of the world; that a single case of a new disease in China can spread around the globe in short order; or that a four-minute video uploaded

by a Korean pop star can turn him into a worldwide sensation in a matter of days. As such, the difficulty of making sense of complex systems has become more salient.

However, even if the level of complexity in our life remained constant over the ages, our continual quest for knowledge would ultimately lead us to study complex systems. As we gain facility and more complete understanding of simple systems, we naturally progress to trying to make sense of increasingly complex systems. Simple population dynamics models, for example, make the implicit assumption that all members of a species are the same, but later, it becomes important to explore the manifold complexity of the food web and how each individual interacts with every other individual. Thus, our need to understand more complex systems is also a natural result of the growth of human knowledge.

As we gain knowledge, we create more sophisticated tools and these tools enable us to ask and answer new questions. As described earlier, the advent of powerful computation enables us to model, simulate, and more deeply probe complex systems.

For the reasons stated, the field of complex systems has arisen and grown. Complex systems theory develops principles and tools for making sense of the world's complexity and defines complex systems as systems that are composed of multiple individual elements that interact with each other yet whose aggregate properties or behavior is not predictable from the elements themselves. Through the interaction of the multiple distributed elements an "emergent phenomenon" arises. The phenomenon of *emergence* is characteristic of complex systems. The term "emergent" was coined by the British philosopher and psychologist G. H. Lewes, who wrote:

> Every resultant is either a sum or a difference of the co-operant forces; their sum, when their directions are the same—their difference, when their directions are contrary. Further, every resultant is clearly traceable in its components, because these are homogeneous and commensurable. It is otherwise with emergents, when, instead of adding measurable motion to measurable motion, or things of one kind to other individuals of their kind, there is a co-operation of things of unlike kinds. The emergent is unlike its components insofar as these are incommensurable, and it cannot be reduced to their sum or their difference. (Lewes 1875)

Since Lewes's time, scholars have struggled with how to best define emergence—some definitions succinct, others more involved. For our purposes, we define emergence as *the arising of novel and coherent structures, patterns, and properties through the interactions of multiple distributed elements*. Emergent structures cannot be deduced solely from the properties of the elements, but rather, also arise from interactions of the elements. Such emergent structures are system properties yet they often feedback to the very individual elements of which they are composed.

Important features of emergence include the global pattern's spontaneous arising from the interaction of elements, and the absence of an orchestrator or centralized coordinator—the system "self-organizes." Structure (or rules) at the micro-level leads to ordered pattern at the macro-level. Because the macrostructures are emergent, composed of many

elements, they are dynamic, and perturbing them often results in them dynamically reforming. Another way of thinking about such structures is to view them not as entities, but rather, as processes holding the structure in place, which are often invisible until the structure is disturbed. However, a reformed structure, while recognizably the same structure, will not be identical, since for most emergent structures, randomness plays a role in each reformation. From a micro-level perspective, this suggests that the formation rules need not be deterministic. Indeed, in many complex systems, probabilistic and random processes contribute to, and are even essential to, the creation of order.

In complex systems, order can emerge without any design or designer. The idea of order without design has been controversial throughout the history of science and religion. In modern times, the supposed impossibility of order without design has been a linchpin of the intelligent design movement against naturalistic evolution, as supporters argue that life's manifold and irreducible complexity could not arise "by chance" without a designer. Yet, complex systems theory is ever finding more complex systems that may at first seem irreducible but are found to be self-organized or evolved rather than intelligently designed by a designer.

## Understanding Complex Systems and Emergence

We have said that understanding complex systems and emergence is hard for people. Emergence, in particular, presents two fundamental and distinct challenges. The first difficulty lies in trying to figure out the aggregate pattern when one knows how individual elements behave. We sometimes call this *integrative* understanding, as it parallels the cumulative integration of small differences in calculus. A second difficulty arises when the aggregate pattern is known and one is trying to find the behavior of the elements that could generate the pattern. We sometimes call this *differential* understanding (aka *compositional* understanding), as it parallels the search in calculus for the small elements that produce an aggregate graph when accumulated. Let's now consider two examples that illustrate these concepts.

### Example 1: Integrative Understanding

Figure 0.1 presents a system composed of a few identical elements following one rule. Each element is a small arrow. We imagine a clock ticking and at each tick of the clock the arrows follow their rule. We initialize the system so that each individual arrow starts on a circle (of radius 20 units). We start them all facing clockwise on the circle. Now, we give them one movement behavior (or rule). At every tick of the clock, they move forward 0.35 units then turn right one degree. As the clock ticks, they continue to move and turn, move and turn, moving clockwise along the circle.

Now suppose that we slightly alter these rules. Instead of moving forward 0.35 units, we have them move 0.5 units while still turning one degree. What will be the aggregate

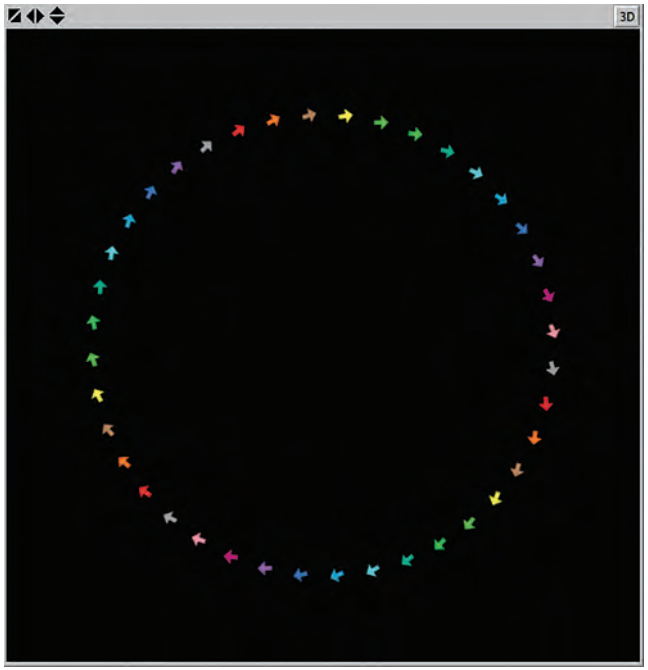


**Figure 0.1**
Some arrows moving clockwise around a circle of radius 20.

pattern that we see? Before reading further, take a moment to imagine what the pattern will be.

