ROUTLEDGE ADVANCES IN EXPERIMENTAL AND COMPUTABLE ECONOMICS

Agent-Based Computational Economics

How the idea originated and where it is going

Shu-Heng Chen

Agent-Based Computational Economics

This book aims to answer two questions that are fundamental to the study of agent-based economic models: what is agent-based computational economics and why do we need agent-based economic modeling? This book provides a review of the development of agent-based computational economics (ACE) from the perspective of how artificial economic agents are designed under the influences of complex sciences, experimental economics, artificial intelligence, evolutionary biology, psychology, anthropology, and neuroscience.

The book begins with a historical review of ACE by tracing its origins. From a modeling viewpoint, ACE brings truly decentralized procedures into market analysis, from a single market to the whole economy. The book also reviews how experimental economics and artificial intelligence have shaped the development of ACE. For the former, it discusses how ACE models can be used to analyse the economic consequences of cognitive capacity, personality, and cultural inheritance. For the latter, the book covers the various tools used to construct artificial adaptive agents, including reinforcement learning, fuzzy decision rules, neural networks, and evolutionary computation.

This book will be of interest to graduate students researching computational economics, experimental economics, behavioural economics, and research methodology.

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How the idea originated and where it is going

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Preface

The idea of this book is to review the development of agent-based modeling in economics from a perspective that the author considers most generic. It is, therefore, not a survey of the application domains of agent-based modeling in economics, which itself can be a subject of interest, but now also becomes difficult given its quick expansion. The perspective taken in this book centers on *the idea of using agents as a bottom-up design for the study of emergent complexity*. The book takes John von Neumann's contribution to cellular automata as a starting point to see how this idea grows and evolves; in particular, how the use and hence the design of agents changes after constant interactions with other disciplines: computer science, artificial intelligence, experimental economics, behavioral economics, evolutionary economics, and econometrics. These constant interactions enrich the design of agents with the coexistence of several different principles, from the original simple design to more complex and intelligent design. They will be presented in this book with various illustrations from agent-based macroeconomic models to agent-based microeconomic models, from artificial financial markets to evolution of technology. This perspective, while it may be narrow, is focused enough to distinguish this book from other similar work in the literature.

The plan of the book began in May, 2008, when the author was generously invited by Prof. Kumaraswamy Velupillai to the University of Trento to give a two-day workshop on agent-based modeling in economics and finance. The skeleton of the book emerged as a preparation for the workshop. During the workshop, the author further benefited from discussions with Stefano Zambelli, Charlotte Bruun, Francesco Luna, and Stephen Kinsella, which helped grow many fine details. In fact, they are all experts on agent-based modeling in economics, although the skeleton of the book is not extensive enough to accommodate all of their contributions in this area.

From October to November 2009, the author was honorably invited as a visiting professor to Trento to give a course on Heterogeneous and Multi-Agent Modeling in Economics for the second-year PhD students at the Interdepartmental Centre for Research Training in Economics and Management (CIFREM). The lecture was given in a very interactive and stimulating environment. Prof. Kumaraswamy Velupillai attended all of my lectures, and encouraged me to prepare my lecture into a book format, generously inviting me to submit a book proposal for his editing series on Routledge Advances in Experimental and Computable Economics. This invitation gave the author the impetus to start a book project.

Around this time and in the following years, the author was luckily invited to give tutorials in summer schools or plenary speeches in international conferences. These invitations provided the author further momentum to carry out the book project, to lecture on some preliminary versions of the book and, most importantly, to receive feedback from audiences. These events were:

- The First Chinese Forum on Intelligent Finance, Chinese Academy of Sciences, Beijing, China, February 26–28, 2009.
- The Summer School of the 15th International Conference Computing in Economics and Finance, University of Technology, Sydney, Australia, July 14, 2009.
- The Central European University Summer School on Complex Systems and Social Simulations, Budapest, Hungary, July 23, 2009.
- APCTP (Asia Pacific Center for Theoretical Physics) School on Econophysics, Pohang, Korea, August 24–27, 2009.
- Facing Crisis: International Seminar on How to Develop Methods of Economic Research, Beijing, China, September 10–11, 2009.
- International Conference on How and Why Economists and Philosophers Do Experiments: Dialogue between Experimental Economics and Experimental Philosophy, Kyoto Sangyo University, Kyoto, Japan, March 27–28, 2010.
- Sino-foreign-interchange Workshop on Intelligence Science and Intelligent Data Engineering, Harbin, China, June 3–5, 2010.
- The 16th International Conference on Computing in Economics and Finance, City University London, UK, July 13–17, 2010.
- The Second Edition of the International Workshop on Managing Financial Instability in Capitalist Economies (MAFIN 2010), Reykjavik University, Reykjavik, Iceland, September 23–25, 2010.
- Conference on Quantitative Behavioral Finance, University of Nice Sophia Antipolis, Nice, France, December 8–10, 2010.
- First Workshop on Quantitative Finance and Economics, International Christian University, Tokyo, February 21–23, 2011.
- International Conference on Nonlinear Economic Dynamics and Financial Market, South China Normal University and Guangzhou University, Guangzhou, China, March 31–April 2, 2011.
- Third International Conference on Econophysics and Summer School on Teaching and Enterprise, Department of Physics and School of Science, Loughborough University, UK, September 24–29, 2011.
- Lecture Series on Agent-Based Computational Economics: A Historical and Interdisciplinary Review, School of Management, Harbin Institute of Technology, Harbin, China, November 7–9, 2011.
- Third International Workshop on Managing Financial Instability in Capitalist Economies, Genoa, Italy, September 19–21, 2012.

- The Fifth Edition of Epistemological Perspectives on Simulation, Trinity University, San Antonio, Texas, October 10–12, 2012.
- Workshop on Computational Finance and Economics, Mexican Central Bank, Mexico City, Mexico, October 17, 2012.
- Eleventh International Conference of Socionetwork Strategies: Understanding Complex Society from Agent-Based Simulation, Research Institute for Socionetwork Strategies, Kansai University, Osaka, Japan, February 27, 2014.
- Fifth World Congress on Social Simulation, São Paulo, Brazil, November 4–7, 2014.
- First Cross-Straits Symposium on Economic Frontier and Policy Simulation in China, China Southern Normal University, Guangzhou, China, November 15–16, 2014.

The author is greateful to Heping Pan, Carl Chiarella, Xue-Zhong (Tony) He, George Kampis, László Gulyás, Guocheng Wang, Sobei Oda, Lei Xu, Wei Zhao, Giulia Iori, Marco Raberto, Seunghwan Kim, Woo-Sung Jung, Gabjin Oh, Jorgen Vitting Andersen, Taisei Kaizoji, Mauro Politi, Duo Wang, Fahuai Yi, Feodor Kusmartsev, Zhong-Yu Wang, Silvano Cincotti, Yu Zhang, Dante Suarez, Alexandrova Kabadjova Biliana, Edward Tseng, Kazuhito Ogawa, Jaime Sichman, Zhiqiang Dong, and Lianqing Peng for their generous invitations and kind arrangement.

The book in its manuscript form has been used as lecture materials for a one-semester course given at the Master of Finance Program in Tianjin University, in years 2012 and 2014. This class probably has the most devoted students in China. The teaching experience in this class is challenging but breathtaking. The book has substantial context on the natural allied relationship between agent-based computational economics and experimental economics. The leadership of Wei Zhang has helped Tianjin University build the strongest academic environment for this new research paradigm. On this occasion, the author is particularly grateful to Wei Zhang and his colleagues at College and Management and Economics, including Xiong Xiong, Yongjie Zhang, Da Ren, Xu Feng, Dehua Shen, and many others, for providing the author with a very stimulating and inspiring research-oriented teaching environment.

While writing the book, the author witnessed and was accompanied by the fast-growing agent-based communities in both economics and social sciences. The author constantly benefited from participation at some major events organized by the Society for Computational Economics, the Society for Economic Science with Heterogeneous Agents, the NYC Computational Economics and Complexity Workshop, the Pan-Asian Association for Agent-based Approach in Social Systems Sciences, the International Foundation for Autonomous Agents and Multiagent Systems, the Computational Social Science Society of the Americas, the IEEE Computational Intelligence Society, and the Asia-Pacific Econophysics Conference. The author would like to give thanks to a number of active members who have not just helped the author to learn this subject, but also contributed

themselves to the shining history of the communities. In addition to those who have already been mentioned above, they are David Kendrick, Leigh Tesfatsion, Thomas Lux, Jasmina Arifovic, Robert Marks, Hans Amman, Blake LeBaron, Barkley Rosser, Alan Kirman, Herbert Dawid, Cars Hommes, Nick Vriend, John Duffy, Robert Axtell, Frank Westerhoff, Giovanni Dosi, Maruo Gallegati, Domenico Delli Gatti, Massimo Ricottilli, Pietro Terna, Jason Barr, Troy Tassier, Leanne Ussher, Chris Ruebeck, Alan Isaac, Myong-Hun Chang, Andreas Pape, Nigel Gilbert, Claudio Cioffi-Revilla, William Griffin, David Sallach, Bruce Edmonds, Scott Moss, William Rand, William Lawless, Flaminio Squazzoni, Van Dyke Parunak, Akira Namatame, Yuji Aruka, Hiroshi Deguchi, Takao Terano, Shingo Takahashi, Aki-Hiro Sato, and Siew Ann Cheong.

