Chapter 7
Agent-Based Modeling and Complexity

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Abstract Complexity theory provides a common language and rubric for applying agent-based processes to a range of complex systems. Agent-based modeling in turn advances complexity science by actuating many complex system characteristics, such as self-organization, nonlinearity, sensitivity, and resilience. There are many points of contact between complexity and agent-based modeling, and we examine several of particular importance: the range of complexity approaches; tensions between theoretical and empirical research; calibration, verification, and validation; scale; equilibrium and change; and decision making. These issues, together and separately, comprise some of the key issues found at the interface of complexity research and agent-based modeling.

7.1 Introduction

Complexity theory and the accompanying trappings of complex systems provide the theoretical basis for agent-based models (ABMs). While modelers are usually interested in addressing specific theoretical questions and working in particular substantive areas, they almost invariably draw on complexity concepts when using an agent-based approach. The relationship between ABM and complexity is mutually beneficial. While complexity has much to offer ABM in terms of underlying concepts, modeling advances complexity by making real many of the often fuzzy concepts on which complexity science relies. Advances in ABM are allowing modelers to move beyond studying complex systems in just metaphorical or rhetorical terms by giving them the tools to represent complex phenomena. Many disciplines are using ABM to enhance understanding of the interplay of complexity concepts, ranging from policy fields

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(Carrillo-Hermosilla 2006; Gatti et al. 2005; McKelvey 1999) to the natural sciences (Brose et al. 2004; Phillips 2006; Rind 1999) through to the social sciences (Batten 2000; Manson and O'Sullivan 2006; Sampson et al. 2002) and into the humanities and arts (Nowotny 2005; Portugali 2006).

When the theoretical questions regarding complexity are combined with the broadly applicable research allowed using ABM, a number of issues stand out, including:

- Reconciling a range of complexity approaches
- Navigating the tension between theoretical and empirical research
- Implementing calibration, verification, and validation of models
- Dealing with scale
- Balancing the corollaries of equilibrium and change
- Representing features of decision making.

These issues, together and separately, comprise some of the key points of contact and contention among the various components of complexity research and ABM. Ongoing examination of these issues is spurring further ABM research that illuminates phenomena studied in the physical environment, social systems, and their combination via human-environment research.

7.2 Complexity Approaches

Complexity theory is less a singularly defined, discrete conceptual entity than an interdisciplinary focus for which individual fields and researchers use a common set of queries, concepts, and approaches. Given this lack of a single, identifiable core, the terms 'complexity theory' and 'complexity sciences' can therefore fittingly refer to an array of research methods. In order to provide an organizational schema to this diverse field, we identify three streams of complexity research: algorithmic complexity, deterministic complexity, and aggregate complexity (cf. Byrne 1998; Cilliers 1998; Lissack 2001; Manson 2001). At its simplest, algorithmic complexity conceives of any system in terms of the computational or heuristic processes needed to replicate system behavior. Deterministic complexity envisions a system through the lens of nonlinear dynamics and chaos theory, in order to try to capture system dynamics via a small set of mathematical equations. Aggregate complexity focuses on how complex systems arise from interactions among individual entities. It is this final kind of complexity, aggregate complexity, that most ABM researchers tend to invoke when modeling, although algorithmic and deterministic complexity make their own contributions to ABM.

Complexity in any of its above-mentioned forms typically applies to a system, a set of entities connected to each other and the external environment in a way that gives it an overall identity and behavior. An ABM in its most basic form represents a system of such discrete entities. Systems can be of almost any scale, from atoms bound together in a molecule to households in an economy to planets in the solar system. The key to modeling any of these systems, and therefore the key to complexity research and ABM, is the capture of core characteristics among system entities and, critically, their interrelationships. An ecosystem, for example, is self-contained in terms of much of its structure and function but also has many connections to the larger climatic, geophysical, and biotic environment. The model must also have system boundaries that set it apart from its larger context. An urban area, for example, can be defined in a number of ways, but most models focus on elements of the built environment such as buildings and populations (e.g., workers, homeowners) that have relationships via migration, capital flows, and environmental relationships with the larger world.

