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Social Simulation in the Social Sciences: A Brief Overview

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Abstract

This article provides an overview of the social simulation approach to the study of social phenomena. We focus especially on the relevance of heterogeneity of social behavior and dynamics and the complex interplay of agent behavior and social structure. The article identifies the peculiarities and the explanatory achievements of this approach and then discusses its prospects and challenges. Special attention is given to (i) how micro-level behavioral detail can be used to understand social patterns and dynamics; (ii) the importance of the meso level of social networks; and (iii) the two-way, process linkages between micro and macro aspects as a fundamental source of social uncertainty and unpredictability.

Keywords

social simulation, computer simulation, agent-based modeling, heterogeneity, social dynamics, social networks, complexity, micro–macro link

Introduction

Although relatively young, the behavioral and social sciences have unraveled important social processes that guide human thinking and behavior, such as social learning, empathy, and norms (e.g., Hoppitt & Laland, 2013; Shafir, 2013; Tomasello & Vaish, 2013). Nevertheless, even in ideal situations, it is hard to understand the aggregate behavior of groups of people whenever they interact over any significant period of time. This is due to the nonlinear interaction effects between individuals and the interplay between individual behavior and social dynamics and structures. These complications make any micro–macro mapping extremely difficult: Even quite comprehensive knowledge of behavior at a small scale does not necessarily help in understanding implications at a macro scale (e.g., Miller & Page, 2007). This is important as many social, economic, and political issues that have serious consequences on human well-being may pivot upon such complex group behavior.

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Examples of these consequences include economic crises, civil wars, and environmental problems, all of which occur on spatially large, real-time scales and take place within and between different social groups. All of these have macro implications, such as public budget restrictions and increasing urban ethnic segregation. These macro implications may have, in turn, important micro-level counterparts, such as increasing perceived insecurity and discriminative attitudes. Therefore, managing such large-scale problems requires a systematic understanding of the processes at both the individual and the group level—in other words, we cannot ignore the micro–macro mapping if we are to address these problems.

Recently, analyses of people's opinions, beliefs, and behavior have been used to account for globally significant societal events, for example, the rise and fall of communist systems, the conflicts in the Middle East, and the current financial and economic crisis. While understanding observed phenomena is fundamental to any scientific endeavor, managing such phenomena is an equally important project. One of the most important challenges for social sciences is to finds ways to manage complex social systems in such a way that we can avoid socially or economically undesirable outcomes. If we can produce models that facilitate a greater understanding of such phenomena and allow us to explore possible effects of different policy options, this would be a valuable tool in such a project.

It is not surprising that economics is considered the more advanced field for such modeling, since money lends itself to be quantitatively measured, and this allowed the building of apparently predictive formal models based on "hard data" and well-understood theoretical bases. As such it contrasts markedly with qualitatively based approaches based upon psychosociological concepts.[1] However, when we consider the recent global financial crisis, it is evident that such predictive models might only be applicable when socioeconomic systems show stable, in equilibrium, properties, which are the exception rather than the rule (e.g., Ormerod, 2012).

This lack of applicability has negative implications as management and policy are fundamental in turbulent more than in business as usual situations (e.g., Ball, 2012; Room, 2011). Indeed, in these situations, even well-informed experts have radically different ideas about what to do. For example, in the current European crisis, some experts suggested to downsize Europe, others to reduce national debt by increasing taxation, others to reduce taxation to stimulate the market, finally some even contemplated a return to national currencies. Unfortunately for us, the world is not an experimental laboratory where it is possible to find the most effective policy using such models and, even if it were, the considerable number of different policies that would need to be tested over time would impose an exponential growth of scenarios to be tested, which would make the exercise infeasible. Although increasing computing power might help do the complex scenario analysis, the indigestible quantity of results would make this exercise poorly informative both for understanding and for management.

Although precise prediction seems a dead-end street, we argue that significant advances can be made by a social simulation approach capable of combining agent-based computational modeling and strong social science contents. In our view, computational modeling can help us identify the processes that are responsible for the emergence of social phenomena and facilitate an exploration of the collective implications of complex social dynamics (e.g., Conte, Edmonds, Scott, & Sawyer, 2001; Edmonds & Meyer, 2013; Hedström, 2005; Helbing, 2012; Macy & Flache, 2009; Macy & Willer, 2002). Thus, it could be a valuable tool for understanding events in the real world and contemplating possible strategies for its management (e.g., Geyer & Rihani, 2011; Rhodes, Murphy, Muir, & Murray, 2011). In this sense, formal computational models that can relate to quantitative data might support a more qualitative process of policy making that may deal with the complexity of our social and economic challenges (e.g., Cairney, 2012; Durlauf, 1997; Squazzoni & Boero, 2010).

