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What is agent-based computational sociology all about?

There is no doubt that the last twenty years have brought radical changes to the use of computers in social research (Heise and Simmons 1985; Gilbert and Abbott 2005). In the past (and even still today), social scientists used computers to provide analytic solutions to complicated equation systems that represented a given system's structure, or more generally to estimate statistical models for data. From the 1990s onward, they started to use advanced computational techniques in an innovative way to simulate and analyze implications of agent interaction in social structures (e.g., Epstein and Axtell 1996; Axelrod 1997a; Epstein 2006; Miller and Page 2007).

Computational sociology, that is, the use of computationally intensive methods to model social phenomena, is not a recent development (Brainbridge 2007). It is a branch of sociology that has a long and, to a certain extent, venerable tradition that goes back to the 1960s. At that time, under the influence of systems theory and structural functionalism, computer simulation was used to model control and feedback mechanisms in systems, such as organizations, cities, or global populations. The idea was to simulate complicated differential equation models to predict population distribution as a function of systemic factors, such as urban traffic, migration, demographic change, or disease transmission. Inspired by Forrester's work on world dynamics (Forrester 1971) and the idea of systems theory and cybernetics, the focus was on systems and aggregates rather than on agents and behavior, and on prediction rather than understanding and explanation (Sawyer 2005).

Nevertheless, against this trend, some pioneers started to use computer simulation to investigate models of micro social processes. In the 1960s, James S. Coleman led the most active research center for computer research in sociology in the US.

Agent-Based Computational Sociology, First Edition. Flaminio Squazzoni.

At Johns Hopkins University, he published some interesting contributions to plead the cause of simulation models in sociology aiming to investigate agent interaction (Coleman 1962, 1964b). Raymond Boudon also published an article on prosecutions in France with a simulation model as a key element (Davidovitch and Boudon 1964). Some years later, in his famous book on the mathematical approach to sociology, he systematically examined the similarities and differences of equation-based and computer simulation models to understand social processes from a micro–macro perspective (Boudon 1970). Ahead of their times, these leading sociologists pre-empted the agent turn of the 1990s.

Computer simulation approaches and techniques changed over time, as we will see later. From the 1990s onward, sociologists started to analyze macro social aggregates as the resultant properties of micro interaction, by explicitly modeling agents, interaction and environment (i.e., geographical space, institutional settings, and/or social structures). The growth of computational capacity applied to research, as well as its ubiquitous and distributed nature, allowed the creation and diffusion of the first agent-based model (ABM) open-source simulation platforms, easily manageable even with portable computers. This innovation in research technologies set the stage for an 'agent-based turn' in social research and helped agent-based computational sociology to materialize.

The aim of this chapter is to introduce agent-based computational sociology as *the study of social patterns by computer models of social interaction between heterogeneous agents embedded in social structures (e.g., social networks, spatial neighborhoods, or institutional scaffolds)*. The first section identifies predecessors and founding fathers. Herbert Simon, James S. Coleman, Raymond Boudon, Thomas Schelling and Mark Granovetter have been included as they pioneered and/or largely influenced this type of research. As we will see, not only is there a certain coherence between the work of these authors, but also a *fil rouge* links these studies to certain streams of sociology today that revolve around the idea of the 'generative' approach to sociological investigation. These research streams have recently been systematized under the name of 'analytical sociology', where emphasis is given to the explanation of social patterns from agent interaction and where agent-based modeling plays a pivotal role (Hedström and Swedberg 1998; Hedström 2005; Bearman and Hedström 2009; Hedström and Ylikoski 2010; Manzo 2010).

The second section illustrates the main ideas of this new type of sociology. They are as follows: (a) the primacy of models, (b) the generative approach to explanation, (c) a pragmatic approach to the micro–macro link, (d) process and change as key elements of sociological investigation, (e) a reconciliation of deduction and induction, theory and data through models, and (f) a tendency towards a trans-disciplinary/issue-oriented style of research. While ideas from (a) to (e) have application in the literature, (f) is still in the latent phase, though not less important.

The third section illustrates ABMs as the tool that has made this new type of research possible. It is worth noting that agent-based computational sociology does not totally conflate with ABMs, as the latter is used also in physics, biology and computer sciences with different purposes. Here, ABMs specifically target the properties of social behavior and interaction and addresses relevant empirical sociological puzzles. Without entering into technical detail, a comparison between ABMs and other simulation techniques is presented that examines the peculiarities of ABMs for sociological investigation. Finally, the fourth section looks at ABM classification, illustrating differences in its use in research. Certain implications are made to link theory and empirical data treated in detail in Chapter 4. Examples and attention to substantive issues will be looked at in Chapters 2 and 3.

1.1 Predecessors and fathers

Perhaps unexpectedly, the ABM approach has a venerable legacy in sociology. In common with traditional mathematical sociology, it includes the idea that formalized models can make sociology more scientific (Coleman 1964a; Fararo 1969). However, it makes no sacrifice to analytic solutions or top-down deductions. Indeed, the ABM perspective espouses a more complex view of sociological models, where (a) theory should be the result of bottom-up data exploration, and (b) models should look at nonlinear local agent interaction and global out-of-equilibrium system behavior, rather than pre-constituted structural behavior and equilibrium. It shares the idea that computational formalization can help to improve the theory building process, by revealing non-obvious mechanisms and providing for a theory test.

However, the ABM approach aims to develop sociologically rich models that mimic the properties of social behavior and interaction. Indeed, ABMs aim to understand what is taken for granted in more functionalistic, macro-oriented simulation approaches, such as system dynamics, that is, the emergence of social patterns, structures and behavior from agent interaction. This also helps us to understand under which conditions, certain social patterns might emerge in reality.

One of those who has contributed the most to this type of research, is a non-sociologist, the Nobel Prize winner, Herbert A. Simon. One of the most prominent social scientists of the last century, Simon influenced a wide range of disciplines, from artificial intelligence to organization science and psychology. One of his simplest ideas was that there is no isomorphism between the complexity that social systems show at the macro level and their complexity at the micro level. In many cases, the former is nothing more than the result of interaction between simple micro processes. Therefore, computer simulation is pivotal to simplify and model complex social systems from a micro–macro approach (e.g., Simon 1969).

Simon was also interested in understanding what he called ‘poorly understood systems’, that is, those in which the modeler has poor or no knowledge of the laws that govern inner systems. By suggesting the rationale for simple computer simulation models that look at these types of systems, he argued that:

> resemblance in behaviour of systems without identity of the inner systems is particularly feasible if the aspects in which we are interested arise out of the *organization* [italics in original] of the parts, independently of all but a few properties of the individual components (Simon 1969, p. 17).

The first lesson is that understanding the interaction mechanisms between individual components is pivotal to look at the complex behavior of a social system. The second is that by pinpointing the explanatory power of interaction, sociology can omit detailed knowledge of the behavior of each individual component, at the same time avoiding referring to supposed causal autonomy of macro social entities to understand macro system behavior. The latter should be viewed as fully shaped by organizational micro processes.