Algorithmic complexity focuses on representing systems in computational and mathematical terms. The component fields of computational complexity theory and information theory examine the difficulties of computing the solution to problems and representing a system or reproducing its behavior (Chaitin 1974; Gell-Mann 1994). At its most useful, algorithmic complexity provides a number of different measures of how a system is composed and represented. One helpful side effect is that some measures will identify problems that cannot be solved mathematically or computationally with our current state of knowledge, but that may yield to simulation or heuristic approximations. Beyond these instances, the use of algorithmic complexity in complexity research and ABM has been limited given the greater interest in deterministic and aggregate complexity (O'Sullivan 2004).

Deterministic complexity is defined by approaches that use sets of mathematical equations to describe the state and trajectory of system dynamics. Deterministic complexity is so called because it finds for complex systems a few key variables and equations to describe system state and evolution; in this sense, system behavior is 'determined' by these equations and variables. Positive and negative feedback are important components of deterministic complexity, spurring changes that self-reinforce or diminish over time, respectively. Given the potential for such feedback, deterministically complex systems exhibit both sensitivity and nonlinearity. The former refers to how systemic changes can result from small perturbations while the latter refers to how these small changes can give rise to disproportionately large changes in system structure or behavior (Phillips 2003). The combination of sensitivity and nonlinearity is exemplified by the 'butterfly effect,' where slight variations in initial model parameters, due to the displacement of air by butterfly wings, can lead to large meteorological changes in a modeled weather system (Lorenz 1973). The elements of sensitivity and nonlinearity are further adopted and extended by aggregate complexity for the modeling of agent-based systems.

Aggregate complexity focuses on how complex systems arise from the local interactions of system entities. With this perspective, the structure and dynamics of a system such as a city must be understood as driven by individual components and their relationships. In a city, these entities are people, households, firms, and organizations whose relationships are defined by exchanges of matter, energy, and information. These entities have relationships with other entities and play multiple roles within the city. Some of the stronger relationships give rise to larger aggregations (e.g., families, neighborhoods) that may act as entities in and of themselves. This potential for larger entities and behaviors to arise out of local interactions is seen as a form of self-organization, whereby entities and their relationships are sufficiently strong yet flexible enough to allow the overall system to adapt to a changing environment (Easterling and Kok 2002). In some settings, self-organization leads to self-organized criticality, where the system rapidly reconfigures entities and internal relationships, in response to internal perturbation or external shocks (Bak 1996). Self-organization is related to the concept of emergence, whereby system characteristics or behavior result less from additive effects of system entities and their behavior and more from synergistic relationships among entities (Funtowitcz and Ravetz 1994; Holland 1998). One important kind of emergence is supervenience, where changes in system structure or behavior at one level of aggregation are driven by changes at a lower one (Sawyer 2002). In sum, aggregate complexity demonstrates how system entities and their relationships define the behavior of sub-systems and the system as a whole through self-organization and its offshoots, self-organized criticality, emergence, and supervenience.

While it is useful to denote various types of complexity – algorithmic, deterministic, aggregate – it is also important to note that complexity draws on many conceptual antecedents. Since much of current complexity research, particularly aggregate complexity, relies on notions of synergy and holism, it reflects philosophies tracing back to Aristotle's definitions of unity being more than the sum of parts and Whitehead's philosophy of organism, which contends that understanding nature requires more than recourse to fixed laws, and instead identifies it as a system that is continually evolving (Whitehead 1925). More recent antecedents include cybernetics and feedback (Wiener 1961), neural networks and other biological analogs (McCulloch and Pitts 1943), work in computing including cellular automata (von Neumann 1966), and importantly, general systems theory, which holds that many systems have underlying similarities (von Bertalanffy 1968). Complexity departs from earlier related work by focusing on how systems emerge from the simple and local interactions among system entities. While complexity shares with much previous work the assumption that systems can exist in equilibrium, it also actively explores the possibility of perpetual or repeated disequilibrium or near-chaotic behavior. In many respects, then, complexity draws on key features of holism and synergy while also focusing on evolution and the balance between equilibrium and disequilibrium.