Most people do not predict the resulting pattern. We have heard people predict that the arrows will move onto a larger circle, a smaller circle, a flower shape, and many others. In fact, the pattern that emerges is a pulsating circle. All the arrows stay in a circle, but the circle changes its radius, first expanding, then contracting and repeating this cycle forever.

### Example 2: Differential Understanding

Now let's consider the flip side of these difficulties. There are many coherent, powerful, and beautiful patterns we observe in the world. What accounts for their prevalence? How do they originate?

The secret to understanding the formation of these patterns is to understand that they are emergent, arising from the interactions of distributed individual elements.

One such prevalent (and often beautiful) pattern is the flocking of birds. Birds fly together in many different formations, from the classic V formation of goose flocks to the

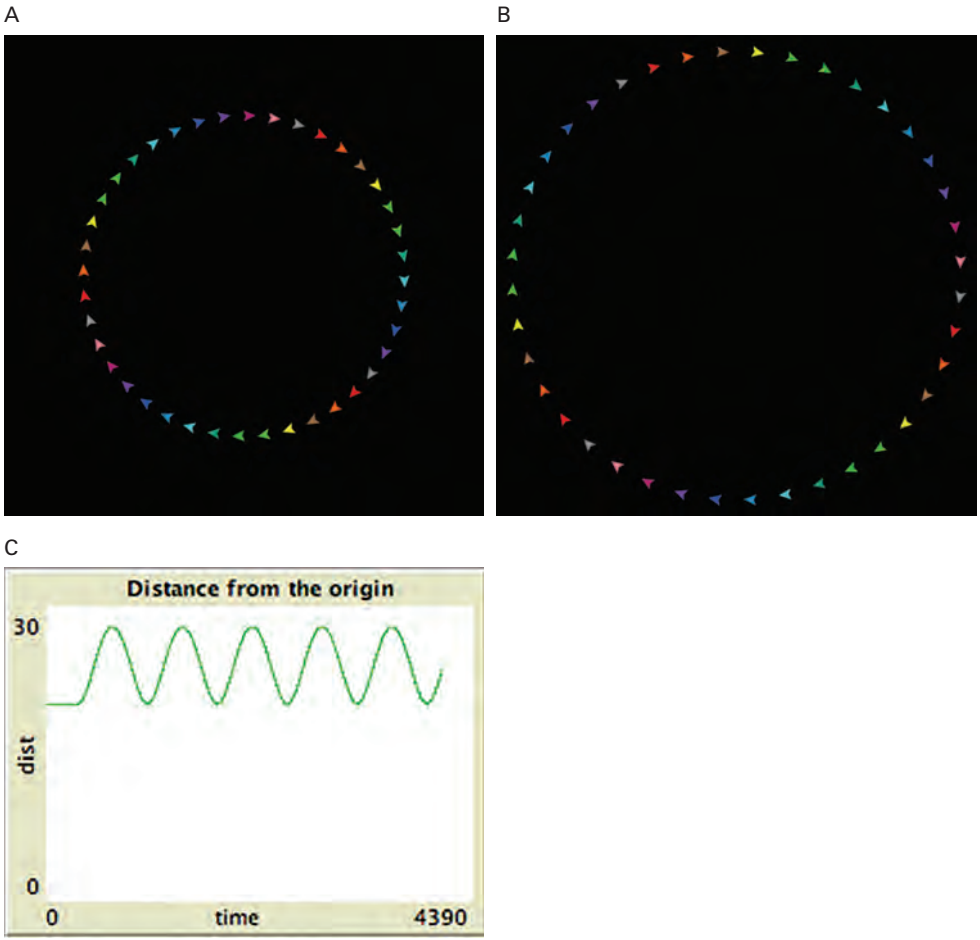


**Figure 0.2**
Pulsating circle, moving between large and small radius.

large, very dense flocks of starlings that resemble insect swarms. How and why do these flocks emerge?

Another more common (though less beautiful) pattern—this time, from the social rather than the natural world—is the traffic jam. In most industrial societies with individually driven vehicles, we see traffic jams. We tend to think of traffic jams as being composed of thousands of individual cars, but seen from a bird's-eye view, traffic jams appear as a single object moving backward against the flow of traffic.[1] What causes these jams to form?

1. See (*Wilensky, 1997a*) for a NetLogo model of a traffic jam.

**Figure 0.3**
Flock of geese flying in a classic V formation.

In the 1980s and early '90s, Wilensky and Resnick interviewed people from a wide range of backgrounds, asking them to explain how such patterns arise. The results suggested a phenomenon, or cognitive pattern, called the deterministic-centralized mindset, or DC mindset. The pattern stemmed from two main empirical findings: (1) Most subjects did not see any role for randomness in creating these structures, randomness was seen as destructive of pattern, not a force for creating pattern (the D component); and (2) Most subjects described these patterns as arising from the actions of a centralized controller or orchestrator (the C component).

When asked by the interviewer how geese get into V-formations, subjects typically responded that "it's the leader bird in the front and he is followed by his lieutenants" or "it's the mother bird up front and she is followed by her children" or "the biggest bird is up front pushing the air back and the next strongest follow." Similarly, when asked to explain why there is a traffic jam ahead, they hypothesized that there was an accident ahead or a radar trap.

All of these explanations reflect a commonly held DC mindset. Subjects imposed an orchestrated order on the elements—that they get into formation because of some social organization; some communicated social agreement, or some specific centralized cause. Furthermore, they saw such patterns as deterministic. The same bird is up front, determined

A

B

**Figure 0.4**
Flocks of starlings (thousands of birds) acting as a swarm.[2]

2. For beautiful video of massive starling swarms, called murmurations, see: http://www.huffingtonpost.com/2013/02/01/starling-murmuration-bird-ballet-video_n_2593001.html, http://www.youtube.com/watch?v=PnywhC36UVY, http://www.youtube.com/watch?v=XH-groCeKbE, or http://www.youtube.com/watch?v=iRNqhi2ka9k.