The book was mainly written at the AI-ECON Research Center, National Chengchi University. The center is one of most active research units in promoting agent-based computational economics. The author is very blessed by being surrounded by many supportive colleagues, students, post-docs, and visitors. Many of them became co-authors in a number of the author's other projects. Here, acknowledgements are specifically given to Shu G. Wang, Wei-Lin Mao, Chu-Chia Lin, Chung-Ming Kuan, Been-Lon Chen, Mei-Lie Chu, Yih-Chyi Chuang, Sun-Chong Wang, Sai-Ping Li, Chen-Yuan Tung, Nai-Shing Yen, Reuy-Ming Liao, Lee-Xieng Yang, Ray-May Hsung, Chia-Hsuan Yeh, Wo-Chiang Lee, Wei-Yuan Lin, Chueh-Yung Tsao, Tzu-Wen Kuo, Ya-Chi Huang, Bin-Tzong Chie, Chung-Ching Tai, Chia-Ling Chang, Hung-Wen Lin, Ye-Rong Du, Chia-Yang Lin, Ying-Fang Kao, Nicolas Navet, Tina Yu, Tong Zhang, Michael Kampouridis, Tong-Kui Yu, Jie-Jun Tseng, Tzai-Der Wang, Kuo-Chuan Shih, Umberto Gostoli, and Ragupathy Venkatachalam. I am in great debt to them and to my family, without whom it would have been impossible to complete the book. Finally, I am grateful to Lisa Thomson and Routledge's professional editing team for being so supportive and helping me accomplish the last mile of the book.

Shu-Heng Chen
March 15, 2015

Part I

Ideas and structures of the book

1 Economics in an interdisciplinary context

Humans are heterogeneous in many ways. Nothing can be more evident than this simple fact. Yet, in mainstream economics, the device of the homogeneous agent or, more formally, the *representative agent*, has been employed for quite a long, yet uneasy, period of time. Psychologists, on the other hand, have acknowledged the heterogeneity of agents right from the beginning. Various developments in psychometric testing simply show us that humans are empirically different. They are not just bounded rational; they are heterogeneous in cognitive capacity as well as personality. Moreover, anthropologists and sociologists show us that, when put in a social context, they are under different sets of beliefs or norms. From the viewpoint of genetic biology, some human heterogeneities are inherited from parents or ancestors. Nevertheless, mainstream economics has long been silent on all of these *human factors*, assuming that they are not *economically sensible*. The empirical evidence accumulated in recent years, however, shows the significance of cognitive capacity, personality, emotion, cultural inheritance, and social norms, from micro to macro. Nevertheless, the modeling techniques which can incorporate agents who are heterogeneous in these dimensions and demonstrate the emergent aggregate behavior through their interactions are less well established in economics.

The purpose of this book is to place the study of economics in an interdisciplinary framework so that the underlying mathematical or computational modeling can be grounded in various kinds of empirical evidence ranging from genetic biology to neural sciences, sociology, psychology, and, of course, experimental economics. In fact, this interdisciplinary modeling has already existed by different names among people with different backgrounds. For people with a conventional economics, psychology, or mathematics background, its familiar name is *behavioral economics*; for people with a mixed background of economics and computer sciences or computer engineering, its familiar name is *agent-based computational economics*; for the recent immigrants from physics to their "colony" in economics, it is called *econophysics*. Each of its names represents an origin of its development. Behavioral and econophysic modeling is more analytically demanding, whereas agent-based computational economic modeling is computationally intensive.

Regardless of different names, models with these tags and origins share a great common feature, i.e., they can each replace the conventional representative agent

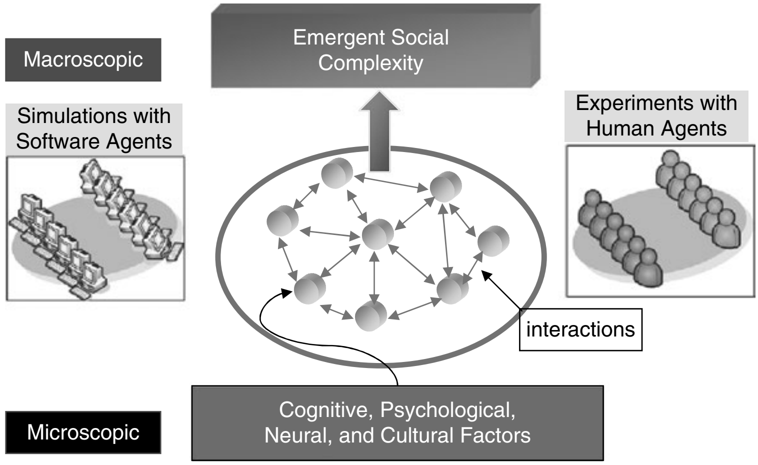

Figure 1.1 Microfoundations and macroeconomics.

Source: Adapted from Chen and Wang (2011), Figure 2.

model and provide an alternative *microfoundation*. Figure 1.1 shows this common feature. We will come back to this figure and elaborate on its essence in Section 1.1. Here, we only provide a brief list to exemplify the microfoundational work already done in each of the three research areas.

Behavioral macroeconomics

There is a series of works on behavioral macroeconomics by George Akerlof, the 2001 Nobel Laureate in Economics. The most notable features of this are his Nobel Prize lecture (Akerlof, 2002), his American Economic Association Presidential address (Akerlof, 2007), and his advice on the current financial tsunami (Akerlof and Shiller, 2009). This series can be augmented by a number of macroeconomic laboratory experiments (Duffy, 2009).

Agent-based computational economics

Agent-based computational economics, almost since its beginning, has been devoted to the study of macroeconomic issues. Leigh Tesfatsion, on her Iowa State University web page, http://www.econ.iastate.edu/tesfatsi/amulmark.htm, has a collection of these studies. Among them, Chen (2003), Delli Gatti *et al.* (2008), LeBaron and Tesfatsion (2008), and Delli Gatti *et al.* (2011) provide various illustrations with different motives. Due to the financial crisis which occurred in 2008–2009, attention has been paid to agent-based computational economic modeling as an alternative approach to maintaining better tabs on the increasingly complex and intertwined economy (Buchanan, 2009; Farmer and Foley, 2009). In addition, a series of conferences were organized in the year 2010 to reflect on the crises in economic theory with regard to the economic crisis of 2007–2009. In 2009, George Soros pledged to give 50 million dollars over ten years to set up the Institute of New Economic Thinking as a reaction to his feeling that "false theory" has resulted in tremendous damage to the world economy. Agent-based economic modeling is considered to be a candidate for an alternative.

Econophysics

In physics, during the late nineteenth century a fundamentally new approach referred to as *statistical mechanics* was advanced by James Maxwell (1831–1879), Ludwig Boltzmann (1844–1906), Josiah Gibbs (1839–1903), and others. This approach, which significantly contributed to the study of molecular dynamics, was also formally introduced to the study of economics and even the social sciences in the 1990s.[1] This new field is broadly known as *econophysics* or *sociophysics*.[2] An econophysics approach to macroeconomics can be exemplified by a series of work done by Masano Aoki (Aoki, 1996, 2002a; Aoki and Yoshikawa, 2006).

1.1 The interdisciplinary framework

Figure 1.1 has all the ideas to be included in this book, albeit expressed in a highly simplified way. Let us start with the middle part of the figure, which intends to picture *a system of interacting agents*.[3] For a physicist, this picture may be read as a *particle system*, with two important departures:

Heterogeneous agents

First, agents (particles) are not homogeneous; instead, they are heterogeneous. Abandoning the device of the representative agent is exactly the concept conveyed at the beginning of this book. In Part VI, we will provide corroborative evidence and discussions as to why heterogeneous agents should not be viewed as an exception but as a rule in the future of economic modeling.

Interactions

Second, the relations among the agents (particles) are not just random bumping but *social* in the sense that these agents mutually *influence* each other, so that their behaviors change along with these interaction processes. These agents are, in general, not independent. This feature allows us to accommodate concerns from anthropology, religion, culture, sociobiology, and evolutionary psychology.

Social networks

Although the interactions among agents can be erratic, they may not be entirely random. Implicitly or explicitly, the interactions take place through social networks. The topologies of social networks can be another crucial factor for the interactions, and the topologies, in general, are endogenously determined.

Homo sapiens

Let us move to the bottom of Figure 1.1, which describes these individual agents. In conventional economics, the description of the agents is simple: *Homo economicus* or economic man. They are identically infinitely smart, hyperrational, self-interested, unemotional, and utility-maximizing agents. While these creature have been surviving in mainstream economics for decades, economists are now becoming more interested in knowing *Homo sapiens*—emotional beings (Thaler, 2000).[4] This broader interest has brought about significant growth in interdisciplinary engagement between economists and other social scientists or even scientists. Psychology and computer science both come into play from this side.