7.3 Issues of Complexity and ABM

7.3.1 Tensions Between Theoretical and Empirical Modeling

ABMs are valuable for both theoretical exploration and empirical investigation of complex systems. For theoretical inquiry, modeling serves as a means to better understand how elements of interest and the relationships among them contribute to overall system behavior over time. For empirical investigation, modeling is a vehicle for presenting all known and necessary initial conditions – defined in large part by system entities and their relationships – in order to determine how they have brought about an observed state and how they could bear on future possible states. ABMs also offer many opportunities to combine theoretical and empirical approaches, although not without raising issues regarding the model's simplicity and complexity.

Theoretical inquiry with ABMs usually entails running "controlled experiments" that may spur the discovery of laws about complex processes (O'Sullivan 2004: 288). Purely theoretical ABMs are based on hypotheses that specify certain rules for the behavior of actor agents and their interaction with the environment. When using ABMs to model urban transportation, for example, actor behavior may be defined by utility maximization, as measured by housing quality or work proximity, and transportation cost minimization determined by distance to housing and work and modal choice. While many theoretical models are built for illustrative purposes, such as confirming what their underlying theories predict, some models generate convincing, and sometimes surprising, theoretical implications. Work on racial segregation simulation based on Schelling models, for example, continues to spur debate (Fossett 2006). ABMs contribute to the longstanding use of computer simulation to allow examination of many possible futures or pasts for a given system (Manson and O'Sullivan 2006).

Empirical models focus more than theoretical ones on using actual data to simulate real-world phenomena, although the two foci can be complementary. The increasing number of theoretical models, the growing volume of empirical data, and the use of lab experiments to create rules of agent behavior have all contributed to recent expansion in the development of empirical models (Janssen and Ostrom 2006). These models usually extend aspects of theoretical models using empirical data and have the ability to make predictions and prescriptions under different demographic, economic, and policy scenarios. Since one of the aims of creating empirical ABM is to accurately describe real-world processes, a tension exists between the descriptive power granted by specificity and the desire to generalize to other settings. A model must therefore maintain a balance between fitting the empirical data and highlighting the processes of interest (Manson 2007).

The relationship between theoretical and empirical foci in ABMs highlights how the modeling of empirically complex phenomena with relatively simple or foundational rules is a difficult task. For example, because it is impossible to completely simulate all aspects of natural or human organization without reduction and simplification, all urban complexity models will have a theoretical component (Irwin et al. 2009). Similarly, although complexity theory seeks to capture underlying dynamics, we still face a world where it is difficult to divine many characteristics of the economic state of a city beyond a few years. Any model that attempts to capture the necessary specificity of the myriad system entities may be regarded less for its complexity than for its complication (Torrens and O'Sullivan 2001). When adding a large number of features to a model, the modeler strays from the notion that a small number of rules describing the behavior of agents will lead to complex systems. This challenge arises when modeling urbanization and land change, for example, as

ABMs become more common and sophisticated. Modelers can represent many entities and relationships at the risk of moving away from the ethos of generating complex outcomes based on simple conditions and rules (Parker et al. 2003).

7.3.2 *Calibration, Verification, and Validation*

Agent-based complexity models require careful and thorough evaluation, which is comprised of calibration, verification, and validation (Manson 2003). Calibration is the adjustment of model parameters and specifications to fit certain theories or actual data. Verification determines whether the model runs in accordance with design and intention, as ABMs rely on computer code susceptible to programming errors. Model verification is usually carried out by running the model with simulated data and with sensitivity testing to determine if output data are in line with expectations. Validation involves comparing model outputs with real-world situations or the results of other models, often via statistical and geovisualization analysis. Model evaluation has more recently included the challenge of handling enormous data sets, both for the incorporation of empirical data and the production of simulation data. Modelers must also deal with questions concerning the relationship between pattern and process at all stages of calibration, verification, and validation. Ngo and See (2012) discuss these stages in ABM development in more detail.