Obviously, this was not Simon's only contribution to the ABM approach in social sciences. We can mention his investigation into the foundations of human behavior and his theory on bounded rationality (Simon 1982). He influenced all ABM scientists who have tried to understand how a population of boundedly rational agents can spontaneously and endogenously give rise to patterns of collective intelligence in diverse spheres of the economy and society (e.g., Epstein and Axtell 1996).[1]

The Nobel Prize winner Thomas C. Schelling, with his pioneering work on the micro–macro link and his famous segregation model in the 1970s, has had an incommensurable influence on agent-based computational sociology. In the first pages of his influential book *Micromotives and Macrobehavior* in 1978, he illustrated the crucial challenge of understanding macro behavior from agent interaction by using this simple example:

> There are easy cases, of course, in which the aggregate is merely an extrapolation from the individual. If we know that every driver, on his own, turns his lights on at sundown, we can guess that from our helicopter we shall see all the car lights in a local area going on at about the same time. [. . .] But if most people turn their lights on when some fraction of the oncoming cars already have their lights on, we'll get a different picture from our helicopter. In the second case, drivers are responding to each others' behaviour and influencing each other's behaviour. People are responding to an environment that consists of other people responding to *their* [italics in original] environment, which consists of people responding to an environment of people's responses. Sometimes the dynamics are sequential [. . .]. Sometimes the dynamics are reciprocal [. . .]. These situations, in which people's behaviour or people's choices depend on

[1] Although not very influential in sociology, the Austrian economist, Nobel Prize winner Fredrick von Hayek was among the first to realize the importance of studying collective social properties which emerge from dispersed, decentralized and local interaction among agents (e.g., Hayek 1976). To a certain extent, he could be considered as one of the founding fathers of the contemporary complex adaptive systems theory, which has much in common with agent-based computational sociology. Indeed, complex adaptive systems theory aims to understand how decentralized and local interactions among boundedly rational and adaptive agents following simple behavior can create collective patterns which have robust, intelligent and evolving properties, such as flexibility and resilience against environmental perturbations (e.g., Anderson Arrow and Pines 1988). Although largely underestimated by sociologists, a system-environment approach might be important as it might help to enlarge the sociological attention from the individual/collective couple to the individual/collective/environment dimension and to reason in an evolutionary perspective. It is worth noting that the latter is dramatically neglected from current sociology.

> the behaviour or the choices of other people, are the ones that usually don't permit any simple summation or extrapolation to the aggregates. To make that connection we usually have to look at the *system of interaction* [italics in original] between individuals and their environment [. . .]. And sometimes the results are surprising. Something they are not easily guessed. Sometimes the analysis is difficult. Sometimes it is inconclusive. But even inconclusive analysis can warn against jumping to conclusions about individual intentions from observations of aggregates, or jumping to conclusions about the behaviour of aggregates from what one knows or can guess about individual intentions (Schelling 1978, pp. 13–14).

The difficulty of mapping micro and macro levels when nonlinear agent interactions are involved is the premise that avoids both conflating or contrasting the various levels of social system analysis (Squazzoni 2008). This was evident in Schelling's famous segregation model, which is now a standard example in ABM literature, where the dynamics of residential mobility and segregation by race and ethnicity, that is, a long lasting pattern of many large cities in the US, were explained not as the result of racist preferences, but in terms of social influence and interaction (we will return to this model in detail in Chapter 3) (Schelling 1971, 1978). Schelling's idea of 'contingent behavior', for example, individual behavior that depends on what others do, emphasizes the relevance of studying agent interaction to understand how individual actions cause unplanned and unexpected social patterns. By looking just at the aggregate level, sociology cannot explain where these patterns come from.[2]

This was confirmed by Mark Granovetter in his contributions to understanding collective behavior in social systems during the late 1970s and early 1980s (e.g., Granovetter 1978; Granovetter and Soong 1983, 1988). Following Schelling, he contributed to current literature on 'critical mass' or 'tipping point' models of collective behavior. The latter also has hit the headlines of popular science in a couple of bestsellers (e.g., Gladwell 2001; Ball 2004).

By modeling riots in a population subjected to social influence and examining the relevance of interaction structure, Granovetter showed that, when interaction and contingent behavior matter, 'it is hazardous to infer individual dispositions from aggregate outcomes' (Granovetter 1978, p. 1425). In his view, the most important point for sociology is the understanding of 'situation-specific' aggregation processes. To put it in Granovetter's words:

> By explaining paradoxical outcomes as the result of aggregation processes, threshold models take the 'strangeness' often associated with collective behaviour out of the heads of actors and put it into the dynamics

[2] This was also the intuition of the neglected Sakoda's checkerboard model, which was published in the same journal issue of Schelling's, but has been developed by the author in the late 1940s for his PhD dissertation, after an experience in a relocation center for Japanese minorities during World War II in the US (Sakoda 1971).

> of situations. Such models may be useful in small-group settings as well as those with large numbers of actors. Their greatest promise lies in analysis of situations where many actors behave in ways contingent on one another, where there are few institutionalized precedents and little pre-existing structure [...] Providing tools for analyzing them [*these situations*] is part of the important task of linking micro to macro levels of sociological theory (Granovetter 1978, p. 1442).

The pivotal role that agent interaction plays in determining social patterns has also been investigated by two leading sociologists, James S. Coleman and Raymond Boudon. In the 1960s, Coleman significantly contributed to developing mathematical sociology (Coleman 1964a), but also worked to extend equation-based models through computer simulation. Against the functionalistic mood of the time, he argued that computer simulation could motivate an agent-based turn in sociology. He correctly predicted that this approach would contribute to 'a shift away' from social systems tradition and their 'large-scale problems of social speculation' to 'problems which can be studied by systematic research' (Coleman 1962, p. 61).

He also provided interesting examples on how to use simulation models both to compensate for the impossibility of looking at social mechanisms in sufficient detail with analytic deductive models, and to include not only quantitative but also qualitative data. In 1964, in a review on equation-based models and computer simulation, he emphasized that through analytic deduction sociologists could only mirror certain components of social interaction, by isolating simple micro processes. Given that social processes are bound up in a complex system, computer simulation would become extremely valuable to synthesize these processes into formalized models to understand their implications for system behavior (Coleman 1964b, p. 1046).

While referring to a Simmel-like case of triadic relationships in social groups, Coleman wrote that 'this example illustrates a general strategy in social simulation: to link together known micro processes in a particular structural configuration, in order to examine consequences at the level of the system' (Coleman 1964b, p. 1054). He emphasized that simulation models could be viewed as a 'bridge between individuals, upon whom most of the sociologist's observations are made, and social systems, which are his objects of interest' (Coleman 1964b, p. 1055). He concluded by prefiguring the agent-based turn: 'much of the social simulation of the future will have purposive actors in roles as its principal elements' (Coleman 1964b, p. 1059).

At the same time, Boudon worked on a simulation model to examine the prosecution rates of abandoned cases by State prosecutors in France between 1879 and 1931. This was a theoretical model aiming to find a precise statistical pattern in historical data. By anticipating one of the main advantages of computer simulation, that is, to generate empirically testable data, he indicated that the model aimed to 'verify a certain set of hypotheses on the mechanisms that were responsible for the empirically observed variations of these rates'. He said that the added value of simulation was to help to formalize models capable of generating certain patterns 'that might be compared with empirically observed statistical patterns [*my translation*]' (Davidovitch and Boudon 1964, pp. 212, 217–218). Specifically, the model was pivotal in revealing the interaction between the seriousness and frequency of crime and changes in the classification of prosecutions over time. This interaction was also responsible for the variation in the rates of abandoned cases empirically observed.

In a subsequent and more systematic contribution on computer simulation of social processes, Boudon explained similarities and differences between analytic and simulation models. Of the similarities, he highlighted the ideas of specification, simplification and reduction as cornerstones of any rigorous sociological investigation. Of the differences, he pointed out that computational methods could help sociologists to overcome the limits of analytic tractability imposed by mathematics, which penalizes disciplines like sociology that deals with complex systems.

Boudon therefore suggested that, while in some cases computational models could be mere extensions of equation-based models, they should be viewed as a completely new formalization method when systems involve complex interactions and there is no possible mathematical counterpart. In these cases, the aim is not to help deduction, but to allow for inductive observation (Boudon 1970, pp. 379–380). By relying on his experience of these models, he also suggested that by looking at interaction effects, simulation models could complete the weaknesses of statistical models in treating these important sociological aspects (Boudon 1970, p. 402).