Psychological fundamentals

On the one hand, we certainly hope to give a more realistic description of the human agents by at least not missing their essential dimensions; on the other hand, we want to make this description programmable. The former motivates an increasing number of economists to learn from psychologists and coherently ties economics and psychology in an unprecedented way. This interdisciplinary collaboration between the two has also promoted a new subfamily in economics, namely *behavioral economics*. Economists are now more alert to the social consequences of widely documented agents' behavioral *biases*. More recently, psychology has helped economists to reshape a proper definition or representation of an individual economic agent. A series of recent studies indicates that *cognitive capacity* (the intelligence quotient) and *personality* are two important missing elements in conventional characterizations of economic agents. In fact, these two human factors should be thought of as the *fundamentals* of the economy; they are certainly more concrete than *preference*, a very controversial idea, both historically and currently.

Artificial agents

We program the artificial agents to reflect various kinds of psychological fundamentals, behavioral rules, or behavioral biases. Artificial agents is not a term commonly used in behavioral economics, although all the models inevitably start with some artificial agents. The whole of Part III is devoted to this construct, but most materials introduced there were produced in the earlier stages of agent-based computational economics when it was still distinct from behavioral economics. In agent-based computational economics the focus of artificial agents is on learning, whereas in behavioral economics the focus is on preference and utility. In the future, the gap between the two will be narrowed as *behavioral agent-based computational economic models* are gradually developed. Chapter 19 presents one case in point.[5]

1.2 Organization of the book

Normally, the table of contents of a book suggests that the reader can read the book in a sequential order. While the table of contents must be unique, that kind of suggestion is not. Therefore, in this section, we elaborate on the organization of the book and suggest some alternative tables of contents which could be used by different readers with different purposes or different pursuits.

1.2.1 Two fundamental questions

The book tries to answer two questions which we consider to be quite fundamental to the study of agent-based economic models, namely, *what* and *why*? What is agent-based computational economics? Why do we need agent-based economic modeling of the economy? These two questions are generally shared by other social scientists who are also interested in agent-based modeling. Therefore, they are better addressed in a broader background, i.e., *agent-based computational social sciences*. To answer the first question, it would be nice if we could start with some very simple agent-based social or economic models which, however, all have the essences of agent-based models. Chapter 4 serves this purpose. It is mainly composed of the three simplest agent-based social models, namely *Schelling's Segregation Model*, *Conway's Game of Life*, and *Wolfram's Edge of Chaos*. This chapter can help beginners to quickly grasp what an agent-based social model is.

The most direct way to address the second question is to ask whether we can have a collection of successful agent-based models in the social sciences. By success, we mean that these models are capable of explaining or predicting some social phenomena which are hard to capture using the conventional models of the respective disciplines or are able to provide new insights. While we cannot be absolutely sure what these models are, Chapter 2 does make such an attempt. In addition to that, Epstein (2008) provides a long list of answers to the issues involved, and in Chapter 2 we shall review some of them.

1.2.2 Novelty discovery: toward autonomous agents

The book will start with a concrete example of agent-based (economic) modeling, namely *cellular automata* (Chapter 4). The reason we choose cellular automata as our kick-off example is partially because we consider *a model of agents* to be the first part of agent-based modeling. However, to clearly indicate our departure from *Homo economicus* to *Homo sapiens*, we would like to provide a simple historical background on the development of economic agents in economics; specifically, from *algorithmic (behavioral) agents* to *autonomous agents* (Chapter 5). This will quickly lead us to see that part of the economic agents is defined by the associated algorithms. In fact, Chapters 5 to 7 provide many more illustrations on the algorithmic aspects of economic agents, as they are called algorithmic agents.

Autonomous agents are first exemplified in Chapter 6 via an artificial intelligence tool called genetic programming (GP), while the foundation work for autonomous agents is not given until later in Part IV. This line of exposition is then further extended to Chapter 8. Chapter 8 can be read together with Section 14.5 and Part VIII, and are all concerned with a central theme of the book, which I shall refer to as *the legacy of Marshall*. Together they demonstrate one unique feature of agent-based modeling, i.e., its capability of modeling *intrinsically constant changes*. One essential ingredient of triggering constant change is equipping agents with a *novelty-discovering* or *chance-discovering* capability so that they may constantly exploit the surrounding environment, which causes the surrounding environment to act or react, and hence change constantly.

1.2.3 Microstructure dynamics

If economics is about constant change, and that happens because autonomous agents keep on searching for chance and novelties, then change in each individual and change in the microstructures must accompany the holistic picture of constant change. A number of chapters in this book attempt to have *microstructure dynamics* as their focus. Part V illustrates the rich microstructure dynamics in agent-based financial markets. Chapter 14 is mainly devoted to the study of microstructure dynamics in light of the *statistical mechanical approach* (Section 14.4). With this approach, the set of behaviors or strategies is finite or bounded. A finite set allows us to study the microstructure dynamics on solid ground, but it inevitably implies the absence of novelties and their discovery, which is the other focus of the book. Section 15.4, therefore, extends the analysis of the microstructure dynamics into an infinite set so that rich microstructure dynamics are embedded within the novelty-discovering processes.

These chapters are connected by two hypotheses, namely the *market fraction hypothesis* in Chapter 14 and the *dinosaurs hypothesis* in Section 15.4. The two hypotheses are further connected by using genetic programming to formulate and test them (Section 15.4).

1.2.4 Agent engineering

A large part of the book is concerned with the design of software agents used in agent-based modeling. In general, this task is known as *agent engineering*. On the one hand, the book reviews a number of tools which have been used to design agents with different degrees of sophistication; on the other hand, the book also addresses how to use these tools properly. The latter subject involves the empirical grounds of agent engineering. The behavior of human agents observed in experimental economics provides one empirical ground. Using this empirical ground to build software agents naturally ties software-agent simulations and human-agent experiments together.

The tools used to build software agents are mainly introduced in Part IV, which covers reinforcement learning (Chapter 10), artificial neural networks (Chapter 12), and evolutionary computation (Chapter 13). In this repertoire, do agents follow reinforcement learning to learn? Or do they learn as predicted by artificial neural networks? When is evolutionary computation a more sensible description of learning? A number of chapters contribute to the study of these issues. Chapter 7 is concerned with the idea of *calibrating artificial agents* using data from human-subject experiments. Similar to Chapter 7, Chapter 16 introduces work using real data (field data) to estimate the parametric behavioral rules, and is not necessarily restricted to learning.

1.2.5 Experimental economics

A large part of the book is also written to reflect the intertwined connection between experimental economics (EE) and agent-based computational economics (ACE). Several different developments of algorithmic agents are all inspired or related to experimental economics. The double auction (DA) market (Chapter 8) is probably the most illuminating illustration of the connection between agent-based computational economics and experimental economics. Having said that, we notice that the DA market is the context in which various versions of agents, crossing both realms of EE and ACE, have been proposed. The motivation behind inventing *zero-intelligence agents* consists of replicating the market behavior observed in the double auction market experiments (Section 8.3). The *programmed agents* or *human-written agents* are part of the tournament-like offline experiments (Section 9.2). The idea of *calibrated agents* is first introduced to replicate human choice behavior in the multi-armed bandit experiment (Chapter 7). Finally, autonomous agents are also inspired by both online and offline human experiments in double auction markets (Sections 9.3 and 9.4). Needless to say, the idea of algorithmic agents is enriched by interaction with observations from experimental economics.

1.2.6 Econophysics

It is fair to say that agent-based modeling was first used by physicists, though known by different names, including cellular automata, the kinetic model, percolation model, Ising model, etc. The recent massive economic and financial applications of these models by physicists have contributed to a significant part of the field known as *econophysics* (Chen and Li, 2012). In Chapter 4, we present the *cellular automata tradition* of ACE. The tradition initiated by von Neumann (1903–1957; von Neumann, 1966) is then passed on to Thomas Schelling (Schelling, 1978), John Conway, Stephen Wolfram (Wolfram, 1994), Peter Albin (1934–2005; Albin, 1975, 1998), Duncan Foley, Joshua Epstein, and Robert Axtell (Epstein and Axtell, 1996), and further down to the arising of the spatial agent-based models extensively applied in geography, city planning, and ecology. This series of literature enables us to see the connection between the particle system in physics and agent-based modeling in economics. They together serve as a gateway leading to the current development of complex science and the later more general development of complex networks (Chapter 22).

Econophysics, in spirit, also concurs with the *randomization approach* or the *maximum entropy approach* in agent-based modeling (Section 8.5.1). The capability of this approach to replicate complex financial dynamics systems shows that some aggregate phenomena generated from human-agent systems with the complex motives and behavioral rules of humans can be rather well approximated by a system with rather simple agents characterized by simple motives and simple rules. In a sense, it indicates that adding more complex strategies to the agent-based models may have little by way of macroscopic effect since these complex strategies may interact in such a way that they mutually annihilate each others' forces. It is this possibility that prompts us to think about a general physical system which is equipped with the most rudimentary forces but can overarch several seemingly unrelated social phenomena, for example from pedestrian counterflow, the Schelling segregation model (Vinkovic and Kirman, 2006), the El Farol Bar problem (minority games), and then to financial markets.[6]

Notes

1 What may interest both economists and physicists is that the early study of molecules in physics was motivated by observing interactions among humans (Ball, 2006).