**Figure 0.5**
*Traffic Jam* by Osvaldo Gago, 2005.

by a pecking order; the jam occurs at a specific place because the accident or radar trap was there, rather than at random locations along the road.

To be sure, accidents and radar traps cause some traffic jams. Most, however, arise from the random entry of cars into, say, a highway and the resultant statistical distribution of cars and speeds.[3] Similarly, science has established that bird flocks are not centrally organized; rather than the same bird staying at the apex of the V formation, different birds occupy that spot. The composition of the formation, hence, is not deterministic, but rather, emergent from birds' independent movements as they head in a particular direction, trying to avoid other birds and yet not get too far from their neighbor birds.[4] We will further explore models of flocking in chapter 7.

In further analyses of the interviews, Wilensky and Resnick (1999) identified a key component of the DC mindset and an obstacle to thinking about emergent phenomena: the problem of "thinking in levels." Emergent phenomena can be described as existing on at least two levels: the level of the individual elements (cars, birds, people, etc.); and the level of system or aggregate patterns (flocks, traffic jams, housing patterns, etc.). Most

3. For a video of a fascinating experiment to create traffic jams, see http://www.newscientist.com/article/dn13402-shockwave-traffic-jam-recreated-for-first-time.html.

4. For a NetLogo model of birds flocking, see *Wilensky (1998)*.

people fail to distinguish between these levels, instead "slipping" between levels to attribute the properties of one level to the other. Consider a V- flock, which appears to be stable and to have a consistent shape. The *appearance* of stability often leads people to conclude that the individual elements of the flock (the birds) *are* stable and have a consistent place in the flock. As we have seen, however, this is a misunderstanding based on a slippage between levels, and is an example of a failure in differential understanding. In this example, the shape of the flock is salient; the birds' behavior is less so. The natural direction of levels slippage is from aggregate to individual. We are seduced into transferring a property of the aggregate to the individual elements. With the case of traffic, we are much more familiar with the ways individual cars move then we are of aggregate traffic patterns. When we typically think about traffic, we are seated inside a car, very aware of its movements and how it responds to the movements of other cars. When we encounter a jam, we are likely to think of it as behaving like a car; we imagine it as responding to the stopping of a car in an accident and moving forward like a car, rather than moving backward as jams actually do. Here, the direction of levels slippage is opposite to that of bird flocks: the properties of the individual elements, the cars are transferred *to* the aggregate pattern, the jam. This is an example of a failure of integrative understanding.

Wilensky and Resnick also showed a host of examples where this levels slippage interfered with both integrative and differential understanding of complex phenomena in the natural and human social worlds. Furthermore, this mindset is not just a problem of the scientifically naïve. Trained scientists also fall prey to the DC mindset.[5] Wilensky and Resnick presented a host of examples across an array of content and contexts (e.g., economic markets, predator-prey relations, slime-mold behavior, human housing patterns, growth of crystals, insect foraging) where levels slippage interfered with understanding. Many of these examples (and a host of new ones) will appear in this book. Indeed, in the past two decades, researchers have found that emergent phenomena are endemic to the natural and social worlds and that using an emergent lens to make sense of complex patterns is a vital need in a twenty-first-century world.

## Agent-Based Modeling as Representational Infrastructure for Restructurations

Returning to Roman-to-Arabic numerical restructuration analogy, we suggest that new computer-based representations can help restructurate our knowledge in many domains. With the aid of new computer-based modeling environments, we can simulate complex patterns and better understand how they arise in nature and society. Whereas in many areas

5. Keller and Segal (1985) described the scientific study of slime molds and how it was shaped by the DC Mindset. At certain stages of their life cycle, slime molds gather into clusters. Early in the study of slime molds it was assumed that there was a "founder" or "pacemaker" that controlled the aggregation process, but later it was discovered that there was no need for a specialized coordinator. Yet the centralized view was embraced and vehemently defended for more than a decade, despite strong evidence to the contrary.

of science we have relied on simplified descriptions of complexity—often using advanced mathematical techniques that are tractable and allow us to calculate answers—we can now use computation to simulate thousands of individual system elements, called "agents." This allows new, more accessible and flexible ways to study complex phenomena—we simulate to understand.

Agent-based modeling is a computational methodology that enables one to model complex systems. As the name suggests, agent-based models are composed of *agents:* computational entities that have properties, or *state variables and values* (e.g., position, velocity, age, wealth, etc.). Agents usually also have a graphical component so you can see them on the computer screen. An agent can represent any element of a system. A gas molecule agent, for instance, might have properties such as "mass" with value 30 atomic mass units, "speed" with value 10 meters per second, and "heading" with a value of the angle it is facing. A sheep agent, by contrast, might have properties such as "speed" with value 3 mph, weight with value 30 lbs., and fleece with a value of "full" (a discrete-textual rather than numerical value). In addition to their properties, agents also have rules of behavior. A gas molecule agent might have a rule to collide with another molecule; a sheep agent might have a rule to eat grass if there is grass available nearby. In an agent-based model, we imagine a universal clock. When the clock ticks, all agents invoke their rules. If the conditions of the rules are satisfied, (e.g., they are at the edge of a box, or grass is nearby), they enact the behavior (i.e., bounce or eat grass). The goal of agent-based modeling is to create agents and rules that will generate a target behavior. Sometimes the rules are not well known, or you just want to explore the system's behavior. In that case, ABM can be used to help you better understand a phenomenon through experimentation with rules and properties.

A working hypothesis of representational theorists is that anything that is perceived as difficult to understand can be made more understandable by a suitable representation. We contend that ABM's enable restructurations of complex systems so that the (a) understanding of complex systems can be democratized and (b) the science of complex systems can be advanced. This hypothesis begets a design challenge: Can we design a suitable representational language that supports both parts of the claim, enabling scientists to author scientific models in this language while simultaneously enabling a wider audience to gain access to (and understand) complex systems?

