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

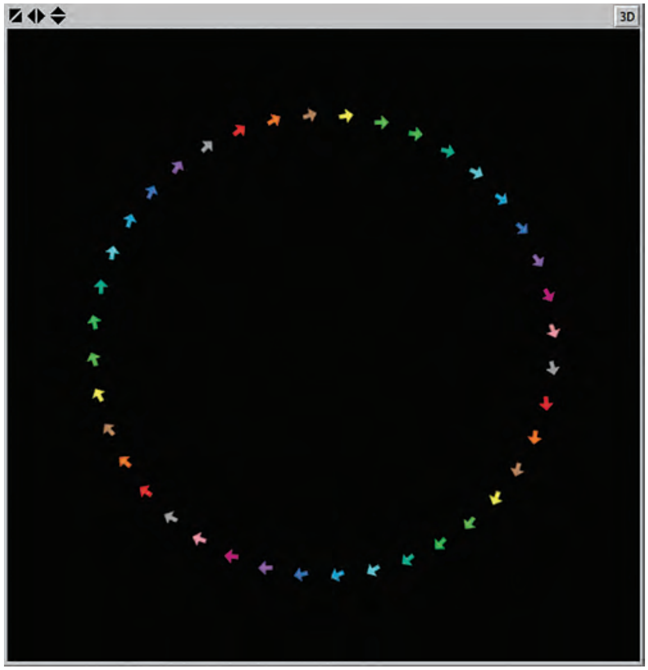

Figure 0.1
Some arrows moving clockwise around a circle of radius 20.

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

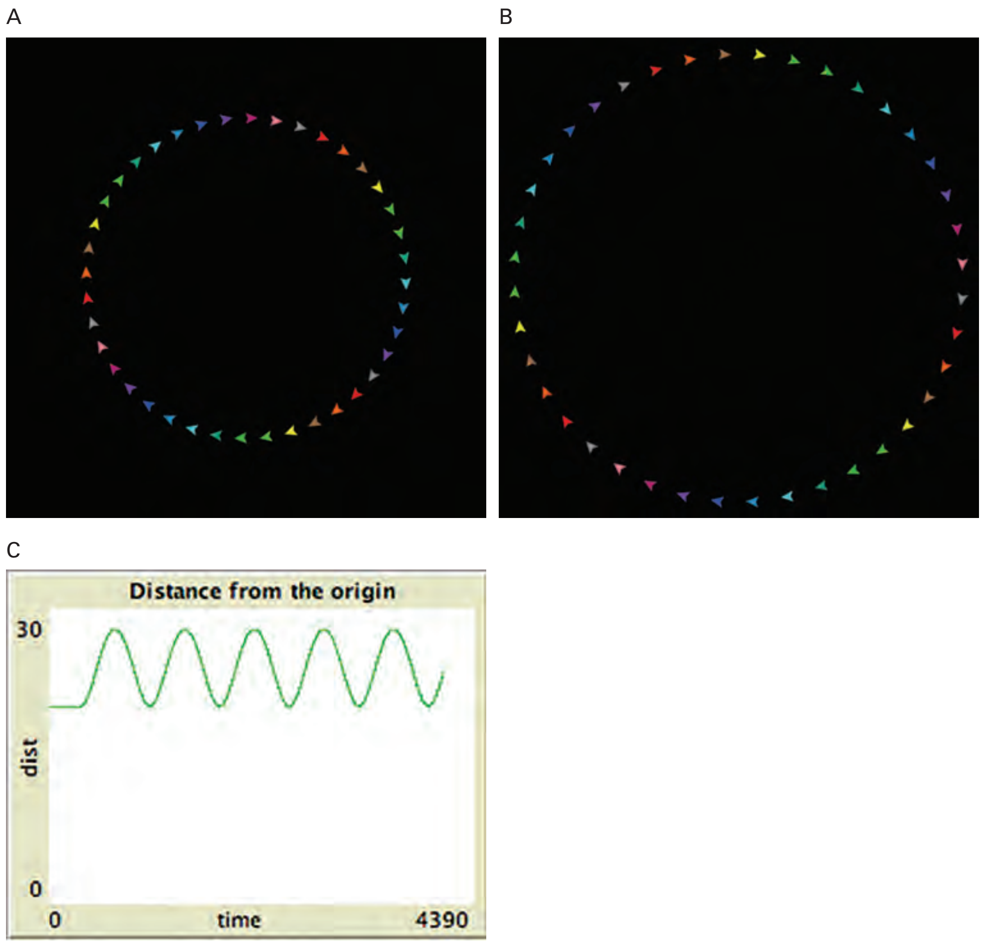

Figure 0.2
Pulsating circle, moving between large and small radius.