2 Galam (2004) gives a personal account of the origin of sociophysics, but a more interesting and even earlier review of the interdisciplinary relation between classical physics and classical economics was documented by Cottrell *et al.* (2009).

3 The size of the system, which can be another important consideration in this book, does not have to be as small or finite as the one drawn here.

4 Thaler (2000) particularly characterizes the shift in the interest by distinguishing the *normative* description of human behavior from the *positive* description of human behavior.

5 Nonetheless, there is another major difference which we would like to point out here, i.e., heterogeneity. Despite the findings of so many *anomalies*, behavioral economics does not necessarily resist the device of a representative agent. In fact, the device of the representative agent is still extensively used in various behavioral economic models, in particular, behavioral macroeconomics, since that may make it easier for us to present the aggregate consequence of a certain class of behavioral biases by not *averaging them out*. For example, Stracca (2004) states that "what matters for aggregate market prices is the behavior of the representative agent, so we do not have to care, in principle, about behavioral biases that cancel out in the aggregate" (p. 378). However, neoclassical economics used to consider exactly the opposite, namely, these biases will cancel each other out when being summed up. Therefore, it seems important to *show*, rather than to *assume*, that these biases will not go away in the aggregates. For that reason, we believe that *heterogeneous behavioral economic models* should be more persuasive than the homogeneous ones, or, naturally, be the next step or the extension of the latter (Thaler, 2000).

6 It is possible to simulate the financial time series using *social force models for pedestrian dynamics* (Parisi, 2010). The social force model is one kind of agent-based model which is not much different from the particle system in physics. The agents (particles) in this system have simple objectives and follow simple rules.

2 Agent-based modeling in the social sciences

Over the last decade, there has been much evidence of agent-based modeling and simulation being extensively used among different social science disciplines. This tendency has enabled agent-based social scientists to find a common language among them to facilitate the resultant interdisciplinary communication and collaboration, which in turn has defined a number of common interests shared by the social scientists. This gathering has also caused the emergence of a new discipline across the social sciences, which is known as *computational social sciences* (CSS).

2.1 What is it?

Computational social science presents a comprehensive view of the social sciences, the study of social phenomena. However, it does not use or follow any single-disciplinary viewpoint or framework to examine these social phenomena. While the social phenomena exemplified in computational social science include voting, identity, segregation, social exclusion, discrimination, financial crises, urban dynamics, social networks, leadership, congestion, disease transmission, gossip and mass media, culture and social norms, interpersonal relations, and prosocial behavior, we do not study them in the way that they are treated in the parent disciplines to which they conventionally belong, be they economics, sociology, the political sciences, management, or psychology. Instead, we study each of these phenomena as a social process and place these social processes (emergent processes) together into a *coherent framework*, in which they can be communicative with each other as if there were only one social science.

To do so, we search for the generic properties or common ground of these social processes. This coherent framework is agent-based modeling and simulation.[1] The social science studied using agent-based modeling and simulation is known as *computational social science*. Different names also exist, such as agent-based social sciences (Trajkovski and Collins, 2009), bottom-up social sciences (Epstein and Axtell, 1996), algorithmic (behavioral) social sciences (Saunders-Newton, 2006; Velupillai, 2009), generative social sciences (Epstein, 2007), and complex adaptive social systems (Miller and Page, 2007).

Several different attempts have been made to provide a review of this rapidly accumulating literature.[2] Among the many existing reviews or work on

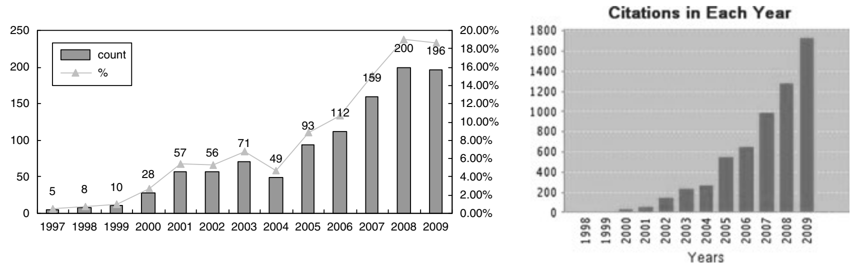

Figure 2.1 Number of published papers in ABSS (left panel) and citations in each year (right panel).

Source: Adapted from Chen, Yang, and Yu (2011).

computational social science, the collection of work resulting from the efforts of Nigel Gilbert (Gilbert, 2010) can be considered to be one of the most comprehensive. In this four-volume collection, Gilbert inclues 66 articles on computational social science. The overall collection places an article on cellular automata, one of the origins of agent-based modeling (see Chapter 4 of this book), as its leading chapter. Pioneering work built upon cellular automata (checkerboards) by James Sakoda and Thomas Schelling (the checkerboard model) is also included (see again Chapter 4 of this book). Many other articles are classif ed according to the arena in which the distinguishing features and signif cant contributions of agent-based modeling can be found, such as the formation (emergence) of markets, opinions, groups (segregation), networks, norms, organizations, leaders, and pro-social behavior. In addition, there are sections containing collections devoted to foundational and methodological issues, plus one section devoted to the modeling of cognitive and psychological agents. This four-volume collection gives a concrete demonstration of what computational social science is and summarizes various research directions that have been developing and unfolding since the 1970s.

By retrieving data from the Social Sciences Citation Index database, Chen, Yang, and Yu (2011) found a total of 1051 papers on agent-based social simulation (ABSS) that had been published during 1997–2009. Figure 2.1, in the left panel, illustrates the number of published papers in ABSS, and in the right panel shows the annual citations of the published papers in ABSS. The results appear to suggest that the number of papers in ABSS has increased distinctly since 2001, and that respective citations have also increased with each passing year.

2.1.1 Three constituents of CSS

The critical feature that makes agent-based modeling so relevant for the social sciences is that social behavior and social dynamics involve many details, which are nontrivial but are frequently oversimplif ed by alternative paradigms, such as equation-based models or variable-based models. The following three constituents of an agent-based model can be lucidly illustrated by one of the classics, namely Schelling's segregation models, which will be detailed in Section 4.1.

Software agents

First are the details about individuals. This partially explains why CSS is referred to as *algorithmic social sciences*, because each agent (actor) is represented by an algorithm or a computational program. This algorithm (program) corresponds to the decision rules, behavioral models, or even preferences that characterize the agents. In a sense, it is a simple model of a man, in light of Herbert Simon (Augier and March, 2004). In borrowing the term from computer science, one may also refer to CSS as *software agents* or *autonomous agents*.

Embeddedness

Second are the details of the environment within which the agents are embedded. In Schelling's segregation model (Section 4.1), the embeddedness is a *two-dimensional cellular automaton* (a city) which defines the geography of the space in which agents live. The geography (topology) of the city further defines a *social network* for each agent. In addition to the geographies or social networks, other embeddedness includes institutions, cultures, histories, etc.

Aggregation (emergence)

Finally, with these details, individuals interact through the embeddedness and the resulting patterns and macrobehaviors, also known as the emergent properties, are normally hard to predict. This also explains why CSS is referred to as "bottom-up social sciences." In Schelling's segregation model, the segregation phenomenon as an aggregation phenomenon is a sum of the interactions of fairly tolerant people. Obviously, this is not a linear scaling up. "From the bottom up" normally refers to the surprising phenomena that would not be predicted from the model itself, which focuses on the actions of individual agents rather than overarching downward-focused principles.[3]

2.1.2 ACE scissors

The design of an agent-based model, therefore, is composed of two parts, the *behavioral part* (software agents) and the *institutional part* (embeddedness). These two parts then jointly determine the emergent outcomes. These two parts together provide "scissors" for understanding social phenomena and conducting policy designs.

To fulfill the aforementioned purpose, one can use an agent-based model to identify the cause of an emergent phenomenon. For example, is financial volatility mainly attributed to the agents' behaviors, such as herding tendency, or attributed to institutional arrangements, such as the trading matching rule, or both (the combined effect)? This analytical framework would, therefore, be very much different from conventional policy analysis, which largely leaves out the behavioral considerations or simply assumes that agents are all rational. Instead, the ACE scissors naturally open the sensitivity issue of a policy design: is the design robust to different behavioral assumptions? As the Chinese proverb goes: an orange becomes a trifoliate orange after crossing the Huai River. Whether a policy design is proper may crucially depend on the agents' behaviors in which it intends to intervene. In the spirit of the proverb, the same design when applied to the area south of the Huai River can result in oranges being grown, but when applied to the area north of the Huai River, it can only result in trifoliate oranges (whose fruit is bitter and not edible raw) being grown.

2.1.3 The third way

While deduction and induction are the two familiar types of reasoning, one has to realize that agent-based computational modeling and simulation constitute neither a method of deduction (theory) nor a method of induction (statistical inference). The distinction from the usual deduction and induction has been well acknowledged by economists and social scientists (Axelrod, 1997a; Axelrod and Tesfatsion, 2006; Gallegati and Richiardi, 2009). Axelrod (1997a) proposed that agent-based social simulation can be considered as the third approach, i.e., in addition to deduction and induction, to science.