The computer language used in this text, NetLogo (*Wilensky, 1999*), was developed by Uri Wilensky for these express purposes.[6] It is a general-purpose agent-based modeling language designed to be "low-threshold"—that is, novices can quickly employ it to do meaningful and useful things—but also "high-ceiling"—meaning that scientists and researchers can use it to design cutting-edge scientific models. The language borrows much of its syntax from the Logo language, which was designed to be accessible to children.

6. NetLogo is freely available from ccl.northwestern.edu/netlogo.

Like Logo, NetLogo calls its prototypical agent a "turtle." However, while in Logo, the user directs the turtle to draw geometric figures, in NetLogo, this is generalized to thousands of turtles. Instead of drawing with pens, they typically draw with their bodies, moving according to rules, and the configuration of their bodies presents a visualization of the modeled phenomenon. NetLogo was first developed in the late 1990s, and it is now in use by hundreds of thousands of users worldwide. Thousands of scientific papers have utilized NetLogo to construct and explore models in a wide variety of disciplines. It has also been employed by policymakers to model policy choices, business practitioners to model business decisions, and students to model subject matter in their coursework across virtually the entire curriculum. Many NetLogo-based courses have sprung up in both universities and in secondary schools.

As of yet, no textbook has been written that gives a general and systematic introduction to NetLogo in all of its features and shows how to use it to model phenomena across many different domains. It is our hope that this textbook will serve to enhance and further democratize ABM literacy. We envision it being used as a primary textbook in an agent-based modeling course, but it can also serve as a supplementary textbook in virtually any university course whose subject matter is amenable to agent-based modeling.

We further maintain that virtually every university subject can benefit from a basic familiarity with agent-based modeling. Some subject domains have embraced agent-based modeling from the start, such as chemistry, biology, and materials science. Others embraced it in a second wave, such as psychology, sociology, physics, business, and medicine. Recently, we have seen the growth of agent-based modeling in economics, anthropology, philosophy, history, and law. While different fields have different degrees of structurational inertia, there is no end to the domains of application for ABM. However, differences in structurational inertia render some fields more easily adaptable to ABM restructurations than others. To illustrate the potential power of widespread agent-based modeling literacy and restructuration, we will look briefly at two examples derived from different content domains: predator-prey interactions and the spread of forest fires.

#### Example: Predator-Prey Interactions

Let us start with the study of predator-prey interactions. This domain is often first introduced qualitatively in high school, then quantitatively at the university level. In its quantitative form, the population dynamics of a single predator and prey are introduced by the classic Lotka-Volterra differential equations, a pair of coupled differential equations that proceed as follows:

$$\frac{dPred}{dt} = K_1 * Pred * Prey - M * Pred$$

$$\frac{dPrey}{dt} = B * Prey - K_2 * Pred * Prey$$

The first equation says that the number of predators increases as predators interact with prey (by fixed constant $K_1$) and decreases by a constant mortality rate ($M$). The second equation says that the number of prey increase by a constant birthrate ($B$) and decreases in interaction with predators (by a fixed constant $K_2$). The solution to these equations resembles the classic sinusoidal curves that show a cycling of the predator populations with one ascendant when the other is at a trough.

These equations are fairly straightforward if you are familiar with differential equations; but, even then, the mechanisms that cause these dynamics are not readily apparent from the equations. We are still left to ponder: How do predators increase through interacting with prey? One can speculate on several chains of mechanisms for this increase, but they are not explicit, and neither is why this increase happens at a constant rate, $K_1$.

By contrast, an agent-based representation of predator and prey, such as the one illustrated in figure 0.6, would typically employ simple algorithmic models. They might give each predator and prey a store of energy that is depleted when they move and increased when they eat. If their energy dips too low, they die. If it is high enough, they might reproduce. And when they move, if they encounter food (which, for the predator, is the prey), they eat it. These instructions are explicitly stated in an easy-to-read language that

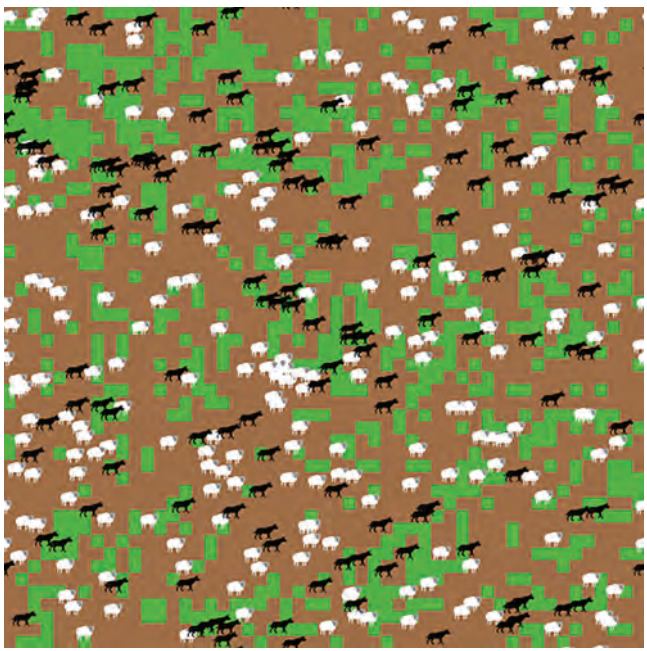

**Figure 0.6**
An agent-based Wolf Sheep Predation model. (See *Wilensky, 1997c*)

instructs each agent in how to behave, and accompanies the visual model. This kind of representation makes its mechanisms explicit; as such, they are usually quite understandable by even young children. They also can be challenged more easily and tested. We will explore such predator-prey models in detail in chapter 4.

There are many advantages to agent-based representations. First, it does not require knowing calculus. Requiring calculus to be able to reason about predator-prey interactions sets the entry threshold quite high. In the United States, only a small percentage of adults have ever taken calculus, and far fewer are familiar with differential equations. So calculus serves as a gatekeeper limiting access to important content to a small minority of adults and to almost all children. Yet the content of the predator-prey model can be made quite accessible to a non-calculus audience through ABM. This gatekeeper problem may seem less formidable when thinking about an audience of scientists who have likely had calculus. Even with this audience in mind, it is still often difficult to uncover the mechanisms behind the equations, to challenge them, and to propose alternate mechanisms and new equations.