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

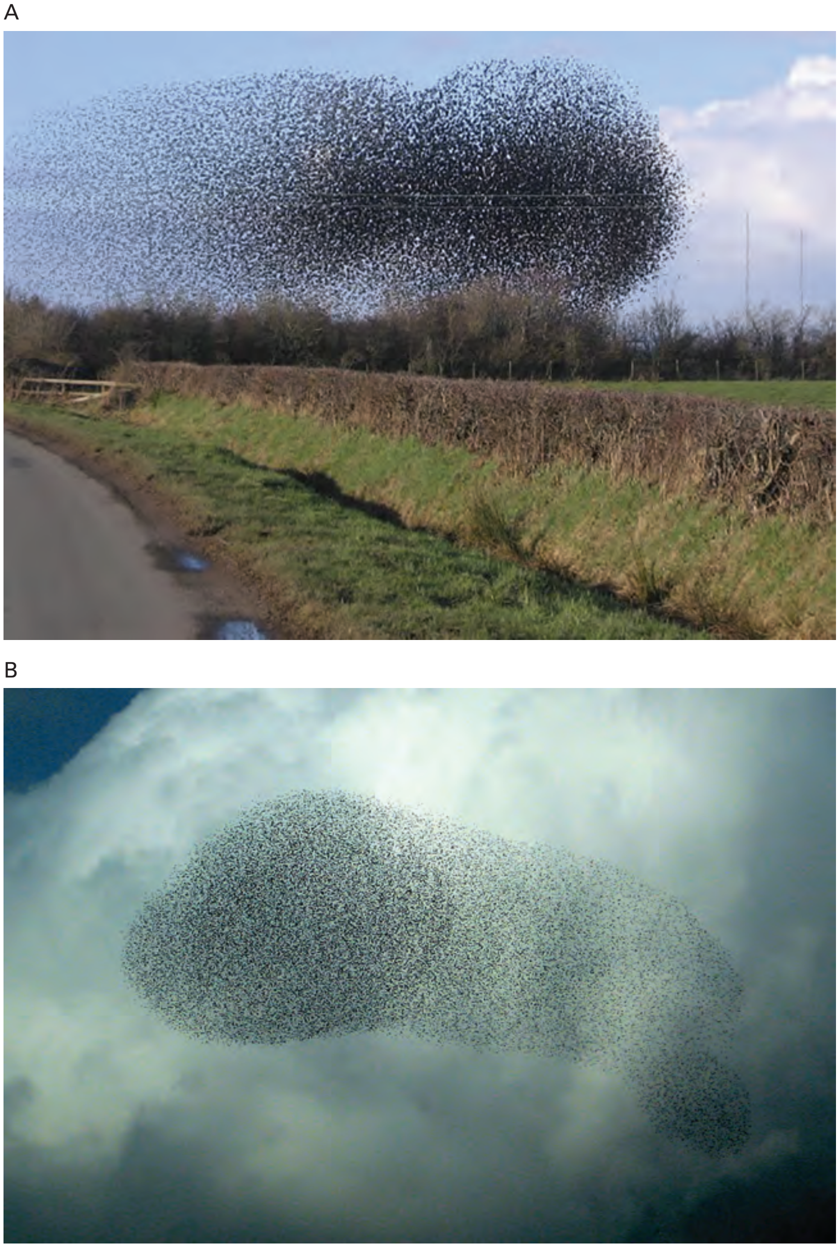

Figure 0.4
Flocks of starlings (thousands of birds) acting as a swarm.[2]

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.