Empirical ABM modelers struggle to obtain the data necessary for proper calibration. From a practical standpoint, simulating a complex system such as an urban housing market requires initializing a range of key components including agents, organizations, and the environment. Modelers rarely have the necessary individual-level data, however, to populate agents such as households, and may similarly be missing information on organizational dynamics or features of the environment. They typically have either a limited set of random samples (e.g., household surveys, phone interviews) or more often, spatially aggregated data at various scales that are collected for other purposes by different government agencies (e.g., census data, regional economic information). Exogenous parameters (e.g. for urbanization, drivers such as population growth rates, interest rates, and federal taxes) can often be derived from actual data, but sometimes are the results of educated guesses, simple linear interpolation, or extrapolation (Brown and Robinson 2006; Torrens 2007).

Proper calibration and validation also entails the integration and reconciliation of data across multiple scales and formats. In ABMs involving both human and environmental elements, for instance, integrating vector and raster data that describe human and natural phenomena respectively at different scales can create problems like ecological fallacies (drawing incorrect inference on individuals from aggregated data) or inappropriate classification when assigning attributes and aggregating features. There are also broader conceptual issues that arise when reconciling data from different scales (e.g., household data vs. census information vs. regional socioeconomic statistics) and linking these observed data to the agents of interest (e.g., households versus parcels versus neighbourhoods). In response to these issues, modelers may need to generate individual data from random samples or from aggregate data, such as census data. Promising approaches include iterative proportional fitting procedures, where tabular data are modified to new levels of aggregation, or Monte Carlo simulation, where multiple probabilistic draws are taken on a sample data set (Wheaton et al. 2009).

While complexity modelers often lack sufficient data for ABM calibration and validation, they also face challenges when generating simulation data. Understanding the dynamics of the attributes of different kinds of agents of even a moderately sophisticated simulation demands great effort to visualize, analyze, and replicate the modeled phenomenon or process (Janssen 2009). The nature of intermediate attribute and behavioral data of actor agents, for example, is rarely discussed in the literature, although such data are potentially useful for the validation of agent behavior and the social processes that produce such behavior. Here, complexity theory can allow the researcher to triangulate among different approaches and viewpoints, because it focuses on identifying generic features of complex systems without getting the inquiry mired in a need to address ontological or epistemological questions (O'Sullivan 2004).

In terms of broader validation challenges, distinctions between theoretical and empirical approaches lead to questions concerning pattern and process. Patterns that are often generated in complexity models, including fractals and information-theory measures, may not reveal much about the processes that generate them, much less whether the processes are complex in the sense meant by deterministic or aggregate complexity. The potential disconnect between pattern and process may influence how the modeler chooses between empirically-driven explanation and description (which usually tilts toward pattern) versus theoretically driven discovery and hypothesis generation (which is often biased towards process). A number of authors, for example, incorporate variables and rules into a model that bring about a community pattern for the Anasazi civilization in the southwest United States previously determined by archeologists and historians (Axtell et al. 2002; Dean et al. 2000). The ABM identifies how discrete entities and their relationships give rise to higher-level systemic processes, but this focus on scale raises the specter of equifinality, where different variables and processes may lead to the same outcome, or similarly, where only a few key variables determine model outcomes (Janssen 2009). For theoretical models, the modeler has more leeway to set initial conditions and formulate iterative rules that can illuminate a theoretical question, although validation becomes difficult in the absence of empirical data. Axelrod's (1997) culture dissemination model, for example, demonstrates how regions adopt or reject the cultural practices of neighboring regions. The model results, while not reflecting the real world in detail, elicit interesting questions about interactions between actors across space and over time.