Our example of the restructuration of numeracy and the example above might lead the reader to believe we are arguing for the replacement of equational representations with ABMs. That is not our intent. Agent-based models can serve as powerful complements to equation-based models. They are particularly effective entry points into scientific domains. But they also have some disadvantages as compared to equations. For an expert, an equation can more compactly represent a phenomenon than can an ABM. Moreover, when the equation is solvable, it enables the direct calculation of results without the need to run a model. When a model requires a large numbers of agents, its execution time can be so long as to be impractical as a way of calculating results. The corresponding equation-based models must often make many simplifying assumptions to gain this increase in speed. These simplifications are most justifiable when the agents are sufficiently homogenous that it can be advantageous to treat them as average quantities as opposed to the heterogeneous individuals often used in ABM. In this textbook, we will provide some guidelines as to when an ABM approach is likely to be most effective and when other approaches may be better. In general, exploring complementary approaches to a single problem provides us with deeper insight. If multiple different approaches find a similar pattern of behavior at different levels of analysis, then there is better confirmation of the underlying result.

One disadvantage of ABM representation is somewhat ironic. Many people are more prone to accept the differential equation representation at face value and can be quite critical and skeptical of the ABM representation. That is a consequence of the way ABM concretizes mechanisms and makes reasoning more accessible. For example, people might critique the simplification of having reproduction happen asexually in a predator-prey model or of the particulars of the movements of the predators and prey. This can lead critics to conclude that the ABM model is not well justified, whereas the equational model

is the more valid. But the equational model is not more valid; it, too, is a model, and a highly simplified one at that. In fact, we now know from the works of biologists such as Gause (1936) that the equational model is less accurate than an ABM in the isolated predator-prey situation for which it was intended. In particular, the equational model underrepresents extinctions, since the model uses real numbers to represent the population densities. This means that the prey population, for example, can dip to 0.5, or 0.1, or 0.01 and yet still come back. In the real world, however, populations are discrete. When the model goes below one prey (or a pair), it reaches a functional point of no return.

#### Example: Forest Fires

Our second example is about the spread of a forest fire. This domain is not usually present in the K-12 or university curriculum, but when taught, it typically falls under the subject matter of physics, described in terms of two classic partial differential equations. The first is the classic heat equation, which describes the distribution of heat in a given region over time, where theta represents the thermal diffusivity of the material through which the heat is traveling.

$$\frac{dH(x,t)}{dt} = \theta \frac{d^2H(x,t)}{dx^2}$$

The second equation physicists use to describe the spread of a forest fire treats the fire as if it were a potentially turbulent fluid, thus using the Reynolds equation of fluid flow.

$$\frac{dU_i}{dt} + U_j \frac{dU_i}{dx_j} = -\frac{1}{\rho}\frac{dP}{dx_i} + v\frac{d^2U_i}{dx_j dx_j} - \frac{d}{dx_j}\overline{u_i^t u_j^t}$$

Needless to say, these equational representations are well beyond students in the K–12 years and, we would guess, the vast majority of undergraduate science majors. Understanding what they mean and how to compute them requires significant knowledge of higher-level physics as well as the machinery of partial differential equations.

Contrast this with the ABM approach to modeling forest fires (illustrated in figure 0.7), which would typically model the environment as a grid of cells with trees occupying certain cells. Modeling the spread of fire consists simply of giving rules to the cells that are on fire as to when to spread to neighboring tree cells. This representation is so simple, we have seen elementary school students comprehend and explore it. They can experiment to see how different densities of trees in the forest affect the fire spread and they can modify the basic model to ascertain the effects of wind, or wood type, or fire source. We will explore an ABM of a forest fire in chapter 3 and consider such extensions. Of course, a very simple ABM of forest fire spread would not correctly model a particular fire, but it does give insight into the dynamics of any fire and once we know the details of a particular fire, we can add in whatever data or rules that apply to the situation. This enables

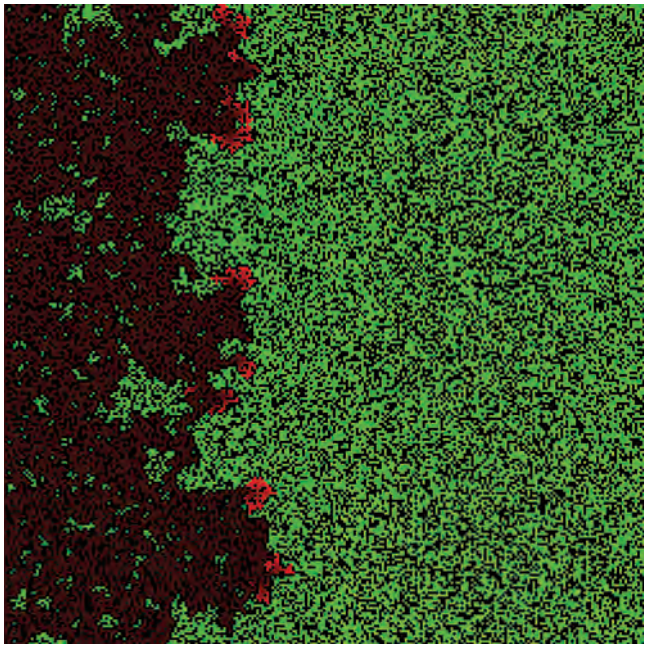

**Figure 0.7**
An agent-based model of a forest fire. (See *Wilensky, 1997b*)

even scientists to experiment much more fluidly with different models of spread, iteratively refining their models. ABM methods are starting to be used to model and fight real forest fires (see, e.g., www.simtable.com for a company that does agent-based modeling of emergency management including wildfires).

The restructuration of these systems using ABM provides several representational benefits. They make use of discrete rather than continuous representations, which are more easily comprehensible, more closely match real-world situations and require much less formal mathematics to employ. They are easier to explore and much easier to modify. They present immediate feedback with visualizations that allow researchers and practitioners to understand and critique them at two levels, the level of the overall aggregate pattern, such as the fire spread or predator population levels, but also the level of the behavior of the individual animals, and the fire spread to particular trees. Though these two examples highlight some of the advantages of agent-based restructurations, the full potential of ABM restructuration is not yet evident either in these examples, or in science as a whole.