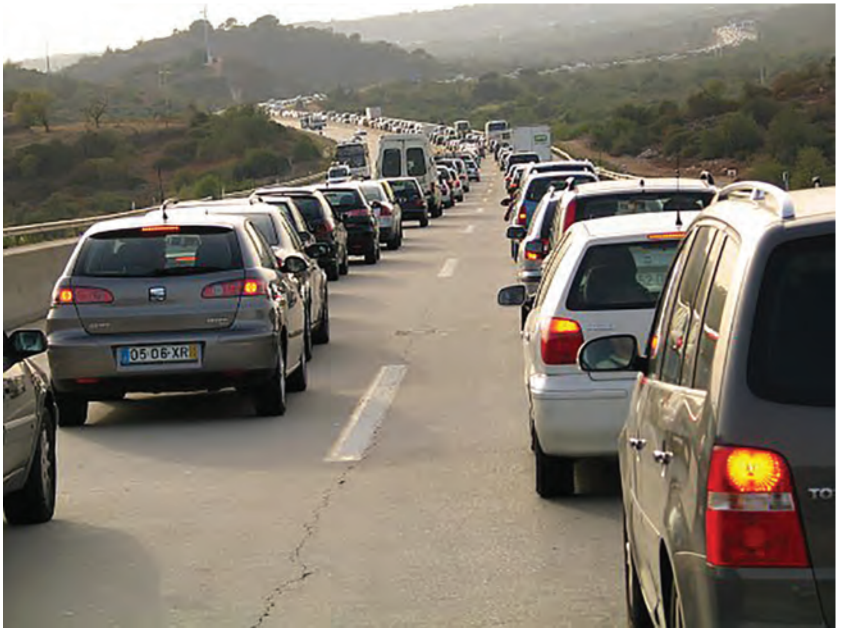

Figure 0.5
Traffic Jam by Osvaldo Gago, 2005.

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

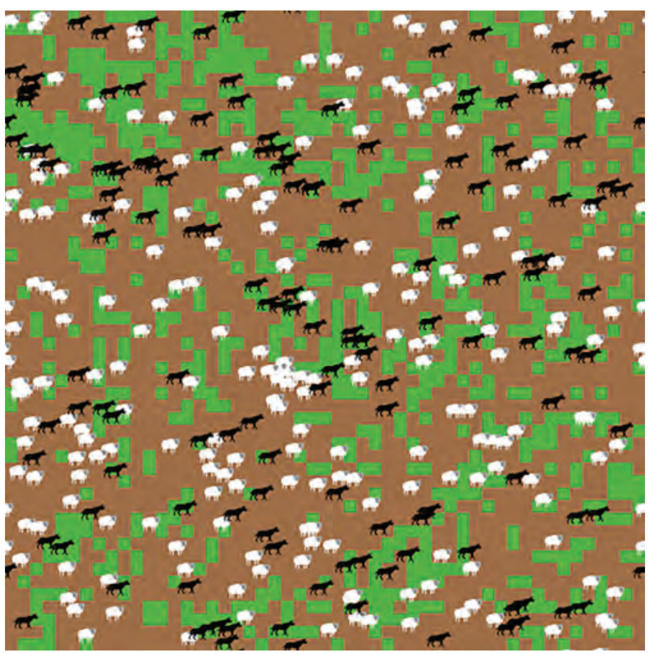

Figure 0.6
An agent-based Wolf Sheep Predation model. (See *Wilensky, 1997c*)

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.

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

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.

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

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

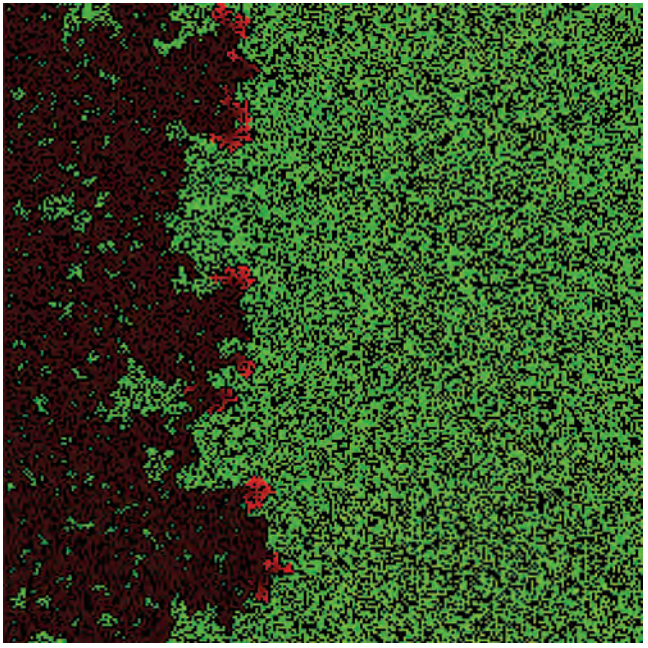

Figure 0.7
An agent-based model of a forest fire. (See *Wilensky, 1997b*)

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.