This contribution was also important for another reason. Boudon quoted an example of a model by Breton, who examined the emergence of collaboration norms in organizational teamwork, to emphasize the powerful ‘realism’ of these models. By realism, he meant that these models allow sociologists to ‘rule out the imprecise concept of norm internalization’ and understand that social norms ‘can socially dominate [. . .] simply as aggregate consequences of rational individual behavior [*my translation*]’ (Boudon 1970, pp. 386–387). As we will see throughout the book, this idea of the added value of ‘realism’ and a methodological individualism basis are intrinsic to agent-based computational sociology.

Subsequently, Boudon launched the idea of ‘generative models’ in sociology to study unintended macro consequences of social behavior (Boudon 1979, 1984). In a commentary to Robert Hauser’s review of Boudon’s famous book on education and social inequality, Boudon depicted the generative approach by contrasting it with descriptive accounts of data, and discussed the limitations of variable-based theorizing in sociology. By using the example of Schelling’s segregation model, and so defending the idea of the added value of simplified theoretical models, he wrote that ‘we must go beyond the statistical relationships to explore the generative mechanism behind them’ (Boudon 1976, p. 1187).

In short, all these authors highlighted one of the key ideas of agent-based computational sociology, that is, the relevance of ‘generative models’ capable of explaining social patterns from agent interaction, by paying due attention to micro mechanisms. This idea was first suggested by Robert K. Merton in the late 1940s, where he argued that the challenge of sociology was neither to produce broad theories of everything, nor to fill university libraries worldwide with books of detailed and fascinating empirical accounts. The challenge was rather to work with theoretical models capable of looking at causal mechanisms for well-specified empirical puzzles (Merton 1968).

This was also expressed by Coleman in 1962, when he wrote about the added value of simulation models:

> Perhaps simulation is the wrong word, for it suggests that the attempt is to mirror in detail the actual functioning of a social system. Instead, it is very different. The aim is to program into the computer certain theoretical processes, and then to see what kind of a behaviour system they generate. The aim is to put together certain processes at the individual and interpersonal level and then to see what consequences they have at the level of the larger system (Coleman 1962, p. 69).

This idea touches upon a crucial point for the use of simulation in the social sciences. The aim of a simulation model should not be to mirror the complexity of empirical reality, but to abstract certain micro social mechanisms that might be responsible for system behavior.

More recently, one of the leading social scientists who contributed to the popularization of ABMs in social sciences was Robert Axelrod. In 1981, together with the evolutionary biologist W. D. Hamilton, he published an article in *Science* where an ABM was constructed to show the key role of reciprocity for the emergence of cooperation in a population of rational self-interest agents (Axelrod and Hamilton 1981). Some years later, he published his famous ground-breaking book *The Evolution of Cooperation* (Axelrod 1984), which greatly influenced the ABM field of cooperation and social norms and showed the potential of combining experiments, game theory and computer simulation. This ABM field blossomed into a trans-disciplinary approach, receiving recognition in, for example, *Nature*, *Science* and *PNAS* (examples will be provided in Chapter 2).

After Axelrod's initial contributions, the ABM approach started to materialize in social sciences both in the US and in Europe. In the US, the establishment and success of the Santa Fe Institute in New Mexico in the late 1980s and early 1990s, launched a world-wide research program for the study of the common properties of complex systems in many fields, including social sciences. They used the first ABM open source simulation platform ever, that is, SWARM (Minar *et al.* 1996), now maintained by the Swarm Development Group (see: http://www.swarm.org/index.php/Main_Page).

SWARM was first released in 1994 by a multidisciplinary team at the Santa Fe Institute and a large trans-disciplinary community of developers/users started to form. The success of SWARM testified to the presence of a growing and vibrant community interested in ABM research also in the social sciences and opened the door to a rich ABM platform market. The books *Growing Artificial Societies: Social Science from the Bottom-Up*, by Epstein and Axtell (1996) and *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration*, by Axelrod (1997a), not to mention the proceedings of a workshop on complex systems and economics held at the Santa Fe Institute (Arthur, Durlauf and Lane 1997), gained such popularity as to spread this type of research worldwide.

At the same time in Europe, a series of foundational symposia and workshops on computer simulation in the social sciences, the first in Guildford in 1992, were crucial in creating a scientific community of ABM social scientists. Their proceedings were widely published and provided the first coherent picture of the potential ways through which ABM research could cross disciplinary barriers between social, computer and natural sciences (e.g., Gilbert and Doran 1994; Gilbert and Conte 1995; Hegselmann, Mueller and Troitzsch 1995; Conte, Hegselmann and Terna 1997). The establishment of *The Journal of Artificial Societies and Social Simulation* (*JASSS*) in 1998 was the consecration of this process. Subsequently, special issues published in other important journals testified to the growing maturity of this field.[3]

1.2 The main ideas of agent-based computational sociology

Agent-based computational sociology revolves around the following six ideas: (a) the primacy of models over grand theories and descriptive accounts; (b) the generative approach to explanation; (c) a pragmatic approach to the micro–macro link; (d) the pursuit of an unexcluded middle ground between deduction and induction, theory and data; (e) the focus on dynamics, process and change; and (f) a tendency towards a trans-disciplinary/issue-oriented style of research (Squazzoni 2010).

1.2.1 The primacy of models

A model is a simplified representation – small scale, less detailed, less complex or all of these together – of an empirical target, for example, a social structure, system or phenomenon (Gilbert and Troitzsch 2005, p. 2). Rather than studying the empirical target directly, because it is impossible or difficult, a model is built that can scale down the target, simplify it to make it more tractable or substitute it with analogical examples (e.g., the hydraulic model of an economic system or the computer model of the mind). It can have a theoretical purpose, for example, understanding macro implications of theoretical assumptions about micro processes, or a more empirical one, for example, drawing intuitions from existing raw data (Hartmann and Frigg 2006).

Epstein (2008) reported a detailed list of reasons to build models in social sciences. They are as follows (not in order of importance):

> [predict], explain, guide data collection, illuminate core dynamics, suggest dynamical analogies, discover new questions, promote a scientific habit of mind, bound (bracket) outcomes to plausible ranges, illuminate core uncertainties, offer crisis options in near-real time, demonstrate

[3] Here are some of the special issues devoted to ABM research in social sciences: *American Behavioral Science* 1999, *IEEE Transactions on Evolutionary Computation* 2001, *Journal of Economic Dynamics and Control* 2001 and 2004, *Computational Economics* 2001 and 2007, *Proceedings of the National Academy of Sciences* 2002, *Artificial Life* 2003, *Journal of Economic Behavior and Organization* 2004, *Journal of Public Economic Theory* 2004, *Physica A* 2005, *American Journal of Sociology* 2005, *Advances in Complex Systems* 2008, *Journal of Economics and Statistics* 2008, *Nature* 2009, *Synthese* 2009, and *Mind & Society* 2009.

> tradeoffs/suggest efficiencies, challenge the robustness of prevailing theory through perturbations, expose prevailing wisdom as incompatible with available data, train practitioners, discipline the policy dialogues, educate the general public, reveal the apparently simple (complex) to be complex (simple) (Epstein 2008, 1.9).

For whatever reason, generally, models make reality more understandable in scientific terms and a significant proportion of research is carried out on them rather than on reality itself (Hartmann and Frigg 2006). They have a learning function, as scientists can learn about the target exactly because they discover features and ascertain facts by manipulating the model. In this case, the model itself becomes the ‘real’ object of research as it and only it can be subjected to peer scrutiny, extension, testing, and comparison.