> Simulation in general, and ABM [agent-based modeling] in particular, is a third way of doing science in addition to deduction and induction. Scientists use deduction to derive theorems from assumptions, and induction to find patterns in empirical data. Simulation, like deduction, starts with a set of explicit assumptions. But unlike deduction, simulation does not prove theorems with generality. Instead, simulation generates data suitable for analysis by induction. Nevertheless, unlike typical induction, the simulated data come from a rigorously specified set of assumptions regarding an actual or proposed system of interest rather than direct measurements of the real world. Consequently, simulation differs from standard deduction and induction in both its implementation and its goals. Simulation permits increased understanding of systems through controlled computational experiments.
>
> (Axelrod and Tesfatsion, 2006, p. 1650)

While Herbert Simon, to my knowledge, did not write directly on this issue, he did notice the limitation of normal induction.

> Students are always told that they can't run a successful experiment if they don't have a hypothesis ... I believe that is a very bad criterion for the design of experiments ... If you look down the list of outstanding discoveries in the physical sciences or the biological sciences—look at Nobel awards in those fields—you will note that a considerable number of the prizes are given to people who had the good fortune to *experience a surprise*.
>
> (Simon *et al.*, 1992, p. 22; emphasis added)

At this point, agent-based simulations are related to Simon's comment since some emergent phenomena coming out of agent-based simulation bring us novelties and surprises, which inspire us to make hypotheses of these observations. In this sense, some economists, such as Gallegati and Richiardi (2009), also relate agent-based social simulation to what Charles Peirce (1839–1914) called *abduction*. Peirce advocated that there is a type of logical reasoning beyond deduction and induction. He called this unique type of reasoning abduction, and suggested that it was the logic of discovery (Peirce, 1997). While, for many philosophers of science, abduction is treated as a part of induction, Peirce forcefully distinguished between the two by indicating that induction is about the test of an established hypothesis using observations, and that abduction is about the formation of the hypothesis.[4]

In addition to simulation and abduction, others have suggested the term *computational paradigm* to distinguish agent-based modeling from the conventional scientific paradigms (Hoekstra, Kroc, and Sloot, 2010). Wolfram (2002) even calls it "a new kind of science," to which we shall come back later in Section 4.3.1. Very much sharing the same view of simulation and computation, Gintis (2012) makes the following remark, related to his series of agent-based general equilibrium models (for more details, see Section 3.2).

> Those unused to working with complex dynamics systems may object that a computational proof is no proof at all. In fact, a computational proof may not be a mathematical proof, but it is a scientific proof: it is evidential rather than tautological proof, and depends on induction rather than deduction. The natural sciences, in which complex systems abound, routinely use mathematical models that admit no closed-form analytical solutions, ascertain their properties through approximation and simulation, and justify these models by virtue of how they conform to empirical reality.
>
> (Gintis, 2012, p. 60)

2.2 Why?

Why do we need agent-based modeling in economics or, generally, in the social sciences? Briefly, there are three reasons for this. Let us spell them out first, and then elaborate on each of the three.

1. Agent-based modeling and simulation refer to a repertoire of tools to make complex systems easier to study.
2. Agent-based modeling and simulation constitute a set of new instruments; their invention, like many other instruments, enables us to observe objects which are otherwise difficult to see, and hence expand the *interval* by which a science is defined.
3. Agent-based modeling and simulation make the experimental social sciences possible.

2.2.1 Universal literacy

Regarding the first point, in his keynote speech given at the 2010 Computational Social Science Society of America annual meeting, Uri Wilensky, the founder of Netlogo, pointed out that agent-based modeling can help reduce the barrier or threshold for studying complex (adaptive) systems. Using the predator–prey model and forest fires as two illustrations, Wilensky showed how the complex phenomena conventionally studied by high mathematics, such as differential equations, can be much more easily approached by agent-based modeling (Wilensky and Reisman, 2006; Goldstone and Wilensky, 2008; Sengupta and Wilensky, 2011). By using agent-based modeling, not only can we make complex adaptive systems have high accessibility for general people, i.e., a lower threshold, but they can also allow us to explore or address more questions than we would be able to with the conventional approaches, such as differential equations, i.e., a high ceiling. Hence, agent-based modeling helps enhance *universal literacy* by introducing a *low threshold* and *high ceiling*.

In fact, as we shall see in Section 4.3.1, in light of the similar argument of computational irreducibility or "a new kind of science" (Wolfram, 2002), agent-based modeling is probably the "right mathematics" to do science (Borrill and Tesfatsion, 2011). Wilensky's argument has been further substantiated by a group of people who are engaged in K-12 complex systems education.

2.2.2 Higher resolution and yet better integration

As to the second point, each science, to be well defined, needs to decide its boundary, which is an *interval*, starting from the lowest level (the microscopic level), then passing through the middle levels (mesoscopic levels), and ending at the highest level (macroscopic level). A rough example in physics is the interval from "small" physics to "big" physics. This interval, however, is not constant and, to some extent, its expansion can be regarded as scientific progress. In economics, for example, the progress can be characterized as a move further up to the level of the world economy (international economics) or a move further down into the level of neurons (neuroeconomics). However, the interval cannot be broadened in a fragmentary manner such that the bottom and the top do not talk to each other. Mobility into different levels and their successful integration into a coherent body is, nonetheless, constrained by technology: the computer, the database, the fMRI, and various fine machines enabling us to measure them. Advancing to larger intervals and the coherent integration of different levels within this interval is progress in science.

As we shall see, agent-based economic modeling normally involves a lot of *functional details* which enable us to broaden the interval between economics and the social sciences in a coherent manner. Students of economics and the social sciences may experience very few of these functional details. One example is what Leigh Tesfatsion called "the procurement processes" (Tesfatsion, 2006), which are what make a more realistic economy behave, be it efficient or not. Reading through a series of ACE studies, students may easily be motivated to cook their own models since it will not be too hard to find some imperfections in previous models. The students do not have to worry about the solutions of their models because ACE models, by definition, are algorithmic and computational, and they are what Wilensky called "low threshold, high ceiling" models. This enhancement of universal literacy may easily cause the various economic models to flourish.

The usual defense for agent-based modeling is its superiority to its alternatives, mainly top-down system dynamics or equation-based systems. This superiority can mean a better understanding (explanations) of social phenomena, better forecasting of the future, and other things.[5]

2.2.3 Scalable extensions and replications of human-subject experiments

Finally, the third answer for using agent-based modeling is that it is an extension of *experimental economics* or *experimental social sciences*.[6] It had been held for a long while that economics was not an experimental discipline. The following reservation given by Samuelson and Nordhaus (1985) is well known:

> Economists cannot perform controlled experiments like chemists or biologists because they can't easily control other important factors. Just like astronomists or meteorologists, they usually have to solely use their observation.
>
> (Samuelson and Nordhaus, 1985, p. 8)

The background underlying the change from the early hesitation to embrace this discipline to its later recognition, in particular by the Bank of Sweden Nobel Memorial Prize and the Swedish Academy in the year 2002, has been documented in Fontaine and Leonard (2005), which gives an extensive review of the idea of experiments in economics, which is not just limited to laboratory experiments, but also to policy experiments as well as thought experiments.

They particularly mentioned computation as a form of experimentation. In this vein, the rise of experimental economics provides us with a good case to expect the coming of agent-based computational economics. As we shall see later, if one can agree on the promises delivered by experimental economics, then it would be easier to accept ACE so long as one realizes that the latter serves to fully deliver the promises of the former.

Having said that, we acknowledge the limitations of experiments with human subjects. The most obvious limitation is *money*. Subjects need to be paid in typical economic experiments. Therefore, the direct cost is the remuneration paid to the subjects in an experiment. Even though the direct cost only increases linearly with the number of subjects, stringent budget constraints can allow most labs to run experiments only with a limited number of subjects (Winter, 2009), a limited number of scenarios, and a limited number of repetitions. Unless we are sure that the experiments we run are *size-independent*, have *little noise*, and are *robust* to a wide range of perturbations, we may not be able to run enough experiments before obtaining sensible results.

In addition to the budget constraints, human agents are not as controllable as initially thought. Running an experiment for many consecutive hours can easily tire human subjects, which adds an additional constraint to experiments. Hence, it is difficult to run any experiment beyond three hours. The third constraint is the physical space of the experimental lab. Currently, it is hard to see any experimental lab which can host more than 100 subjects. This automatically puts an upper constraint on the size of an experiment. Although online web-based experiments may not require a physical lab, not all kinds of experiments can be easily conducted without the physical presence of the subjects.

Hence, replacing human agents with software agents seems to be an attractive alternative when the aforementioned constraints are stringent. Using software agents, one can easily enlarge the size beyond experiments with human subjects, for example by expanding a double auction experiment with a total of 20 agents to a total of 2000 agents. In addition to this direct expansion, using software agents allows us to design some "experiments" that are hard to conduct with human subjects due to any of the constraints mentioned above or other ethical reasons.[7]

Of course, a fundamental challenge for this attraction is whether human agents are replaceable. Is there a free lunch? The ten-dollar hourly rate which we pay for each human subject may enable us to learn something real about *Homo sapiens*, but can we gain the same quality of knowledge from the software counterparts? To answer this question, we have to know to what extent and under what specific circumstances the software agent is computationally or behaviorally equivalent to *Homo sapiens*. Without properly addressing this question, straightforward extensions of human-subject experiments using software agents can be premature. In fact, a great deal of effort has been made to address this question, and part of its development will be reviewed in this book (see Parts III, IV, and V).