The two examples we have given here come from the natural sciences. We believe the potential of ABM restructurations may be even more important in the social sciences. This is because the core representational infrastructure in the social sciences consists of words

and texts. Words and texts do not as easily specify the precision of an idea and can thus be interpreted in fundamentally different ways by different people. Moreover, words and texts are not dynamic representations, so they cannot give you immediate feedback as to the consequences of the assumptions embedded in them. By capturing social science theories in dynamic ABM representations, we make their assumptions explicit, and they become demonstrations of the consequences of their assumptions. If someone wants to disagree with your model, he or she must show how either an assumption is incorrect or missing or show how the logic of the interactions is flawed. The model serves as an object-to-think-with and a test bed for alternate assumptions. This can be particularly powerful when it comes to issues of policy where one can rapidly test many different alternative potential scenarios and examine their consequences. As such, ABMs serve as powerful complements to text-based explanations.

Over the past twenty years, the authors of this textbook have been working on improving the infrastructure, NetLogo, and also on restructurating domains. We have been involved with agent-based restructurations at all levels of schooling, in a wide variety of domains including most of the natural and social sciences and engineering. Restructurations have been performed in a range of fields so diverse as to include cognitive and social psychology, linguistics, biology, chemistry, physics, and many more. Agent-based models are now used in the professions to do research in medicine and law and by policymakers to help them explore effects of alternative policies.

There is still much work to do to establish the representational infrastructure and the science of ABM. What is needed is widespread literacy in agent-based modeling. We are hopeful that this textbook will move us forward and enable a large number of students to learn about and master this new representational infrastructure. We envision a series of textbooks that use agent-based modeling to restructurate many specific subjects. It is our hope that this textbook will help to spread literacy in agent-based modeling, to catalyze these restructurations, and that the widespread use of agent-based representations will take considerably less than five hundred years.

# 1 What Is Agent-Based Modeling?

*Go to the ant, O sluggard; consider her ways, and be wise.*

*—Proverbs 6:6*

## Ants

The ant opens her eyes and looks around. There are many of her siblings nearby, but there is no food. The ant is hungry, so she heads out from the ant colony and starts to wander around. She sniffs a little to the left and a little to the right, and still she cannot smell any food. So she keeps wandering. She passes by several of her sisters, but they do not interest her right now; she has food on her mind. She keeps wandering. Sniff! Sniff! Mmmm … good! She gets a whiff of some of that delightful pheromone stuff. She heads in the direction of the strongest pheromone scent; in the past there has been food at the end of that trail. Sure enough, as the ant proceeds along the trail, she arrives at some delicious food. She grabs some food and heads back to the colony, making sure to drop some pheromone along the way. On the way back, she runs into many of her sisters, each sniffing her way along pheromone trails, repeating the same process they will carry out all day.

What we have just fancifully described is an ant foraging for food. The opening paragraph of this section is in itself a model of ant behavior. By a *model*, we mean an abstracted description of a process, object, or event. Models can take many distinct forms. However, certain forms of models are easier to manipulate than other forms. The textual description in our first paragraph cannot easily be manipulated to answer questions about the ant colony's behavior—for example, what would we see if all the ants in the colony followed the behavior we described? It is difficult to extrapolate from the textual description of one ant to a description of an ant colony. The textual model is not sufficiently generative to answer such questions. It is a fixed description—always "behaving" the same, thus not bestowing any insight into the range of variation in behaviors. And it is not combinatorial—we cannot use the description to understand the interaction of the ants with each other or with the environment.

One way to make the preceding model more generalizable and gain insight into the behavior of an ant colony would be to implement the model in a computational form. A *computational model* is a model that takes certain input values, manipulates those inputs in an algorithmic way, and generates outputs. In computational form, it would be easy to run the "Ants" model with large numbers of ants and to observe the model's outputs given many possible different inputs. We use the term *model implementation* to refer to this process of transforming a textual model[1] into a working computational simulation (written in some form of computer "code"). Besides textual models, there are other forms of *conceptual models* that describe processes, objects, or events but are not computational; conceptual models can also be diagrammatic or pictorial.

This description lends itself particularly well to being implemented, since it results from a particular standpoint, that of an individual ant, or ant *agent*. By the word *agent*, we mean an autonomous individual element of a computer simulation. These individual elements have properties, states, and behaviors.

The ant is an agent. It has properties such as its appearance and its rate of movement. It has characteristic behaviors such as moving, sniffing, picking up food, and dropping pheromone. It has states such as whether or not it is carrying food (a binary state) and whether it can sense how much pheromone is in the environment around it (a multivalued state).

Agent-based modeling (ABM) is a computational modeling paradigm that enables us to describe how any agent will behave.[2] The methodology of ABM encodes the behavior of individual agents in simple rules so that we can observe the results of these agents' interactions. This technique can be used to model and describe a wide variety of processes, phenomena, and situations, but it is most useful when describing these phenomena as *complex systems*. Our aim in this textbook is to facilitate your creating, modifying, and analyzing the outputs of agent-based models. We begin by describing the genesis of the ant foraging conceptual model and how it was implemented as an agent-based model.

### Creating the Ant Foraging Model

Many biologists and entomologists have observed ants in the wild (Hölldobler & Wilson, 1998; Wilson, 1974) and have described how ants seemed to form trails to and from food sources and their nest. In the next few paragraphs we will describe some hypotheses about how the ants accomplish this behavior and what mechanisms are at work that enable ants to find food in this way.[3] Perhaps the trails form as follows: After an ant finds food, it goes

1. Or, more generally, a conceptual model in any form.

2. We will use the acronym ABM in several ways in this textbook. Sometimes we will use it to refer to the practice of agent-based modeling. Other times, we will use an ABM to refer to an agent-based model, or ABMs to refer to agent-based models. We rely on context to disambiguate our use of the term.