Besides the general added value of models for science, there are also specific reasons for formalized models in sociology. By formalizing models, sociologists can discipline discussion and move the dialog out of narrative persuasion to well-founded, organized and really constructive criticism. Models are preliminary exercises of theory and maintain a tight link with empirical reality. As testified by the difficulty of comparing and testing narrative empirical cases and unformalized theoretical accounts, the added value of modeling is that it can guarantee cumulativeness of scientific findings at an inter-subjective level (Giere 1999; Manicas 2006).

This point is of paramount importance. One of the main aims of agent-based computational sociology is to shift the sociological focus from grand theories and descriptive empirical accounts to formalized models of specific social phenomena (Giere 1999; Frank 2002; Buchanan 2007). It is precision, clarity and fine-grained distinctions that are crucial to analyzing complex social phenomena, whereas there is incontrovertible proof that these properties are difficult to obtain from unformalized narrative accounts (Hedström 2005). In championing the cause of models, agent-based sociology also goes beyond the limits of mathematical sociology as it overcomes most of the drastic simplification that the latter assumes for analytic tractability (for more details, see the next section). As such, it can regain the trust of those sociologists who have been frustrated by mathematical modeling and its excessive abstraction (Squazzoni and Boero 2005).

Thinking in terms of models has other relevant advantages for sociology, some of them included in Epstein’s list. First, as mentioned above, it exercises our sociological imagination to look at reality and not simply to mirror or replicate it, but to recognize abstract and essential elements. Secondly, it trains sociologists to explain through generalization, that is, seeing common properties in different empirical situations. It must be said that this is a largely and unfortunately neglected activity in our discipline, while it is fundamental for the scientific progress of any discipline. Thirdly, it prearranges sociological analyses towards empirical validation, as it is easier to empirically test model assumptions and findings than ill-structured and unformalized propositions. At the same time, it is also easier to gather interesting and appropriate data when a model guides us in this direction. Moreover, it allows us to work with artificial data where empirical data cannot be gathered for whatever reason (e.g., ethical prohibitions, time or resource constraints, or lack of sources). This is an ABM-specific added value. Finally, models can be a focal point of teams from many disciplines and so favor trans-disciplinary collaboration.

Obviously, these are general properties of formalization and modeling. But, as we will see later, the point is that a more sociologically friendly formalism definitively enters the picture with ABMs.

1.2.2 The generative approach

ABMs are a means of understanding the social mechanisms which are responsible for the macro patterns under scrutiny. The idea is that the macro behavior of social systems can be better understood bottom-up, rather than beginning with a set of variables and their predefined relations. Here lies the real uniqueness of the ABM approach compared with other approaches that investigate social patterns through the computer (Castellani and Hafferty 2009, p. 135).

As we have seen before, the idea of generative explanation is not a recent development (e.g., Boudon 1979; Barth 1981; Hedström and Swedberg 1998; Cederman 2005). It has also been the aim of certain influential sociologists who never used formalized models in their work (e.g., Elster 2007; Gambetta 2009). The point here is that ABMs allow us to put this idea into practice on a large scale and provide incomparable advantages when looking at macro implications of agent interaction, difficult to achieve both in reality and in the sociologist's imagination. Sociological imagination without strong reference to concrete models is often a poor exercise, or at best is productive only when pursued by real genius. The power of sociological imagination can be better exploited when disciplined by models that help us to dispute findings in an organized and productive way, favoring model replicability and testing. All in all, this is extremely difficult to achieve with descriptive and unformalized accounts of social behavior.

Joshua M. Epstein used the idea of the 'generative experiment' to summarize this approach as follows:

> Given some macroscopic *explanandum* [italics in original] – a regularity to be explained – the canonical agent-based experiment is as follows: Situate an initial population of autonomous heterogeneous agents in a relevant spatial environment; allow them to interact according to simple local rules, and thereby generate – or 'grow' – the macroscopic regularity from the bottom up. [...] In fact, this type of experiment is not new and, in principle, it does not necessarily involve computers. However, recent advances in computing, and the advent of large-scale agent-based computational modelling, permit a generative research program to be pursued with unprecedented scope and vigour (Epstein 2006, p. 7).

Suppose that we have to explain a macro pattern k_r. We build an ABM of k_r because we have proof or intuition that k_r is a complex outcome, not completely understandable either by direct observation or by analytic deduction. Suppose that

A, B, $C, \ldots$, are assumptions, micro specifications or model components that we introduce to understand k_r, as we expect that they play a role in determining k_r. They could be as follows: numbers and types of agents, behavioral rules followed by agents, the interaction structure (how agents interact) and the constraints of the macro situation where agents are embedded. Note that we could call them 'model parameters', provided that we bear in mind that they could be both quantitative (e.g., number of agents) and qualitative (e.g., rules of agent behavior).

Now, suppose that $A_1, A_2, A_3, \ldots, B_1, B_2, B_3, \ldots$, and $C_1, C_2, C_3, \ldots$, are all possible variations that the model components could take in principle. The 'generative experiment' lies in exploring which of these variations of components $A, B, C, \ldots$, generate k_a, that is, the simulated pattern that should be compared with $k_{r,}$, the empirical pattern. The idea is that if A_2, C_1, D_3, N_5 allow us to generate $k_a = k_r$, then A_2, C_1, D_3, N_5 should be seen as 'sufficient generative conditions' for k_r and therefore are a generative explanation of k_r (Boero and Squazzoni 2005).

According to Epstein (2006, p. 8), *being able to generate a macro regularity of interest with an ABM* is to be taken as a necessary condition for the explanation itself. If explaining implies generating (i.e., specifying and showing the generative process through which interacting agents in a given environment combine to produce the pattern under scrutiny), then ABMs are pivotal to identify candidate explanations that can also guide empirical research. As argued in Boero and Squazzoni (2005), Squazzoni (2008), and Frank, Squazzoni and Troitzsch (2009), given the high sensitivity of social patterns to small contextual and contingent micro details, the shift from discovering *sufficient* to identifying *sufficient and necessary* generative conditions calls for the relevance of careful empirical inspection (see Chapter 4 for details). Nevertheless, although insufficient and incomplete, the capability of discovering 'candidate explanations', such as generative explanations, is a crucial step forward in itself for sociology.

It is worth noting that the generative approach is instrumental to understand complex social systems, where top-down analytic deduction is a poor guide. Complex systems are full of intertwining relationships, so that analytic decomposition does not hold. This simply means that breaking down the behavior of systems into the behavior of their parts is unfeasible as it throws away interaction (Casti 1994, 1999). As we will see, the source of 'complexity' of social systems is social interaction, so that the action of individuals does not simply aggregate at the macro level, as though individuals were isolated 'atoms' following universal and predictable behavior.

The embeddedness of individuals in social structures determines a profound nonlinearity in the aggregation processes, which makes macro outcomes extremely difficult to predict and understand, even if in principle we were aware of the behavior of individuals (which in most cases we are not). Furthermore, the intrinsic heterogeneity of individuals, in terms of behavior, information and position in social structure, implies that the law of large numbers and the focus on average behavior are inadequate to understand system behavior (Miller and Page 2007).

If top-down analytic breakdown does not hold, analytic deduction does not inform, as we do not have a strong theory about system behavior. An outlook of average behavior at the micro level for statistical properties at the macro level is a largely imprecise map. So we must take the opposite direction. This means modeling from the bottom-up to explore various micro specifications and observe their macro consequences. This is the idea behind the 'generative experiment' mentioned by Epstein (2006) and is the most important idea of agent-based computational sociology.