The recent development of agent-based modeling has allowed us to better understand how agent interaction may lead to surprising, unpredictable societal phenomena (e.g., Edmonds & Meyer, 2013). For example, Schelling's (1971) model of segregation was instrumental in showing how a complete segregated society can emerge despite individuals not having a high level of racial intolerance. Similarly, Granovetter's model of threshold behavior (Granovetter, 1978) and subsequent developments (e.g., Watts, 1999, 2002) showed that, when individuals make binary decisions, such as signing a declaration of war, evading taxes, or reporting bullying by a supervisor within a workplace, nonlinear interaction effects can result in unpredictable social outcomes, especially when individuals are sensitive to behavior of others and are embedded in social network structures. In the same vein, Deffuant, Amblard, Weisbuch, and Faure (2002) and Hegselmann and Krause (2002) examined the role of social influence on opinion distribution and dynamics and showed that societies can converge toward polarized or pluriform collective opinions (Huet, Deffuant, & Jager, 2008; Jager & Amblard, 2004), minority positions may become dominant (Galam, 2002), and reputable leaders emerge as a result of social interaction (Dykstra, Elsenbroich, Jager, Renardel de Lavalette, & Verbrugge, 2013). These social simulation studies show that large-scale societal changes may originate from many micro-level interactions and that even unique historic events with significant societal consequences can be partly explained in terms of complex social interaction.

This article aims to illustrate the peculiarities of the social simulation approach to the explanation of social phenomena by looking at some of its achievements and discussing its prospects and challenges. The epistemological and methodological peculiarities of the social simulation approach for the social sciences have been discussed in many recent contributions (e.g., Epstein, 2006; Garcia & Jager, 2011; Gilbert & Ahrweiler, 2009; Squazzoni, 2010; Troitzsch, 1997) and special attention has been paid to the advantages of modeling to fill the gap between quantitative and qualitative aspects, develop empirically testable findings, and promote the cumulativeness of findings by disciplining and facilitating intersubjective dialogue (e.g., Squazzoni, 2012). Here, we focus more on the tangible and general explanatory achievements of this approach, emphasizing especially the role of heterogeneity at the level of behavior and social dynamics. We do not have room for more than a brief survey here, so we have slanted the review toward a few areas of social simulation work that sheds light on a few mainstream social science issues. As a result other areas of social simulation have not been covered, for example, methodological issues, the cognitive architecture of agents and the impact of this, and technical programming issues. We have not covered in any detail cognitive aspects of social simulation, nor on its potential for participating in policy-making processes, choosing to focus rather upon its role in facilitating understanding in the face of complexifying aspects, principally heterogeneity and social embeddedness.

The rest of the article is organized as follows. The next section discusses the importance of heterogeneity and micro detail for the understanding of complex macro social outcomes. While social scientists are interested to understand large-scale collective outcomes solely using macro considerations, often conceived in terms of consequences of relatively stable social structures (such as markets, politics, or the family), the social simulation approach emphasizes the fundamental "microscopicness" of social reality—that dealing with the detail, down to individual behavior and relationships, is crucial. Any bird's eye view of social facts that points only to social aggregates will not help much in understanding the generative processes of social behavior and hence may only result in an illusion of comprehension (e.g., Bruch & Mare, 2009). Here heterogeneity is not restricted to static types/strategies of behavior, as suggested by experimental, game-theory behavioral sciences (e.g., Axelrod, 1997; Gintis, 2009) but includes the dynamic, social attributes of behavior that can be triggered by social interaction. The third section focuses on social interaction, the influence of social networks, and the interplay of behavior and structure. In this case, individual heterogeneity needs to include the positions, roles, and influences, which are triggered by the social structure. A major advantage of social simulation approaches is that it makes large-scale artificial experiments possible, allowing the long-term implications of relatively simple social behavior within more or less realistic social network structures to be explicitly traced. By visualizing such spatial–temporal dynamics, which are hardly observable empirically, it is possible to understand the deep linkages between changing behavior and dynamic social structure at the micro level. Finally, the last section discusses some of the prospects and challenges of social simulation for the development of social sciences, in particular how it might interface with the cognitive/neurosciences as well as in understanding the complex interplay between genetics and social environment.