2.3 Agent-based modeling in different disciplines

A cursory review of the use of agent-based modeling in various disciplines of the social sciences is given in this section.[8]

2.3.1 Anthropology, archeology, ethnology, and history

An early collection made by Timothy Kohler and George Gumerman (Kohler and Gumerman, 2000) includes agent-based modeling studies from archeologists, anthropologists, and ethnologists. They demonstrate how recent developments in modeling societies have endowed researchers with the freedom to move from the more traditional analytical techniques to an agent-centered, evolutionary, and generative understanding of how social phenomena emerged and work through time.

In these disciplines, agent-based models are used to simulate the past, some of which we already know from history and some of which happened prehistorically so that we may never know about them. One of the most ambitious projects is to use agent-based modeling to study "big history." Epstein and Axtell (1996) is probably the best illustration in this direction. The idea of the project is whether one can replicate a list of key features observed on a large scale in human history, such as population, immigration, famine, war, trade, disease, and social networks. What distinguishes this work is that software agents are programmed with multiple functions, whereas in most other agent-based models software agents are programmed in a rather low dimension.

While forecasting the future is always challenging, if we have time we will eventually know what the true answer is as times goes on, and hence the accuracy of our forecast. This "easiness," therefore, has no comparison with "forecasting" the past where the true answer may never be known, and we cannot reverse time. Unfortunately, in archeology, this is the best we can do, i.e., very often, we have to "forecast" what happened in prehistorical societies. Given this challenge, the contribution of agent-based modeling is to help us have a system such that all the fragmentary information can be more effectively pieced together so that the missing parts can be recovered to some extent, in particular when the missing parts were generated by humans in complex adaptive systems and their recovery is beyond what straightforward linear interpolation can do.

In this case, agent-based models are used to unravel archaeological mysteries by bringing "the missing complexity." The most well-cited work in this direction is what is known as Artificial Anasazi (Axtell *et al.*, 2002; Diamond, 2002; Gumerman *et al.*, 2003; Kohler, Gumerman, and Reynolds, 2005; Kohler *et al.*, 2008; Janssen, 2009). This project attempts to explain the history of the ancient Puebloan peoples (the Anasazi) that inhabited the Four Corners area in the American Southwest between 1800 BC and 1300 AD and who disappeared from the region in the space of a few years with no evidence of enemy invasions or dramatic environmental catastrophes.

2.3.2 Demography

Demography is the study of (human) population, both in terms of its size and structure. This size and structure change over time, and their projection can be a basis upon which many public policies are built, for example, retirement benefits. Unlike many other disciplines reviewed in this section, simulation had already been applied in this discipline long before agent-based modeling was introduced. In particular, in demography, both macrosimulation and microsimulation are carried out.[9] In fact, soon after Guy Orcutt's pioneering proposal of using microsimulation to study socioeconomic systems (Orcutt, 1957; Orcutt *et al.*, 1961), the microsimulation approach was already being used in demographic studies in the 1960s. A good survey of microsimulation in demography can be found in van Imhoff and Post (1998) and Morand *et al.* (2010).

Microsimulation acknowledges the great heterogeneities of individuals, including their age, sex, family status, education, etc., and the roles of these attributes in forming their decisions as to mate searching, marriage (and divorce), sex, pregnancy, residence, and health care. These individual decisions will then together determine mortality, nuptiality, fertility, and migration, variables that are related to population change. Therefore, it builds the micro-founded behavioral rules using empirical data, and through simulation generates aggregate behaviors, including population projection. This layout makes microsimulation very similar to agent-based modeling, and possibly makes agent-based modeling easier to accept for demographers than in other disciplines where equation-based modeling plays a dominant role.

Agent-based modeling extends microsimulation in several directions, such as adding downward causations, including social interactions with unobserved heterogeneities (social norms or networks), carrying out thought experiments, developing explanation mechanisms, etc. These differences between agent-based modeling and microsimulation have been well discussed in recent literature on agent-based demographic models (Billari and Prskawetz, 2003; Billari *et al.*, 2006). These extensions have resulted in some advances in demographic research, such as marriage (Billari *et al.*, 2007) and population projection (Griffith, Swanson, and Knight, 2012). In addition, agent-based modeling is not necessarily a substitute for microsimulation, for it can be a complement to it and the hybridization of the two can enhance demographic study and population projection (Wu and Birkin, 2012).

2.3.3 Entomology and ethology

If we consider social science broad enough to cover the social behaviors of insects or animals, it would be worth mentioning that agent-based simulation has also been applied to modeling their social behavior. Craig Reynolds's *boids* project is one of most illuminating examples from the early days (Reynolds, 1987). The boids project explores how the simple behaviors of individual birds combine to produce *flocking*. In this model, the birds obey only three rules:

1 *Avoidance*: If a bird is about to crash into another bird, it turns around.
2 *Attraction*: If a bird is far away from other birds, it heads towards the nearest bird.
3 *Alignment*: Otherwise, a bird will fly in the same direction as the bird next to it.

These three rules, later on, were also used in simulating the emergence of fish schools (Parrish and Viscido, 2005), and are, in fact, consistent with what biologists had found in their experimental studies of schools of fish (Partridge, 1981).

In the late 1990s, agent-based modeling was applied to study the social structure of non-human primates. One of the most cited agent-based models in this area is known as "DomWorld" (dominance world), and was proposed by Charlotte Hemelrijk (Hemelrijk, 1999, 2000; Bryson, Ando, and Lehmann, 2012). DomWorld provides an explanation of systematic differences in social organization observed in closely related primate species.

One interesting aspect of these agent-based models of non-human primates is the study of *group decision-making*; in particular, how group decisions are achieved when individual members may have different priorities for their own interest (Pratt *et al.*, 2005; Sellers, Hill, and Logan, 2007). Of course, group decision-making in human systems is also ubiquitous, but agent-based modeling of this class of social behavior is not commonly seen, particularly in economics.

2.3.4 Ecology

Agent-based modeling, alternatively known as individual-based learning, probably has a longer history in ecology than in economics. Its history can be traced back to the 1970s or even 1960s, while it was through the visionary paper by Huston, DeAngelis, and Post (1988) that the use of agent-based modeling in ecology became a self-conscious discipline; the equivalent acknowledgment of agent-based modeling in economics was not available at that time. Grimm and Railsback (2005) document well the historical development of agent-based ecology or individual ecology, and give many illuminating examples of successful replications of ecological patterns, such as the well-known lynx–hare cycle, using individual modeling.

What is coincidental is that when illustrating the difference between the equation-based approach and the agent-based approach, Wilensky chose the Lotka–Volterra equation as the working example. This classical Lotka–Volterra predator–prey model, standing at the heart of ecology, does not allow for the characteristic trait of individuals in the model (of the population growth rate); neither does it allow for spatial considerations and the resultant local interactions. When agent-based ecologists pursued "a genuinely new and different way of doing ecology," these are what they consider important. For them, agent-based modeling has to do with understanding, not simplifying, the complexity of nature (Grimm and Railsback, 2005).

2.3.5 Epidemiology

Modern theoretical epidemiology begins with the research on the spread of malaria by Ronald Ross (1857–1932), the 1902 Nobel Laureate in Medicine. Building upon the work of Ronald Ross (Ross, 1915; Ross and Hudson, 1917), Anderson McKendrick (1876–1943) and William Kermack (1898–1970) published their seminal work on theoretical epidemiology, known as the *Kermack–McKendrick model* or the *SIR model*. The pivotal role that this model has in epidemiology is probably equivalent to the role of the Lokta–Volterra equation in ecology. They both used differential equations to give a fundamental description of the essential processes observed in epidemiology or ecology. Very similar to the agent-based ecological models in relation to the Lotka–Volterra equation, the agent-based epidemiological model works as a complement to the early well-established Kermack–McKendrick (compartmental) models (Bian, 2004; Eubank *et al.*, 2004; Ferguson *et al.*, 2005; Auchincloss and Roux, 2008; Roche, Guegan, and Bousquet, 2008; El-Sayed *et al.*, 2012), and now both these equation-based and agent-based models are recognized as two primary types of disease-spread models.

2.3.6 Geography

Geography, by its nature, deals with highly distributed spatial systems. This nature inevitably makes agent-based modeling a relevant and even powerful tool for geography. In particular, as we shall see later (Chapter 4), one of the pioneering applications of agent-based modeling to social science begins in city dynamics (Schelling, 1971). The cellular automata model used in Schelling (1971) has become a foundation for studying geographical or spatial dynamics (Batty, 2007). The spatial agent-based models are further enriched and developed with the empirical data available from geographical information systems (GIS; Gimblett, 2002; Brown *et al.*, 2005; Baynes and Heckbert, 2010; Heckbert *et al.*, 2010). The integration of GIS and ABM has become a research paradigm to simulate many social, ecological, and environmental processes in a spatial context. Disaster management is one such extension, and criminology is another case in point (Groff, 2008; Liu and Eck, 2008).