3. Our account of ant behavior is inspired by the actual history of the scientific study of ants. It has been simplified here for the sake of exposition. For a more detailed account, see Theraulaz and Bonabeau (1999).

**Box 1.1**
Complexity and Complex Systems

The study of complex systems has become an important scientific frontier. By the term *complex system* we mean *a system composed of many distributed interacting parts*. The field of complex systems or complexity science arose in the mid-1980s and was born out of a variety of disparate fields from economics to physics to ecology. Complex systems science provides a set of tools and frameworks for viewing phenomena. Any phenomenon can be viewed as a complex system, and choosing when to do so depends on assessing when it is most useful to use the lens and/or methodologies of complex systems. One important methodology of complexity science is agent-based modeling. The history of agent-based modeling and complex systems is explored in greater depth in subsequent chapters, and its roots in computer science are described in the appendix.

back to the nest, drops the food off, and communicates to the queen ant, and this queen ant tells the other ants where the food is and sends them off to collect it. Suppose a researcher notices that the food-finding ant never communicates with any kind of "boss" ant before leaving the nest again, so the researcher might reason that food gathering was not working through a centralized leader or controller but rather through distributed control (Bonabeau et al., 1999; Deneubourg et al., 1990; Dorigo & Stützle, 2004).

Another hypothesis that could be advanced is that perhaps the ant did not communicate with a central leader, but rather simply communicated with other ants, and those other ants were able to "diffuse" the information about the food source throughout the nest. There is reason to believe such a hypothesis might be true, since bees work in a similar way; when a bee finds a food source, it returns to the hive and conducts a complicated dance that tells the other bees where to find the food (Gould & Gould, 1988). However, though ants do have some methods of communicating information directly (Hölldobler & Wilson, 1998) most species do not communicate the exact route to a food source in this way. In fact, scientists rarely observe any difference in behavior between an ant returning to the nest with food and an ant returning without food. Most ants returning without food simply leave the nest again and recommence their search for food; the ants act almost exactly like they had before they found food. From this it is possible to reason that there must be some communication method between the ants or the colony could not efficiently gather food. In the mid-twentieth century, biologists such as Wilson (1974) found that ants with food do act slightly differently from ants without food. Ants with food drop a chemical pheromone onto the ground as they are carrying their food. This pheromone interacts with the environment by diffusing and evaporating.

Maybe this pheromone is the key to ant communication? An ant that finds food communicates where the food is by depositing a pheromone into the environment, and the

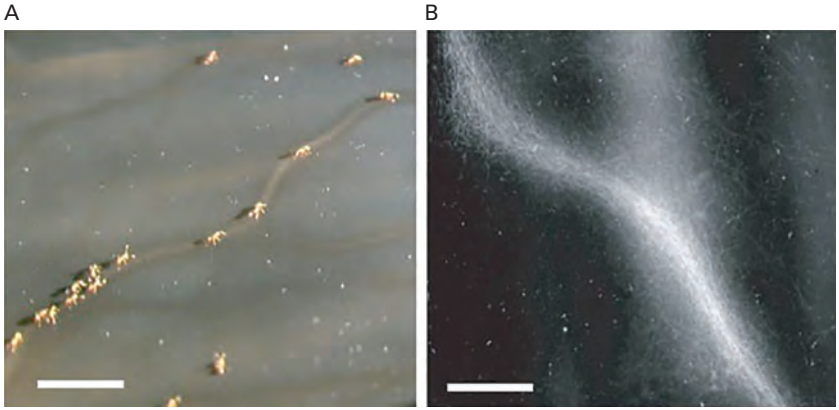


**Figure 1.1**
Ant trails. Pheromone trail networks of pharaoh ants on a smoked glass surface. (A) Part of a network showing bifurcations to smaller trails (scale bar: 1 cm). (B) Close-up of a single bifurcation (scale bar: 0.5 cm).[4]

other ants follow the gradient of this pheromone trail back to the original food source.[5] This would explain not only the trails that the ants form but also additional phenomena that can be observed. For instance, if ants communicated directly about food sources (as in the first two hypotheses), then any ant would have to communicate with the ant that had discovered the food source, or communicate with an ant that had communicated with that ant. However, the pheromone hypothesis does not require such a complex network of communication. Essentially, the new ant simply picks up the pheromone trail in midstream and is able to follow it correctly to the food source. No direct communication between ants is required. It also explains why the ants do not go directly to the food source (i.e., they do not make a *bee line* as bees do, where they fly directly toward the food source); instead, ants tend to follow roughly along the trail. This is because the pheromone trail can get weaker and stronger in different places as it is placed on different surfaces and in different exposures. (See figure 1.1.)

All of these descriptions require that the ants have knowledge of how to return to their nest directly regardless of how much they have wandered away from it. A combination of both experimental evidence and computational models have confirmed that ants can determine the most direct route back to their nest guided by the sun, outlines of the sky, or magnetic north (Wittlinger et al., 2006; Hartmann & Wehner, 1995; Lent, Graham & Collett, 2010).

4. Jackson et al., 2004. Adapted by permission from Macmillan Publishers Ltd: NATURE.

5. The process of communication where information is transmitted by altering the local environment is called *stigmergy* (Grasse, 1959).

Now that we have a basic hypothesis (in the form of a textual model) that describes the behavior of the ant, how do we implement the model so that we can test out this hypothesis and see if our computational model adequately accounts for what we observe in nature?[6] The first step is to create a more algorithmic description of the preceding textual model. This is just another model itself, but one that is more easily translated into an implemented model. Here is one set of rules that an individual ant could follow in order to operate in accordance with the model described earlier. We describe the rules from the point of view of an individual ant.

1. If I am not carrying food, I check if there is food where I am; if there is, I pick it up; if there isn't food right here, I try to sense a pheromone trail nearby; if I find one, then I face "uphill" along the pheromone gradient toward its strongest source.
2. If I am carrying food, I turn back toward the nest and drop pheromone on the ground below me.
3. I turn randomly a small amount and move forward a step.