1.2.3 The micro–macro link[4]

The debate on micro foundations versus macro properties of social systems is the root of our discipline (e.g., Alexander *et al.* 1987; Ritzer 1990; Huber 1991; Sawyer 2005). On the one hand, many supporters of rational choice and of sociological *subjectivism* argue that explanations of social outcomes should be reduced to individual reason and meaningful action. On the other hand, structural sociologists and the advocates of social system theories argue that sociology should dissociate itself from behavioral sciences to understand the concrete ontologies of social reality (such as 'norms', 'cultures', and 'roles'), in terms of structures and their forms and functions. Accordingly, macro social properties, as well as individual actions, are understood as produced by other macro social properties. In the first approach, the role of social structures and constraints upon individual action is taken for granted. At the opposite extreme, supporters of social ontologies over-emphasize the importance of social structures, while under-representing the relevance of individual heterogeneity and action (Granovetter 1985).

The strength of these arguments can also explain the twofold and contradictory meaning that sociologists attach to the term 'emergence'. Authors such as Coleman stressed the relevance of understanding how individual actions combine to generate emergent properties at a macro social system level. Introducing the concept of 'emergence', Coleman firmly stated that 'the only action takes place at the level of individual actors, and the "system level" exists solely as emergent properties characterizing the system of action as a whole' (Coleman 1990, p. 28). This perspective is close to what epistemologists call 'weak emergence', 'epistemological emergence', or 'supervenience' to mean that macro behavior is a resultant property of micro behavior, although often the causal link is difficult to clearly identify (e.g., Bedau 1997; Silberstein and McGeever 1999; Kim 2006).

On the other hand, authors such as Archer (1995) and, more recently, Sawyer (2005), stressed that emergent social structures at a macro level can exercise causal power (and consequently can act) on individuals at a micro level. In this case, the macro social level is viewed as a 'social stratum' populated by ontological entities that are distinct from lower entities, that is, individuals. This perspective is close to what epistemologists call 'ontological emergence', 'strong emergence', or 'downward causation' (Silberstein and McGeever 1999).

It is worth noting that recently, respective positions in sociology have become less clear-cut than in the past. First of all, advocates of methodological and ontological

[4] This section extensively drew on Squazzoni (2008).

individualism now seem more inclined to take into account institutions and social structures as macro constraints upon individual action (Coleman 1990; Udehn 2001; Hedström 2005). Institutions, in their formal and informal/regulative and constitutive meaning, for example, the rules of the game, incentives embodied in institutional setting, or cognitive and cultural behavioral (and identity) frameworks of social actors, are all seen as the main features of the 'social situation' that simultaneously constrain and make individual action possible (e.g., Scott 1995; North 2005).

Furthermore, following Boudon and Coleman, the influence of social structure on individual behavior and in particular that of position within the interaction context, are generally acknowledged as an important explanatory factor by most supporters of methodological individualism (e.g., Boudon 1984, 1992; Coleman 1990; Hedström 2005).

Secondly, some macro sociologists seem more inclined than in the past to recognize the need to combine macro analysis and generative mechanism-based explanations (e.g., Manzo 2007). For instance, in his ambitious attempt to combine empirical research and theory, statistical macro sociology and the theory of individual action, Goldthorpe (2007, p. 16) emphasized that 'the explanation of social phenomena is sought not in terms of the functional or teleological exigencies of social systems, but rather in terms of the conduct of individuals and of its intended and unintended consequences'.

To favor this convergence and understand how micro and macro are concretely linked to determine social systems' behavior, the recourse to formalized models and ABMs is essential (Raub, Buskens and Van Assen 2011). Conversely, the debate tends to perpetuate an ontological 'chicken and egg' dispute between primacy of micro or macro levels without any concrete explanatory achievement.

In this respect, one of the main ideas of agent-based computational sociology is that ABMs can strengthen links and integrative frameworks and 'secularize' the debate between micro and macro levels. This is because it brings the debate away from a foundational and philosophical level to a more pragmatic one. The constraints and rigor imposed by ABM formalism implies that micro and macro levels, rather than being merely theoretical constructions, refer to clear-cut model-grounded concepts. Implications of micro social processes for large-scale macro patterns can be investigated and consequently understood in due detail. The same is true for micro influences of macro patterns (examples will be provided in the following chapters).

Equipped with ABMs, sociologists can therefore study the micro mechanisms and local processes that are responsible for macro patterns, as well as the impact of the latter on the former over time, so that the self-organized nature of social patterns can be subject to modeling, observation, replication and understanding. This relationship between processes at different levels, which is always difficult to empirically examine in sociology, can now be investigated in fine detail (Squazzoni 2010).

To sum up, agent-based computational sociology allows us to approach social interaction modeling as a problem of abstraction and scales (i.e., local interaction vs. global outcomes) more than a problem of ontology and categorical levels (i.e., 'individual' or 'social' primacy) (Petri 2011).

1.2.4 Process and change

One of the traditional problems of sociology is to have methods and tools to understand the evolving nature of social structures and institutions. Most sociologists acknowledge the process nature of social phenomena, but for the sake of tractability or for lack of appropriate modeling tools, they use theories and models that do not seriously reflect this belief. The long ignored German sociologist Norbert Elias (1987) brilliantly emphasized the risk of what he called 'the retreat of sociologists into the present', both for theory development and empirical research. His antidote was a 'processual perspective' capable of putting current social patterns into the appropriate space–time dimension, so as to discover the influence of historical change, dynamics and processes to understand the present.

ABMs are a crucial means of putting process, change and long-term dynamics at the very core of sociology. Thanks to their capability of reproducing, synthesizing and visualizing space–time dynamics through the computer, they allow sociologists to think of social patterns in terms of processes that emerge from agent interaction and change over time. Instead of being the consequence of fixed structures or linear variables, social patterns are the result of nonlinear interaction processes that resemble concrete social reality, where agent behavior is subjected to social influence and contributes to it. 'Rewinding the tape' and exploring different scenarios are activities that are impossible without simulation and are pivotal to study complex social dynamics in the long-term (e.g., Frank, Squazzoni and Troitzsch 2009).

With a few exceptions, unfortunately this perspective seems to be more advanced in anthropology or archeology than in sociology (e.g., Costopoulos and Lake 2010). For example, in anthropology, Lansing and Kremer (1993) modeled a Bali farming community, subject to crisis from the 1960s onwards caused by the Green Revolution. At the time, top-down planners criticized the old social structures used by farmers to manage irrigation and agriculture, in favor of mass agriculture technology progress. Using an empirically grounded ABM, they showed that sociocultural Bali structures were co-evolving with their environmental constraints into a self-organized sustainable path over time.

The simulation findings helped to show how past social structures were more adaptive than Green Revolution inspired mass agriculture technologies, so the farmers' resistance was not driven just by religious conservatism as the planners had claimed. The persuasiveness of this model and its results also helped policy makers change their approach. This is a brilliant example of how much explanatory achievement can be gained if a model looks at dynamics, evolution and social changes over time.

Another well-known example is the Anasazi model, less relevant for policy implications, but exemplary for various types of empirical data, from environmental to social factors, used to calibrate important model parameters. Developed by a trans-disciplinary team at the Santa Fe Institute, this model investigated the history of an ancient community that inhabited the Four Corners area in the American Southwest between the last century BC and 1300 AD. This disappeared from the region in a few years, without any evidence of enemy invasion or dramatic environmental catastrophes (Dean *et al*. 2000).

Simulation helped to rewind the tape and prove that previous claims about the relevance of environmental factors to explain the Anasazi story were false. Similarly, Berger, Nuninger and van der Leeuw (2007) built an empirically grounded model of the Middle Rhône Valley between 1000 BC and 1000 AD to study how particular sociocultural structures could explain the evolutionary resilience of these ancient social systems against environmental perturbations (see also Kohler *et al*. 2007; Varien *et al*. 2007; Wilkinson *et al*. 2007).