The application of agent-based modeling to disaster management systems is mainly due to the attempt to smooth information flow so as to enhance a timely relief operation. To do so, it is desirable to have the whole disaster management system designed in an autonomous decentralized manner, and agent-based modeling is well suited for achieving this goal (Sadik *et al.*, 2010).

A very comprehensive and updated review of the significance of agent-based models to geographical systems can be found in the collection produced by Batty *et al.* (2012). This collection addresses the very fundamental issue of the role of agent-based models in the rising awareness of the increasing complexity of geographical systems, which is capable of distinguishing the strong sciences from the weak sciences, and the models which can *predict* from the models which can *inform*. Issues of geographical systems, including energy, security, epidemics, crime, poverty, migration, aging, urbanization, housing and financial markets, transportation, crowd movement, floods, climate change, and disaster management are discussed using various agent-based models. Given the edge-crossing nature of many of these issues, sometimes we need to integrate or couple various agent-based models so that the dialogues with different pieces of information can be enriched. This trend of further research efforts corresponds well with what we mean by "higher resolution and yet better integration" (Section 2.2.2).

2.3.7 Political sciences and international relations

Computer simulation of political science is not new. Ithiel de Sola Pool (1917–1984), the founder of the political science department at MIT, was considered to be a pioneer in this area. He gave the first computer simulation of decision-making in international crises, i.e., the outbreak of World War I (Pool, 1965). He also gave the first major computer simulation of the American electorate based on public opinion data (Abelson, Pool, and Popkin, 1965). His contributions are well acknowledged, e.g., see Deutsch, Platt, and Senghaas (1971).

After Pool's pioneering work, we have Thomas Schelling in the late 1960s and Robert Axelrod in the mid 1980s. They continued the social simulation approach to dealing with issues related to conflicts, competition, and cooperation (Schelling, 1969, 1971; Axelrod, 1984). Their studies, built upon cellular automata and programmed agents (actors), also laid the foundation for the burgeoning of the agent-based political science in the 1990s, as nicely surveyed in Johnson (1999), Cederman (2001), Kollman and Page (2006), and Susumu *et al.* (2007).

Some noticeable advances include the agent-based modeling of state formation and stability (Cederman, 1997), the rise and fall of nationalism (Cederman, 1997), preference aggregation (the Tiebout model; Kollman, Miller and Page, 1997), the size of wars (Cederman, 2003), ethnic and cultural violence (Lim, Metzler, and Bar-Yam, 2007), and, probably the most focused one, voting and multiparty competition (Fowler and Smirnov, 2005; Laver and Sergenti, 2011).

In international relations, Susumu Yamakage and his colleagues at the University of Tokyo have applied the agent-based modeling technique to the Cuban Missile Crisis in 1962 and conflicts in Northeast African countries (Yamakage *et al.*, 2007). In his study on the Missile Crisis, agent-based modeling is used to simulate the group decision-making process based on a tape recording of a National Security Council meeting called by John Kennedy. This kind of agent-based modeling involves agents' *dialogs*, or how the consensus and decision was reached through the influence of consecutive dialogs.

2.3.8 Management science

Agent-based modeling has also become quite important in management science. The application of agent-based modeling to management and organizations and its significance are well elucidated in a recent collection addressing the relation between complexity and management (Allen, Maguire, and McKelvey, 2011).

2.3.9 Sociology

While sociology has a much less analytical and modeling tradition as compared to economics, the first two articles on using agent-based models in the social sciences were published in the inaugural issue of the *Journal of Mathematical Sociology* (Sakoda, 1971; Schelling, 1971). Of the two authors, Thomas Schelling is largely recognized as an economist, but James Sakoda is undoubtedly a sociologist. The attempt to make sociology analytical and mathematical and hence a part of hard science had long existed before the advent of agent-based modeling. The main pursuit made by James Coleman and the establishment of the field of mathematical sociology in the late 1960s, as well as the launch of the the *Journal of Mathematical Sociology*, have all helped sociology move toward a suitable formalism. The early development of agent-based modeling in sociology has been well surveyed in Macy and Willer (2002), and the most recent developments have been surveyed by Squazzoni (2012).

Eighteen studies published from the year 1996 to the year 2001 were surveyed by Macy and Willer (2002). They classified these studies into two kinds of emergence, namely *emergent structure* and *emergent social order*. The former refers to the formation of social differentiation or homogenization (integration) through social influence and selection pressure, in the form of segregation, cultural clusters, stratification, diffusion, coordination, and the sudden collapse of norms, beliefs and institutions, whereas the latter refers to trust, cooperation, pro-social behavior, and collective action. They further used a kind of decision tree to assign each study attribute. This decision tree takes the following three elements explicitly into account: networks (spatial or social), learning (individual and social), and parameter manipulation (behavioral or environmental). This decision tree is in effect generic when one tries to do taxonomic work on the agent-based research in other disciplines.

Squazzoni (2012) applies the same taxonomy to extend the review by including studies published in the last decade. He, however, started with the emergent order first (his Chapter 2) by focusing on the emergence of pro-social behavior with various cooperation-enhancement mechanisms, followed by the emergence of social structure with a focus on social influence (his Chapter 3). In addition to this main body of literature, a genealogical study is also conducted by tracing the origin of agent-based ideas in sociology. There, he mentions the influence of some early works by James Coleman, Raymond Boudon, Herbert Simon, Fredrick Hayek, Thomas Schelling, and Mark Granovetter. This book is also one of the very few to make a connection between laboratory experiments and agent-based modeling (the subject discussed in Section 2.2.3).

2.4 The ten that make it new

In this chapter, we give a cursory look at the use of agent-based modeling in various major disciplines of the social sciences. By no means are we trying to give an exhaustive coverage here. In fact, some, such as education, law, linguistics, psychology, and social work, have not even been mentioned. However, we hope that the limited survey offered here is sufficient for us to see how social scientists are motivated by the use of agent-based modeling.

While each of these disciplines has its own conventional and well-established methodologies, such as equation-based, variable-based, statistically based, experimentally based, or microsimulation-based methodologies, the appearance of agent-based models can work in a complementary manner. As we have seen earlier in this chapter, and shall see more in the following chapters, *details matter*, not necessarily due to the prediction concern but more because of the understanding concern, since *they are the major driver for the use of agent-based modeling in the social sciences*. These microdetails can be manifested in many different forms in different disciplines. Many times they are beyond data availability and mathematical tractability, and hence agent-based models become the last resort.

Readers with enough patience to go through the cited articles in the various aforementioned disciplines may find that the advent of computational social science or the use of agent-based modeling in social science points to the following ten changes in social science research:

1 from equation-based to agent-based;
2 from analytical derivation to computer simulation;
3 from factors to actors;
4 from macrosimulation to microsimulation, and further to agent-based simulation;
5 from the modeling of population to the modeling of individuals;
6 from spatially free setting to spatially explicit modeling (situated modeling);
7 from statistical identification and estimation of social patterns to searching for the underlying generative mechanism;
8 from forecasting to understanding and explanation;
9 from policy applications to thought or theoretic-oriented experiments;
10 from small-scale laboratory experiments to large-scale laboratory experiments.

On each of these ten, one can find some assertions being made by the articles cited in this chapter. No elaboration shall be given here. We would, however, like to cite Van Dyke Parunak, Savit, and Riolo (1998) for an in-depth illustration of the first point, and Gilbert and Troitzsch (1999) for a comprehensive review of the three-stage evolution of simulation in the social sciences, the fourth point above.

Finally, we are fully aware that agent-based modeling faces different degrees of resistance in different disciplines, partially depending on the strength of their incumbents. Some fundamental questions or consideration of social simulation, or simply simulation, are essential for a comprehensive understanding of the role of simulation in science, its relation to theory, and its contribution to knowledge discovery. On this aspect, one can find a large number of studies with very contrasting viewpoints, for example, Lehtinen and Kuorikoski (2007) and Velupillai and Zambelli (2010). Lehtinen and Kuorikoski (2007) distinguish simulation from computation and argue that, based on the publications of the top journals, economists have not been ready to accept agent-based simulation. They are aware of the acceptance of agent-based simulation in physics, and the reason that it has not been accepted in economics is because economics is rather peculiar in having a love for the "perfect model." It is only if we view simulations as attempts to provide direct representations of real systems, and not abstract models, that the epistemology of simulation can make sense. However, at the very end, they still keep a slice of the positive expectations for the future of agent-based modeling in economics, which is largely consistent with what has been said in Section 2.2.3.

> The recent acceptance of behavioral and experimental economics within the mainstream reflects economists' increasing willingness to break away from these methodological constraints and to make use of results from

> experimental sources. Perhaps this will also mean that computerized quasi-experiments may one day find acceptance within economic orthodoxy.
>
> (Lehtinen and Kuorikoski, 2007, p. 326)

We have now presented the big picture of agent-based modeling in the social sciences. In the following, we shall provide a focused review of the use of agent-based modeling in economics. We start this job by tracing its origins. Part II of the book will trace the footprints along four trails. Some of these four are also shared by other disciplines, but there is at least one which is unique to economics, i.e., *market origin*. We shall start with this one (Chapter 3) and then continue with the rest.

Notes

1 The claim that agent-based modeling can help put the social sciences together is frequently made by many social scientists, such as Kohler (2000).