These rules are easily implemented in a computer language. There are many computer languages in use for many purposes, but only a few are especially tailored to work with agent-based modeling. One of these is NetLogo (Wilensky, 1999a). NetLogo is both a modeling language and an integrated environment designed to make agent-based models easy to build. In fact, NetLogo is so easy to use that, rather than describe algorithms and models in pseudo-code,[7] throughout this textbook we will use NetLogo instead. Describing the preceding rules in the NetLogo language is straightforward. Here, for example, is one translation of rules 1–3 into NetLogo code:

```
If not carrying-food? [ look-for-food ]     ;; if not carrying food, look for it
if carrying-food? [ move-towards-nest ]     ;; if carrying food turn back towards the nest
wander                                      ;; turn a small random amount and move forward
```

This code snippet is not the complete implemented model but it does describe the core components that go into the Ants model. To complete the model we need to describe each of the subcomponents (such as "move-towards-nest," and "look-for-food," and "wander" and "look-for-food" will need to describe the ant's sniffing for pheromone). Each of which is a small amount of code. The result will be a fully implemented computational model. (See figure 1.2.)

Let us quickly try to "read" the code snippet and understand what it is doing. The "if" primitive takes as input a predicate (i.e., a statement that is either true or false) and takes

6. The process of comparing data from a computational model to real-world data is called *validation*. It will be discussed in depth in chapter 7.

7. Pseudo-code is an intermediate form between text and computer code that is often used to describe computational algorithms.

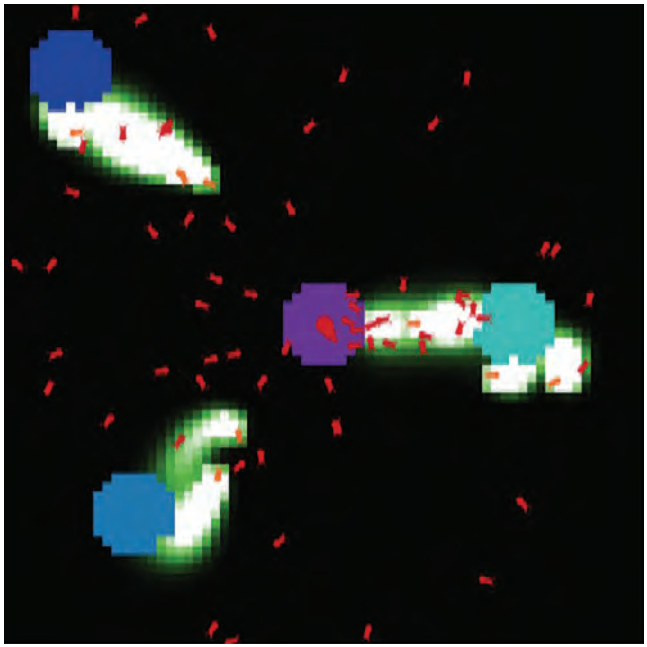

**Figure 1.2**
NetLogo "Ants" model of foraging behavior.[8]

one action if the predicate is true and another if it is false. The first "if" in the preceding code asks if the ant is carrying food. If she is not carrying food, then she takes the first action, that is, to look for food. She does this by checking to see if there is food where she is standing, and if there is not she looks around to see if there is a pheromone trail nearby that she can follow to find food (this is all described in the "look-for-food" procedure). If she is carrying food, then she takes the second action, which is to turn back toward the nest. To head back to the nest, she first determines if she is at the nest, if she is, then she drops her food, otherwise she turns so as to follow the trail back to the nest, dropping some pheromone along the way, since she just came from a food source. Regardless of whether she is looking for food or returning to her nest, the ant wanders a little bit along the direction she is heading. This is to simulate that ants, as with almost all animals, do not usually follow a straight line, but instead take small steps in other directions along the way.

By the end of chapter 3, you will be able to make substantive modifications to this model, and by chapter 4, you will be able to construct such a model on your own.

8. http://ccl.northwestern.edu/netlogo/models/Ants (*Wilensky, 1997*).

**Box 1.2**
Exploring the Ant Foraging Model

To explore this model in more depth, open the Ants model (Wilensky, 1997) (found in the Biology section of the NetLogo models library). Once you open this model, you will see a set of controls that you can manipulate to change the parameters of the model. Try varying some of the parameters (e.g., POPULATION, DIFFUSION-RATE, EVAPORATION-RATE), and explore the accompanying material that discusses this model and the real-world experiments it is based upon. As you manipulate the model, consider the following questions:

1. How does the evaporation rate affect the ability of the ants to form trails to the food? What happens if there is no evaporation?
2. How does the rate of diffusion affect the kind of trails the ants form?
3. How does the number of ants affect the colony's ability to consume the food?

### Results and Observations from the Ant Model

When running the Ants model, the results are initially surprising for someone who has only seen the rules for the individual ants. The "aggregate" or "macro" behavior of the model shows apparently systematic food gathering behavior. It is as if the ant colony has a clear plan for how to gather the food. Yet, we have seen that the Ants model rules do not contain any systematic foraging plan. If we look closely at the model running, we observe that initially the ants wander around at random. Then some ants will wander into a nearby food source. Once they find that food source, they will start to bring food back to the nest, laying a pheromone trail beneath them. If just one lone ant finds the food source, the pheromone trail will not be strong enough for other ants to follow it; but as more and more ants find the food source, the trail will become stronger and stronger. Eventually, the actions of many ants will create a strong pheromone trail from the nest to the food source, and so any ant can easily find the trail to the food source.

The ants as a group appear to exploit food sources in an optimal manner. That is, they first gather food from the nearest food source, then the second nearest, and so on. This appears to be a conscious plan of the ant colony; but as we know from the ant rules, this is not the case. In fact, as you observe the model closely, you will note that sometimes ants operate almost at cross-purposes with other ants, creating additional pheromone trails to farther food sources and distracting some of the ants that are currently harvesting the closer food source. The ants do not have a centralized controller; instead, the nearest food sources are the most likely to be found first by the ants randomly wandering from the nest. The nearest food sources also require the least amount of pheromone since the pheromone only has to cover the shortest path from the nest to the food. Once a sufficient number of ants have found a particular food source, the pheromone trail to it stabilizes and thus