The "Microscopicness" of Social Reality

A fundamental lesson from social simulation is the crucial role of heterogeneity in social systems. Heterogeneity here means the idea that individuals might have different beliefs, preferences, behavior, normative values, and positions in the social structure. The importance of this heterogeneity has been largely underestimated in some more established approaches, such as economics and quantitative sociology (e.g., Macy & Willer, 2002). When dealing with social or economic problems, the standard approach of quantitative macro sociology, econometrics, and economics is to look at aggregates built up from individual attributes and (maybe) the average differences between groups of people. Whether by assuming fictitious "representative" agents or averaging individual attributes from longitudinal or cross-sectional samples, removing outliers and extreme cases may mask any underlying heterogeneity and diversity of individual cases, which can be crucial for understanding how people interact and hence the aggregate implications (e.g., Miller & Page, 2007; Page, 2010).

Social simulation studies have showed that some kinds of social dynamics are driven by the heterogeneity of social behavior and that the so-called outliers may be individuals with key roles in these processes of change. Reducing instead of exploring such heterogeneity may give rise to a misplaced fallacy, namely that one *can* deduce macro outcomes from assumed simplistic micro foundations. For example, in a traditional statistical study on social influence in the purchase of electric cars, Jeremy Clarkson of the BBC car show "Topgear," whose recommendations might have a dramatic impact on public opinion, would have been omitted from the sample as a very atypical outlier, whereas he should be considered as a hub in the sharing of—sometimes radical—opinions (Dykstra et al., 2013). Including, in one's consideration, levels of heterogeneity that reflect what is observed and not assuming any standardized, "rational," or overly predictable behavior can open the way to understanding some of the more complex social dynamics and lead to a more well-rounded appreciation of social possibilities.

This is echoed in recent results from behavioral experimental studies on human behavior that have confirmed the importance of the coexistence of individual heterogeneity even in typified interaction situations, such as public goods provision, cooperation problems, or typical economic exchange under information asymmetry. These results showed that heterogeneity is instrumental to establish social order, institutions, and norms, in cases where their existence and maintenance cannot be fully understood in terms of economic, calculative rationality motives (e.g., Ostrom, 2000).

Let us consider a typical, very simple social dilemma situation, where individuals can choose whether and how much money to put in a common pot, knowing that the pot will be used to buy goods for everyone, even for those who did not contribute. Similar situations occur among groups of friends, colleagues in scientific teams, or between countries deciding whether to sign a treaty on climate change. If, following standard economics and rational choice predictions, we would assume a unique type of behavior, such as self-interest, no one would contribute and the pot would be empty, with anyone worse off. This would be unrealistic as we frequently observe that people do overcome these self-interested temptations and contribute to the creation of public goods. If we also assume that there are some altruistic, normative-oriented individuals, the pot would be full but ready to be later exploited by selfish individuals. In many situations, the presence of a third type of behavior such as people who are willing to punish selfish behaviors, bearing the cost of this at their own expenses (e.g., information cost, retaliation, etc.), can help to establish forms of social order that resembles what it is frequently observed (e.g., Gintis, Bowles, Boyd, & Fehr, 2005).[2]

For example, by modeling a situation inspired by data from mobile hunter-gatherer groups in the late Pleistocene, Bowles and Gintis (2004) showed that the functional coexistence of selfish agents, altruistic, and reciprocators can be instrumental for the emergence and maintenance of cooperation and social order. The argument is set within an evolutionary perspective. Suppose that a group is composed of a certain number of selfish individuals (always tempted to cheat), altruistic individuals (always cooperating under universal norms of fairness), and strong reciprocators (cooperating with the second and capable of punishing the first ones at their own expense) who are interacting together. In a selective environment, cooperators might outperform reciprocators, as they take advantage of the effect of selfish individuals' punishment, accumulating resources against both selfish and reciprocators. Suppose that altruistic individuals replace strong reciprocators in the group, as they accumulate more resources than the latter. If there are a few strong reciprocators present in the group, the expected cost of cheating decreases and selfish behavior starts to proliferate, exploiting the altruistic individuals who unconditionally continued to contribute to the public good. The former receive higher payoffs and eventually replace the latter. When this occurs, the average fitness of the group falls and the group might disband. This means that a certain amount of behavioral heterogeneity should be present inside such groups as otherwise they would similarly disband. Thus, selective pressures of social and cultural evolution may operate not only at level of the single individual (or behavioral "phenotype") but also, and more importantly, at a group level (e.g., Bergstrom, 2002). By removing behavioral heterogeneity, many social science models risk losing sight of the fundamental ingredients of social life, especially those that make social outcomes difficult to understand and predict.