7.3.3 Scale

ABM researchers pay close attention to the spatial, temporal, and organizational scale of the simulation process. As noted above, one of the hallmarks of scalar properties in ABMs is emergence, the phenomenon of processes occurring at one level that are not evident based on a summing up of lower-level processes.

Emergent properties are implicitly scalar, as seen in how humans function based on the workings and interactions of the component organs, the flight patterns of a flock of birds arising from the actions of individual birds, and the traffic gridlock that occurs based on the decisions of individual drivers (Mainzer 1996). Importantly, emergence is often unintentional. Drivers and their vehicles do not generally seek to create gridlock, for example, but their actions and subsequent interactions readily create traffic jams. ABM modelers can draw on several bodies of work to help define and understand scale and emergence as well as adding context to notions of non-linearity and sensitivity. In addition, scale offers an entry point to the modeling of networks using ABM.

One approach to defining scale levels and emergence is provided by hierarchy theory, wherein actors and systems, through their functions and interactions, form larger systems. A regional housing market, for example, can have several subregions as housing market areas; each housing market area also has housing submarkets; a housing sub-market might then include several cities or several school districts with similar socioeconomic characteristics; within such a sub-market exist smaller neighborhoods defined by residents' activity and interaction patterns. Under this formulation, scale levels should be considered as defined by interactions and relationships among entities, but importantly, it is up to the analyst to define these levels instead of taking them as pre-defined (O'Neill 1988). Similar frameworks exist for the emergence of scale from interactions among entities, such as when institutions arise from the interrelationships of individuals (Ostrom 2005) or, more broadly, when human-environment systems such as agriculture or forestry exist at multiple scales of analysis (Easterling and Polsky 2004).

When drawing upon hierarchy theory, the modeler can identify the system's constitutive hierarchies, wherein the components of a subsystem have emergent properties only when they are brought together to form a higher-level system (Gibson et al. 2000). When considering emergent properties in collective behavior, an implicit assumption is made by the modeler that the lower-level processes are individually not as complex as the collective outcome, yet simultaneously each individual entity may be constitutive of emergent properties based on processes one level further down. The modeler can therefore create a series of models that nest these processes within one another, thereby modeling a hierarchically ordered system.

Notions of scale levels defined by constitutive hierarchies provide a useful counterweight to non-linearity and sensitivity as conceived by deterministic complexity and aggregate complexity. When determining both the spatial and temporal scales of inquiry, one may discern linear associations or limits that coincide with scale levels. Identifying the flapping of a butterfly's wings as a cause of super-regional weather phenomena like hurricanes is a powerful idea, but may not account for a large set of temporal conditions that, in concert with the wings, led to the hurricane. Hence, a claim that the butterfly was necessary does not mean that it was sufficient. In regard to social processes that may seem non-linear, such as the ways that a massively distributed photograph or website video of an individual event may influence national or international policy, one must still consider the communication infrastructure and the social networks that represent a series of steps from one hierarchical scale level to the next, with each step imposing filters and meaning. In contrast to the conception of emergence being merely a bottom-up process, co-evolutionary processes play out when entities understand they are constitutive of the system and can modify it. In addition to understanding how social norms emerge from personal interrelationships, for example, it is necessary to determine how emergent norms feed back onto individuals (Ostrom 2005).

One rapidly emerging form of scale in ABM research, mirroring trends in scale and complexity research more broadly, is the notion of networks defining scales (Manson 2008). Networks have interesting scalar properties that are increasingly important to ABM as researchers combine modeling with the rubrics of graphing and topology. The study of small world networks reveals that when just a few additional links between distant nodes are added to a network where most links are otherwise based on proximity, the connectedness of the entire network greatly increases (Watts 2003). Barabasi and Albert (1999) find that many real networks are self-organizing and scale-free, as they follow a power-law distribution due to inherent processes of growth and preferential attraction of new nodes to well-connected ones. They cite examples of scale-free networks that include the World Wide Web, the electrical power grid of the western United States, and citations that link scientific journal papers. Advances in our understanding of networks arise from a confluence of pertinent data and ABMs, as seen with the joining of a variety of social science databases and decision-making agents in the context of economics and politics (Skvoretz 2002).