By examining specific mechanisms that determine the evolution of complex social structures or institutions in the long-term and using simulation to reconstruct particular histories in detail, investigation can provide evolutionary explanations and combine quantitative findings and qualitative insights (Lane *et al*. 2009).

1.2.5 The unexcluded middle

One of the main problems of sociology is that theory and empirical work are rarely mutually reinforcing or even mutually comprehensible. Robert K. Merton was among the first to emphasize the danger of excessive hiatus between theory and empiricism for sociology development (Merton 1968). The modeling attitude of ABMs can have potentially innovative consequences for this, as it can reconcile empirical evidence and theory (Squazzoni and Boero 2005).

First, ABMs allow us to pursue a kind of 'third way of doing science', which combines deduction and induction (Axelrod 1997b). Like deduction, modelers start with a rigorously specified set of assumptions regarding a system under scrutiny, but they are not intended to giving analytic proof of theorems. Rather, models generate (artificial) data suitable for analysis by induction, which help to fully understand logical implications of the assumptions, as well as to develop intuition about macro consequences of interaction processes. At the same time, in contrast to typical induction, data come from an artificial observed system rather than from direct measurement of the real world (e.g., Axelrod 1997b; Gilbert and Terna 2000).

This is important as sociologists are often compelled to investigate reality without the chance of gathering empirical data. On the other hand, by generating 'real' data, the validation of findings against empirical data (if any) is favored and the empirical data gathering process can be more productively guided. In doing this, it is also possible to empirically validate, as well as to derive theoretical implications from empirical data.

The fact that ABMs position research in this unexcluded middle between deduction and induction is shown by ways in which it has affected various social sciences, depending on the prevalence of deductive or inductive practices currently in use. In areas where mathematical formalism, abstraction and deduction are the pillars of a discipline's research style, as in economics, ABMs have been a means to bringing more empirically based hypotheses into theory, relaxing a body of highly abstracted assumptions.

In particular, ABMs have opened the possibility of introducing complexity based upon bounded rationality of agents and out-of-equilibrium dynamics (e.g., Tesfatsion and Judd 2006). In disciplines where qualitative evidence, narrative descriptions and induction form the dominant research style, as in anthropology, ABMs have increased rigor through formalism, simplifying complex narrative constructs and amplifying empirical evidence through theoretical tests (Squazzoni 2010). Given that sociology basically includes this difference within its own field, this approach could help bridge the gap between qualitative and quantitative communities in our discipline.

1.2.6 Trans-disciplinarity

ABMs have raised the possibility and even the promise of a trans-disciplinary reconfiguration of the disciplinary borders between sciences (e.g., Kohler 2000). This is because models can be focal points for various experts, promoting integrative approaches where relevant aspects can be synthesized into the same model (Epstein 2008). A good example is one of the first popular models in the ABM literature, namely *Sugarscape* by Epstein and Axtell (1996). This model included agents that left pollution, died, reproduced themselves, inherited resources, shared information, traded, transmitted disease, and interacted in spatial structures. Therefore, demographic, economic and social aspects and their implications for collective behavior were jointly examined.

The original idea of 'artificial societies' that permeated some initial examples of ABMs in the social sciences in the 1990s (see Section 1.4 for details), was to view computer simulation as a means to explore uncommon connections between disciplinary fields and to favor dialog between various specialists around relevant issues (e.g., Conte, Hegselmann and Terna 1997).

This reconfiguration also revolves around the idea of 'working together' and cross-fertilizing different research methods, starting from the primacy of the issues investigated rather than from disciplinary specialties. This is important as problems in reality do not have disciplinary boundaries. In this process, ABMs are not the only method, but they have a leading role as they help to connect qualitative and quantitative findings, micro evidence and macro implications. A good example of this is the type of research done in socioecological systems and common resource management. Here, qualitative case studies, quantitative surveys, field and laboratory experiments and ABMs are linked or even jointly pursued (e.g., Poteete, Janssen and Ostrom 2010).

This process of reconfiguration is still in its infancy and disciplines will naturally tend to follow their own path. However, it could have important consequences for sociology. First, given that it focuses on broad-range issues, involving different entities, processes and levels, trans-disciplinarity increases the possibility of achieving theoretical generalization and formulating taxonomies.

For instance, in the trans-disciplinary field of cooperation (see Chapter 2), it is now possible to distinguish, compare and order explanatory mechanisms at the level of atoms, molecules, individuals, societies, and ecologies, so that researchers have started to thoroughly understand general features, as well as peculiarities that arise at any particular level. This can improve reciprocal understanding among specialists and provide a more coherent picture of the global implications of an individual phenomenon or levels of interest.

Secondly, trans-disciplinarity favors the sharing of modeling approaches, techniques and best practices in methods which can help innovation to spread. This reduces the self-reference and parochialism of disciplinary fields and is important in sociology, which is a rather conservative discipline where innovation in research technologies and methods is not always the rule. Therefore, it is reasonable to expect that it is only by sharing attitudes and methods with others, that sociologists will participate in such a truly collective enterprise.

Obviously, this aspect is still latent as such research is a recent innovation. We cannot today forecast all the epistemological and institutional consequences that the growing collaboration between specialists, who in the past were confined in their narrow particular fields, may eventually entail. However, it is already evident that the ABM perspective tends to favor this process. In fact, there is no doubt that the knowledge frontier presently revolves around intrinsically trans-disciplinary issues, such as cooperation, socioecological systems, and socially inspired computing, just to name a few, where different specialists are collaborating and share attitudes, methods and concepts on the ground.

1.3 What are ABMs?

An ABM can be defined as a 'computational method that enables a researcher to create, analyze, and experiment with models composed of agents that interact within an environment' (Gilbert 2008, p. 2). From a technical point of view, this modeling tool represents a turning point in the history of artificial intelligence and its application to social sciences.[5]

The rise of distributed artificial intelligence and the diffusion of the object-oriented programming paradigm, on which ABMs are based, started in the 1990s. This allowed researchers to model agents as separate or distinct parts of a computer program which could contain heterogeneous variables, parameters, and behavior. Agents could interact by exchanging information and via communication protocols, and can react to the environment, learn, adapt, and change rules of behavior. Modelers can therefore equip computational agents with cognitive and behavioral properties typical of human agents, while the environment (i.e., social structures and institutions) can be programmed to mimic the real social world in varying degrees of detail.

Unlike equation-based, statistical and standard simulation models, ABMs allow sociologists to: (i) achieve an ontological correspondence between the model and the real-world, since individual agents can be modeled which mimic cognitive and social characteristics of real-world actors; (ii) include agents' heterogeneity, for example, in terms of behavioral rules, information, resources, position in given social structures, whereas standard equation-based models generally assume homogenous representative agents, or no agents at all, for analytic tractability; (iii) study nonlinear

[5] For a technical analysis of computer simulation in the social sciences, where a comparison of different simulation tools is thoroughly developed, the best reference is Gilbert and Troitzsch (2005). For a technical analysis of ABM, see Gilbert (2008).

agent interaction (in various forms) and its (long-term) consequence at the macro level, so that macro patterns can be diachronically studied as bottom-up emergent properties from local interaction (Fararo and Hummon 2005); (iv) provide an explicit representation of the environment (i.e., geographical space, institutional rules, and/or social structures) and the constraints they impose on agents' behavior and interaction; (v) provide sophisticated visualization techniques that allow us to observe and investigate complex interaction dynamics (Epstein and Axtell 1996; Gilbert 2008).

Thanks to these properties, ABMs differ from their computer simulation forerunners such as system dynamics, microsimulation and cellular automata (e.g., Troitzsch 1997). While system dynamics looks at social system behavior as the result of interaction between social structures, microsimulation, although based on micro units, such as households or individuals, cannot look at social interaction. Finally, although similar to ABMs in many respects, cellular automata provide a too simplified picture of human behavior and social interaction. Let us look at the features of these computer simulation techniques in detail.