2 See, for example, Bandini, Manzoni, and Vizzari (2009), Meyer, Lorscheid, and Troitzscho (2009), Heath, Hill, and Ciarallo (2009), and Nikolai and Madeyand (2009). Bandini, Manzoni, and Vizzari (2009) and Nikolai and Madeyand (2009) provide a comprehensive survey of agent-based social simulation (ABSS) platforms. Their goal is to help researchers better choose a toolkit that suits their purposes. Nikolai and Madeyand (2009) have also created a corresponding page entitled *ABSS Software Comparison* in Wikipedia based on their research. Meyer, Lorscheid, and Troitzscho (2009) performed a co-citation analysis to visualize the intellectual structure of social simulation and its development.

3 While the agent-based models exemplified by cellular automata are made up of just two levels, the cell level and the checkerboard level, general agent-based models are not restricted to only two levels, and are referred to as "systems of systems of systems" by Jeffrey Johnson. In general modeling, interaction between the levels is still rarely seen in agent-based social science (see Chapter 24).

4 A concise introduction to Peirce's theory of abduction can be found in Fann (1970).

5 In addition to comprehension and forecasting, Epstein (2008) provides a list of an additional 16 answers to the question "Why model?" This list enables us to be able to evaluate the usefulness of agent-based models as opposed to equation-based models, by not attaching too much weight to their forecasting performance. Among his list of the 16 reasons for modeling, *guide data collection* is the one which deserves more attention, since we normally assume that theory comes after the data. However, here, Epstein (2008) reminds us that it is the opposite that is the case, as without models it is not always clear what data to collect. For economists, theory preceding data is best illustrated by Simon Kuznets's work on gross national product (GNP), which was clearly motivated and guided by Keynes's *General Theory* (Keynes, 1936).

6 Of course, experimental economics is the most obvious; many agent-based models proposed in the 1990s sought to *understand* the human behavior observed in experiments (see Chapter 6). Nonetheless, the research method using laboratory experiments is applied not only to economics but also generally to other disciplines in the social sciences (Webster and Sell, 2007; Morton and Williams, 2010; Druckman *et al.*, 2011).

7 However, if one performs a literature survey and lists all experimental studies on the one hand and all simulation studies on the other hand, it may not be hard to see that these two areas overlap only in a limited domain. In other words, agent-based modeling and experimental economics are more complementary to each other rather than just being a scaling-up or a scaling-down of each other.

8 It will be more interesting to review the advances of computational social sciences by exemplifying some of their successes or superiorities, and one of the most convincing ways to do so is to provide a list of research questions which agent-based modeling seems to tackle more successfully than the existing approaches. The degree of persuasion can be multiplied if one can show that the success is not just established in a few disciplines but in many other disciplines. However, this requires a more extensive and deep literature review, which is beyond the scope of this chapter. We nonetheless believe that the short review provided in this section is still useful for any readers who would like to take part in this adventure on their own.

9 The differences between macrosimulation and microsimulation as used in demography have been detailed in van Imhoff and Post (1998).

Part II

Origins of ACE

There are several origins (traditions) of agent-based modeling in economics and social sciences. In this part of the book, we shall give a comprehensive and interdisciplinary review of ACE by tracing its four origins. The four origins of ACE considered in this part are, in chronological order, the *market origin* (with a long history), the *cellular automata origin* in the 1970s, the *economic tournament origin* (the *game theory origin*) in the 1980s, and the *experimental economics origin* in the 1990s.

These four origins are, of course, not independent of each other. They can be imagined to be four gates to the same castle, with the market origin being the main gate. While tourists may enter the castle through different gates, their experiences of the castle will be similar if they all explore the castle long enough. The four origins selected above are then very much like the answer to the question, "Where did you start your tour in ACE?" Hence, the answer may be Peter Albin and Ducan Foley's model of the non-tâtonnement process (Albin, 1992; Albin and Foley, 1992), Thomas Schelling's segregation model (Schelling, 1971), Robert Axelrod's simulation of the iterated prisoner's dilemma tournament (Axelrod, 1987), Jasmina Arifovic's simulation of cobweb experiments (Arifovic, 1994), or a long list like this. Certainly, these four origins are by no means exhaustive, and different tour guides may have different arrangements. However, as long as we visit the main gate (the markets origin) and explore the whole castle, our choices of the other three origins will have little effect.

Among the four origins, the most important and familiar one for economists is the *market origin*, a derivative of the historically long pursuit for a real construction (procurement processes) and hence a real understanding of markets. This part will begin with this origin (Chapter 3). Chapter 4 will be the cellular automata origin, which makes agent-based modeling a truly interdisciplinary subject, overarching biology, life sciences, computer science, physics, mathematics and logic, and social sciences. The third origin, the tournament origin or the game theory origin, is very much related to evolutionary game theory and, more generally, evolutionary economics. This game theory origin is also extensively shared by other agent-based social sciences, such as ecology (Grimm and Railsback, 2005), political sciences (Laver and Sergenti, 2011), and sociology (Squazzoni, 2012). Chapter 5 will show how agent-based simulation can advance our understanding of the evolutionary nature of games or markets by tracing this game theory origin. Finally, there is an increasingly large group of economists who are interested in using computer agents (software agents) to simulate human-subject behaviors observed in the laboratory. Chapter 6 will trace this experimental economics origin.

3 The markets origin

When Leon Walras (1834–1910) proposed his competitive general equilibrium model in his magnum opus *Elements of Pure Economics* in 1874 and characterized the economy as a set of equations and unknowns, a seed for a long pursuit was planted. The fundamental quest is whether the price discovery process, also known as the tâtonnement process, can actually replace the true market process, and whether the Walrasian auctioneer, or the equivalent advanced supercomputer, can actually do the job of resources allocation as the natural markets do.

Herbert Scarf, one of the founders of the general equilibrium model, once stated:

> In my opinion, the major attraction of markets over centralized calculation, for Gorbachev and his economic reformers, is not so much the mathematical difficulty of a single equilibrium calculation; it is rather that these computations must be performed over and over again in real time, in the face of constantly changing economic circumstances. The economic is in continual flux, with new possibilities constantly emerging, and mathematical solutions to the equilibrium equations will at best represent the solutions to yesterday's problem. If we are to be responsive to the novel conditions of daily life—and to engage the energies and skills of millions of self-interested economic actors—it may be necessary to use the market as an algorithm for solving the equilibrium equations rather than solving these equations themselves on the computer.
>
> (Scarf, 1990, p. 379)

In the history of economic analysis, this quest has been pursued by economists in different forms, including:

1 the debate on the possibility of socialist calculation (Boettke, 2000);
2 the silence of "markets" in economic theory (McMillan, 2002; Mirowski, 2007);
3 the aggregation problem over adaptive interacting heterogeneous agents (Kirman, 1992; Stoker, 1993; Blundell and Stoker, 2005; Gallegati *et al.*, 2006b); and
4 the mathematics suitable for social sciences (Velupillai, 2010; Borrill and Tesfatsion, 2011).

Possibility of socialist calculation

The first form of the quest, the socialist calculation debate, stands in an important position in the history of economic thought. It involves the great economists such as Ludwig von Mises (1881–1973), Friedrich Hayek (1899–1992), Abba Ptachya Lerner (1903–1982), and Oscar Lange (1904–1965). Under the Walrasian formulation, an economy can be seen as a set of equations. Thus, there should be no need for prices. Using information about available resources and people's preferences, it should be possible to calculate the optimal solution for resource allocation. Oscar Lange (Lange, 1936, 1937) even proposed the tâtonnement procedure as the actual computing algorithm for the operation of a centrally planned economy. Nevertheless, Friedrich Hayek responded that the system of equations required too much information that would not be easily available and the ensuing calculations would be too difficult. This is partly because individuals possess useful knowledge but do not realize its importance or do not have the incentive to transmit it (Hayek, 1945). He contended that the only rational solution is to utilize all the dispersed knowledge in the market place through the use of price signals.

Hayek's advocacy of the market for the fusion and use of knowledge (Hayek, 1945) provides an important intellectual inspiration for agent-based modeling through prediction markets (Vriend, 2002; see also Section 9.6.1). Probably for the same reason, sociologist Flaminion Squazzoni also includes Hayek as one of the predecessors of agent-based computational sociology (Squazzoni, 2012).

Silence of "markets"

As to the second form of the quest, one may be surprised to find that economics has little coverage of markets. The strong analytic form of economics inevitably clothes markets with a uniform, hiding their great and wild varieties. In his attempt to demystify the market, John McMillan (1951–2005) provides the following observation:

> Textbook economic theory does not dispel the markets-are-magical notion, for it says little about how markets go about doing their job. Although economics is in large part the study of markets, the textbooks depict them abstractly. The supply-and-demand diagram, expounded in countless Economics 101 lectures, is a bloodless account of exchange. It leaves unexplained much of what needs to be explained. It tells us what prices can do, but is silent on how they are set. Supply and demand bypasses questions of how buyers and sellers get together, what other dealings they have, how buyers evaluate what they are buying, and how agreements are enforced.
>
> (McMillan, 2002, p. 8)

Regardless of the forms in which the issue is presented, they all point to some undesirable consequences when the originally decentralized processes is assumed away or oversimplified in economics.