7.3.4 Equilibrium and Change

Researchers of all stripes have long modeled many systems under the assumption of equilibrium. Agent-based modeling, by focusing on complex dynamics, provides an opportunity to understand the degree of explanatory power that the assumption of equilibrium has for a given system. Deterministic complexity often does not regard equilibrium as a necessary feature, even if a model of system dynamics can capture whether equilibrium is attainable given the initial conditions and process interactions. For example, ABMs are increasingly used to investigate processes such as the spread of smallpox or cultural memes, where the spatiotemporal dynamics rather than system equilibrium are the phenomenon of interest (Epstein 2006). Issues of equilibrium and change lend further context to concepts of sensitivity and nonlinearity in complex systems by offering commentary on system resilience and the potential for dynamic movement among basins of attraction.

Dramatic changes wrought in a system because of its inherent sensitivity and nonlinearity of interactions are countered by the system's resilience, the ability to adjust to disturbance and reorganize without significantly changing its functions or structure, and its transformability, the ability to create a new system configuration when adjustment is not possible (Walker et al. 2004). A system can be highly resilient despite a high degree of instability when it is self-organizing (Holling 1996).

Also, resilience is a scale-dependent characteristic, both temporally and spatially. A system resilient in one span of time may be compromised in a longer span, while a resilient community may endure at great cost to its larger, encompassing region (Levin and Lubchenco 2008).

Deterministic and aggregate complexity research addresses the dynamics of non-equilibrium states found in complex systems. The lower-level, bottom-up forces create processes that are constantly adapting to environmental changes and undergoing organizational transformation. The interactions that give rise to these changes are non-linear and subject to novelty (Holland 1995), resulting in a system sensitive to the introduction of new components and fluctuations of component states. Despite the ever-changing nature of system behavior and structure, it may gravitate toward one of multiple basins of attraction (Holling 1973). Coupled human-environment systems have multiple attractors, as seen when a coupled population-phosphorus system has one attractor situated at a high population state with a balance of economic and ecological drivers, and a low population state representing a restored ecological system (Chen et al. 2009).

Just as scale levels can attenuate non-linearity and sensitivity, complex systems embody a tension between sensitivity to initial conditions and a dynamic movement between basins of attraction. Certain states may experience positive feedback, gravitating to an attraction basin that will not accommodate robust sub-systems and diverse inputs. Decreases in biological diversity and threats to the viability of ecosystem services, for example, represent a state where resilience is low and more vulnerable to disturbance (Folke 2006). Human institution research recognizes the sensitivity of changes to rules in organizational structure, wherein small changes via policy can bring about “a nontrivial probability of error” (Ostrom 2005: 243). Complex systems are susceptible to ‘imaginable surprise’ where seemingly unexpected system configurations are in fact understandable when we allow for complex features such as nonlinearity and sensitivity (Schneider et al. 1998). Sensitivity, as with resilience, is either scale-dependent, such that the system may be regarded as sensitive as it moves from one attraction basin to another, or independent as these attractors, over longer time periods, characterize the typical system states regardless of initial conditions. The ability of ABM to represent these complex systems offers great potential for exploring emergence and surprise in human systems, such as the recent financial crisis in the global economy (Farmer and Foley 2009).

7.3.5 Decision Making

Decision making is the engine of many ABMs, particularly those involving human actors, and in turn it has many ties to complexity. It has long been a core concern of many fields, including geography, economics, management, and psychology. ABMs have helped draw out the similarities and differences among different decision-making theories by emphasizing the importance of developing basic rules for agents to follow, leading to research focused on how such rules embody their decision-making strategies. Agents in an ABM usually pursue certain goals set by the modeler with given resources and constraints. Commuters want to minimize their commuting time, for example, while homebuyers want to purchase the best house within their budget, and parents want to move into neighborhoods with quality public schools. Standard decision-making theory is a logical starting point for modeling these decisions, as seen in the wide use of multi-criteria evaluation and Cobb-Douglas utility functions to enable simulated agents to make decisions regarding parcel development and household migration (Brown et al. 2005; Parker and Filatova 2008). While recognizing the value of assumptions such as utility maximization in classical economics, ABMs have also opened the door to other forms of decision-making theory. Behavioral economics, for example, emphasizes the importance of concepts like incomplete information, bounded rationality, reinforcement over time, expected utility, and market anomalies (Arthur 1991; Simon 1997b).