System dynamics was originally developed in the 1950s to help corporate managers to understand industrial processes better, and now is generally used to support policy analysis and management in the public and private sector. Although it can include nonlinear interaction, as the change of any given system variable depends upon the behavior of other variables, system dynamics starts from the assumption that the system behavior is the result of circular and time-delayed relationships between structural components, factors or variables (Randers 1980; Hanneman and Patrick 1997; Gilbert and Troitzsch 2005).

Therefore, it does not allow for modeling heterogeneous micro behavioral aspects, only interdependence and feedback among macro variables. As such, it presupposes full *ex-ante* knowledge and description of system structures, which conversely are exactly the real *explanandum* of agent-based computational sociology (Grüne-Yanoff and Weirich 2010).

Microsimulation is a modeling technique that focuses on individual units, such as people, households, vehicles or firms, which are treated as a record containing a unique identifier and a set of associated attributes. If the unit is a list of individuals, records could be relative to age, sex, marital and employment status and are derived from empirical surveys or datasets. The modeler assumes certain deterministic transition probabilities that change the state and behavior of each model unit. This might be a change in taxation or stochastic processes that predict the probability of marrying. The purpose is to estimate the impact of these transition probabilities on certain aggregate variables of interest. Although it includes agent heterogeneity, at least in terms of distribution parameters (but not in terms of behavior), microsimulation does not include interaction between units, and consequently cannot provide insight into social interaction (Gilbert and Troitzsch 2005).

Cellular automata are used in a variety of disciplines to model local interaction between units and observe macro implications. They consist of a regular grid of cells, each in one of a finite number of states, such as 'on' and 'off', changing states over time according to the states of their neighboring cells. They have many overlapping properties with ABMs, but reducing the problem of interaction between dispersed micro entities to a single homogenous parameter. The idea of synchronous updating of agent behavior is a poor approximation to understanding complex social interaction (Hegselmann 1996; Troitzsch, 1997, 2009; Gilbert and Troitzsch 2005).

This being said, it will not surprise the reader that sociologists have found ABMs to be a suitable modeling tool to look at the emergence of social patterns from agent interaction in complex social systems (Gilbert 1996). Nevertheless, there is not yet any general consensus on a common way of using ABMs in sociology, or generally in all social sciences.

We can ideally identify two approaches, which have different implications for the relationships between ABMs and conventional analytic research (Axtell 1999). A first group of researchers use ABMs to support and complement analytic models. The aim here is to exploit computational power to extend deductive analysis where certain fixed close solutions are possible *in principle* and *de facto*, but impossible or very hard to find via differential equation systems. As such, ABMs have been conceived as an extension of math models, with object-oriented programming languages used to reproduce or translate equation-based objects.

A second group of researchers use ABMs to completely substitute analytic models, when these do not apply. In this case, object oriented programming languages and their logic are used to model a system of autonomous and heterogeneous agents (Liebrand 1998), where the macro system behavior is not known in advance, and no fixed close and equilibrium solutions are attainable. It is by exploiting the logic and power of these programming languages and by simulating the model, that behavior of the system can be concretely observed and understood (Bedau 1997). In this way, this approach exploits at best the isomorphism between the language of ABMs (i.e., object-oriented, based on logic, instructions and rules) and the language in which most sociological theory is expressed (e.g., Gilbert and Terna 2000).

As we will see, these two ideal-typical approaches coexist in agent-based computational sociology and this makes clear-cut technical distinctions between models a poor guide to understanding the evolution of this field and its long-term potential. The first approach lends itself more to generalization and is often associated with conventional theoretical frameworks, such as game theory. Therefore, ABM sociologists here come closer to conventional formalized science.

The second is more suitable to build sophisticated and empirically grounded models, where the level of empirical details of agent heterogeneity of behavior is more important. ABM sociologists here come closer to empirical social scientists. Given the relative novelty of the ABM approach in sociology, it is reasonable to expect that these differences will not diminish in the future. Perhaps, this could also be beneficial as sociology will continue to be a strongly diversified discipline called to investigate phenomena with different approaches, methods, and levels of detail.

1.4 A classification of ABM use in social research

In the perspective of the model's purpose and the link between model and empirical reality, we can distinguish five types of ABMs in social research (see Table 1.1):

Table 1.1 A map of ABM use in sociology.

	Synthetic models	Analytical models			Applied models
	Artificial societies	*Abstract models*	*Middle-range models*	*Case-based models*	*Applied simulation*
Definition	*In-silico* social system surrogates	Theoretical models on general social phenomena	Theoretical models with a well-specified explanatory empirical range that refers to a specific class of empirical phenomena	Models on (space–time) well-circumscribed empirical phenomena	Replication of a given real system with the due detail
Purposes	Synthesizing components of social life realistically so as to explore intuitions on important aspects of the evolution of social behavior and structures that cannot be studied empirically or experimentally	Theory building and development through models that do not reflect any concrete and specific empirical instance	Improving knowledge on differences and similarities between different empirical instances of a specific class of empirical phenomena Favoring comparison between empirical cases for theory building on specific empirical puzzles	Achieving a fine grained representation of the systems under scrutiny Appreciating complexity of social systems	Obtaining knowledge on a given system's functioning to solve problems, assist planners and decision makers, or improve the knowledge of agents involved about the system's behavior and the consequences of their decision

(*Continued*)

Table 1.1 A map of ABM use in sociology. (*Continued*)

	Synthetic models	Analytical models			Applied models
	Artificial societies	*Abstract models*	*Middle-range models*	*Case-based models*	*Applied simulation*
Positive consequences	New insights might be incorporated/tested in more precise studies Favoring new connections between specialized knowledge might help a big picture view on social puzzles	Findings' generalization Revealing non-obvious properties of social systems Exploring explanatory hypotheses Providing theoretical frameworks for empirical studies	Strengthening the link of theory and empirical evidence Progressively develop and coherently articulate theoretical explanations about well-specified empirical puzzles	Relevant and illustrative case studies can provide intuitions for theory building that might be extended Providing examples for middle-range theories	Promoting research/action methods Improving the learning of real agents Adjusting pre-existing theories through stakeholders' involvement
Critical points	Difficult to transform results into empirically testable findings	Easy to lose sight of real empirical *explanandi*	Difficult to generalize findings and to empirically test them against singular cases	Theoretical generalization	Theoretical generalization

artificial societies, *abstract models*, *middle-range models*, *case-based models*, and *applied simulations*. Abstract models, middle-range models, and case-based models are all examples of an analytical use of ABMs, in order to shed light on well-specified social phenomena (although at a different level of empirical detail and theoretical generalization). Artificial societies have more to do with a 'synthetic' and explorative approach to computer simulation, and applied simulation with a research/action approach.

Before going into the details of each type of model, it is worth noting that, in order to provide a map of ABM use in sociology, we will not focus on the relationships between different types of model. By providing the example of fish market models, in Boero and Squazzoni (2005), we have suggested that the different analytical use of ABMs should be viewed as 'types in a continuum'. This has more to do with general epistemological problems of model generalization and validation that are not relevant here (see Chapter 4 for details).

Another important point to mention is that, obviously, not all these types have been equally explored, as analytic use is dominant in sociology. Moreover, this does not disqualify the added value of each type of model and its potential for the development of our discipline.

Artificial societies are *in-silico* social system surrogates. Here, the modeler's aim is to recreate forms of social life realistically with the computer so as to investigate social phenomena which cannot be looked at in empirical or experimental research for various reasons, for example, ethical/time/budget constraints or absence of data. As such, these types of models do not have precise empirical puzzles to explain or empirical data to look at. They are explorations on surrogates of real social systems. Creating a surrogate means synthesizing basic components of social life by following the original idea of 'artificial life' research (e.g., Langton 1997): *in-silico* systems can help to explore intuitions on important aspects of the evolution of social behavior in real systems.

These models are therefore intrinsically trans-disciplinary as they include aspects that usually pertain to different fields and disciplines, such as demography, linguistics, sociology, economics, environmental and cognitive sciences (e.g., the influence of linguistics on this type of research in Cangelosi and Parisi 2002). At present, this type of research has been poorly developed in social sciences (an exception is Gilbert *et al.* 2006). However, it is important as, by connecting previously unrelated specialized knowledge, it can give the big picture, which could help to give new perspectives for more precise studies. Furthermore, it can provide 'what-if' scenarios which might reveal non-obvious features of reality.

Abstract models focus on social phenomena of a general range. They are neither fine-grained representations of circumscribed empirical phenomena, nor models of specific classes of empirical phenomena. They aim to support theory building and development, generalization being one of their main features. According to Carley (2002), if case-based models are 'veridicality' based, abstractions are 'transparency' based, as they aim to abstract details away under Occam's razor for simplicity which favors inter-subjective scrutiny. As we will see, by working with abstract models, modelers can discover non-obvious properties of social interaction and also provide theoretical frameworks which can be used for empirical study.

Middle-range models are empirically grounded theoretical models intended to investigate specific social mechanisms that account for a variety of empirical phenomena that share common features. They can be based on stylized facts or direct empirical evidence. In another work, we used the concept of 'typifications' to mean that these are models in a Weberian sense, namely heuristic models which allow us to understand certain social mechanisms that operate within a specific class of empirical phenomena, for example, innovation in biotechnology clusters, common resource management in local communities or institutional settings in fish markets (Boero and Squazzoni 2005).[6]

Thanks to their heuristic and pragmatic value, these models should not fully correspond to empirical reality, which is the target of their explanation (Willer and Webster 1970), as they are not designed to represent all possible empirical instances of the class itself. Therefore, qualities which are important for case-based models, such as accuracy, precision, and veridicality, are less important in this case.

According to Weberian 'ideal type', these models synthesize 'a great many diffuse, discrete, more or less present and occasionally absent *concrete individual* phenomena, which are arranged according to those one-sidedly emphasized viewpoints into a unified *analytical* construct' (Weber 1904). The principle is that the further these models are from the empirical instances which the class refer to, the stronger their heuristic value.

Here we call them middle-range models to suggest their Mertonian function, as they point to well-specified explanatory ranges or objectives, are located between abstract models and thin empirical accounts, tend to create a bridge between theory and empirical analyses, and favor the systematization of the theoretical findings in specific empirical fields.

They help to improve understanding of differences and similarities between empirical instances of a common class of phenomena (e.g., Hedström and Udehn 2009). Merton (1968) argued that these types of models are important both to develop well-specified theories to derive testable findings, and to develop and articulate theoretical explanations from the ground up.

Case-based models have an empirical space–time circumscribed target domain. This is because the phenomenon under scrutiny is characterized by idiosyncratic and individual features, that is, what Max Weber called 'a historical individual' (Weber 1904). The aim of the modeler is to achieve fine grained knowledge of the empirical situation, with accuracy, precision, and reliability. As Ragin (1987) argued, case-based models are aimed at 'appreciating complexity' rather than

[6] As Coser stressed (Coser 1977), there are at least three kinds of 'ideal types' in the Weberian sense. The first is historical routed ideal types, such as the well known cases of 'protestant ethics' or 'capitalism'. The second one refers to abstract concepts of social reality, such as 'bureaucracy', while the third one refers to a rationalized typology of social action. The latter is the case of economic theory and rational choice theory. These are different possible meanings of the term 'ideal type'. In our view, the first two meanings refer to heuristic theoretical constructs which aim to understand empirical reality, while the third one refers to 'pure' theoretical (as well as normative) purposes. Such a redundancy in the meaning of the term has been strongly criticized. According to our classification, middle-range models include only the first two meanings, while the third one refers to what we call abstract models.

'achieving generality'. Certain methodological traditions in sociology, such as ethnomethodology, over-emphasized the difference between theoretical models and 'a-theoretical descriptions', for example, where investigations try to be subjective and express the direct experience of agents. It is obvious that case-based models cannot be conceived as 'a-theoretical' models. Indeed, they are built upon pre-constituted theoretical hypotheses and often exploit general modeling frameworks. Fragments of theoretical findings or well-known theories are often used both to approach the empirical puzzle and to build the model.

There is no doubt that, following Weber (1904), a case-based model sometimes allows us to say nothing more than a 'particular story'. However, it is also true that its relevance, as well as its possibility, strongly depends on its relationship to a theoretical framework. This means that cases in science are mostly nothing but instances of a broader class of phenomena, for example, part of a middle-range theory. In order to generalize a local explanation, case-based findings have to be extended to other similar phenomena and abstracted at a more general theoretical level, for example, by being compared with, or contributing to a middle-range model.

For instance, returning to the example of the Anasazi model mentioned above, it is worth noting that by reconstructing the particular history of the ancient population who inhabited the Four Corners, the findings helped to say something about the historical and environmental problems encountered by similar populations during similar historical periods. Therefore, relevant and illustrative case studies can provide insights for theory building. For this purpose, different standard methods can be used to generalize case studies towards middle-range theories (e.g., King, Verba and Keohane 1994; George and Bennett 2004).

Last but not least, *applied simulations* are replications of given real systems with sufficient detail to obtain knowledge on how to solve important practical problems, assist planners and decision makers, support re-engineering options, in the case of organizations, or improve the knowledge and reflexivity of individuals involved in real systems.

Here, analysts build *ad hoc* models that should map real systems as closely as possible, as policy and re-engineering conclusions have to be customized to concrete situations. Largely explored in applied social and environmental sciences, as well as in management and organization sciences, these models promote a research/action method, improve real agent learning and in some cases help to adjust pre-existing theories through stakeholder involvement (e.g., Squazzoni and Boero 2010). Moreover, they can contribute to helping people to appreciate the direct contribution of scientific investigation in solving real problems.

Finally, it is worth noting that recently, other authors have suggested classifications similar to ours. Grüne-Yanoff and Weirich (2010) have suggested a similar analytical use of ABMs. They distinguished between 'full explanations', when models are claimed to explain concrete empirical phenomena (e.g., our case-based models), 'partial explanations', when typification of empirical phenomena is involved (e.g., our middle-range models), and 'potential explanations' to mean theoretical abstractions with large scale explanatory domain (e.g., our abstract models). As in our case, this classification tried to connect specificities of the model's target and of the explanation.

In the same way, Gilbert (2008) suggested distinguishing between ‘abstract’, ‘middle-range’, and ‘facsimile’ models.

To conclude, each type of model has its own positive peculiarities and critical problems. *Artificial societies* can support exploration about difficult-to-observe sociological puzzles, promote counterfactual thinking and overcome disciplinary barriers. Unfortunately, it is hard to transform their findings into something empirically testable. *Abstract models* are of paramount importance for the progress of science, but abstract research can easily lose sight of empirically relevant aspects. *Middle-range models* can do a great deal to connect evidence and theory and to focus on well-specified social mechanisms. However, both their empirical validation in single important cases and their theoretical generalization are extremely challenging to achieve. *Case-based models* might help to refine the validity domain of general theories and provide histories that might inspire theory building, but their theoretical generalization requires an enormous and well-organized collection of evidence, not always at hand. Finally, *applied simulations* might help to fill the gap between representation and reality and to promote customized solutions to challenging social problems. Unfortunately, it is generally hard to translate their findings into scientific investigations.

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