ABMs illustrate how actor agents make decisions to achieve predefined goals in an environment shaped by all agents, and more importantly, how these individual decisions lead to macro patterns that are not predicted by perfect rationality. The concept of bounded rationality, introduced by Herbert Simon, depicts the actor whose decision making is bounded three ways (1997b). The first represents the "skill, habits, and reflexes" (Simon 1997a: 46) that exist beyond our conscious grasp, and presumably, beyond rational decision making. The second is the actor's set of purposes and values, which may differ from those of someone else in an otherwise similar decision making scenario. The third bound is limited information, wherein the actor lacks certain facts or skills that would contribute to a fully informed decision. Representing these three bounds is nascent in ABM but arguably it is this form of modeling that is well suited to advance our understanding of bounded rationality because agents can represent various features of boundedness such as limited computational capacity or rules of thumb (Chen 2005; Dawid 1999; Edmonds and Moss 1997; Manson 2006). In particular, ABMs allow various decision-making strategies, including from rules-of-thumb or heuristics for adapting to a changing environment (Gigerenzer and Selton 2001). Axelrod (1997), for example, sees actors in his cultural dissemination model as not making rational decisions as such, but simply adapting to their environment. More broadly, decision-makers use heuristics to make 'non-rational' decisions, based on the manner in which possible choices are framed (Tversky and Kahneman 1974).

The distinction between an individual decision and a collective one allows for a more sophisticated mechanism to model the choices of actors. Simon notes that decisions "are not made by 'organizations' but by human beings behaving as members of organizations" (Simon 1997a: 281). Social network conceptions of social contagion, for example, address the process of collective decision-making wherein actors receive ideas the way that they may be exposed to the carrier of a disease. Thresholds may be established in which the actor accepts the idea after being exposed to it a given number of times (Granovetter 1978; Watts 2003). When people make migration decisions, for example, they not only want to physically move closer to the friends and relatives in their network, but their criteria for quality housing, their perception of specific neighborhoods, and their knowledge of vacancies are all influenced by the available information in their network (Clark 2008). Social influences on decision making are also evident in the role of reflexivity, such that the past and future are incorporated into present thinking. ABMs address a core question: how does one account for actors that are aware of how their actions may feed into collective outcomes? A person may stay away from social events that are expected to be too crowded or too sparsely attended, for example, as a function of past experience (Arthur 1991). In short, actors often play an expectations game when they act in order to avoid being part of an undesired collective outcome or in order to prevent that outcome from happening (Gilbert 1995).

7.4 Conclusion: Complex Agents, Complex World

Complexity and ABMs offer much to each other. ABM research draws on a range of concepts and approaches from algorithmic, deterministic, and aggregate complexity. In turn, modeling brings to complexity a large number of actual complex systems and attendant theories to advance complexity science. ABMs offer a virtual laboratory that helps researchers navigate between theoretical and empirical research. And while ABM faces many challenges in calibration, verification, and validation, it offers new ways to think about relationships between data and theory, pattern and process. Complexity and ABMs, separately and jointly, are also advancing our conceptualization of scale in a range of complex systems, alongside issues of sensitivity, nonlinearity, resilience, equilibrium, and change. Finally, ABMs are a very promising technique, alongside other approaches, for modeling and understanding decision making. In sum, one may take heart from the many challenges facing researchers working at the intersection of agent-based modeling and complexity science because they arise from the vast potential and promise of these two worlds meeting.

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