Furthermore, heterogeneity is not only important at the level of individual or group behavior but also in terms of agent positions within given social structures and in terms of social learning. For example, Goldenberg, Han, Lehmann, and Hong (2009) showed that besides connectivity, personality traits and knowledge also play a critical role in the influence a person has on others' consumptive behavior, and Van Eck, Jager, and Leeflang (2011) using an empirically grounded diffusion model that formalized opinion leaders within social networks showed that these leaders could facilitate a faster spread of opinion adoption and result in a higher proportion of adopters. Of course, knowledge is partly an emergent property, because consulting a person also implies sharing experiences with this person. A preference for consulting knowledgeable persons by people thus causes a self-amplifying loop between the expertise level of individuals and their consulting attractiveness, and hence part of becoming a reputable expert can be considered to be an emergent property of social learning.

In regard to social learning, recent cognitive studies showed the importance of heterogeneity in terms of information heuristics and the important function that social information can play as a source of learning. On one hand, experimental and empirical investigation on the so-called wisdom of crowds found that collective social intelligence and learning take place when diversity, heterogeneity, and exploration, due to the presence of people with different beliefs and (partial) knowledge, is present at the micro level (e.g., Page, 2010). Brilliant examples of social intelligence and learning, such as Wikipedia and local food traditions, exist because they are capable of aggregating heterogeneous, dispersed knowledge and can stimulate further exploration and heterogeneity at the micro level (e.g., Surowiecki, 2004). In this regard, recent experimental research showed that a large population of individuals with limited knowledge (exploring solutions in parallel), following simple, adaptive heuristics can solve complex problems better than a group of well-focused experts (e.g., Gigerenzer & Brighton, 2009).[3] This is still true if we compare the wisdom of crowds effect to those of single individuals endowed with more time and information to reason on a given puzzle in the context of refining decision-making strategies (e.g., Rauhut & Lorenz, 2010), whereas this effect can be reversed if social influence is added so that the opinions of peers are available to subjects before they try to solve a problem (e.g., Lorenz, Rauhut, Schweitzer, & Helbing, 2011).[4]

Other studies employing social simulation models inspired by experimental research link the importance of diversity and heterogeneity with the meso level of social information, showing that the higher the circulation of social information among economic agents in markets, even if largely inaccurate, the better the capabilities of learning at the macro level (e.g., Boero, Bravo, Castellani, & Squazzoni, 2010). Here, in line with recent experimental research (e.g., Boero, Bravo, Castellani, Laganà, & Squazzoni, 2009; Piazza & Bering, 2008; Sommerfeld, Krambeck, Semmann, & Milinski, 2007), social simulation has significantly advanced our understanding of certain social mechanisms, such as reputation and gossip (e.g., Conte & Paolucci, 2002; Conte, Paolucci, & Sabater-Mir, 2008; Elsenbroich & Gilbert, 2013; Hales, 2002; Janssen, 2006). This research indicates that scientific progress, technological innovation, and market evolution (i.e., collective artifacts that embody relevant social learning and knowledge) would have been impossible without a micro base characterized by heterogeneity, diversity, and exploration.

To sum up, it is reasonable to believe that individual heterogeneity is one of the main sources of uncertainty and unpredictability of socioeconomic systems, and this factor cannot be ruled out or taken for granted when modeling social reality. This holds both for analytical and policy/management-oriented models. The challenge for social simulation is to understand (1) which aspects of heterogeneity should be incorporated in a model to adequately reflect the complexity of social reality and (2) whether heterogeneity should be considered as a dynamic rather than a static property, so as to include the constructive interplay of social environment and individual perceptions and behavior (e.g., Sawyer, 2005). These are hard questions to answer, but at least using social simulation as a way of relating the micro and macro levels, it is feasible that they may be answered.

Social Interaction: Structure and Networks

One of the most popular ideas in sociology is that of "embeddedness" popularized by the famous study on the strength of the weak ties in labor market by Granovetter (1972). This indicates that, when making decisions, for example, whether to apply for a job to a business company or a nonprofit, voluntary association or choosing between buying junkie foods and eating a vegetable salad, individuals are not isolated from their social context (e.g., Smith & Christakis, 2008). Their positions in the social structure, their contacts, and the kind of peers they have can dramatically influence their decision and create significant differences even between otherwise similar individuals (Watts & Dodds, 2009).

In a recent online experiment, Salganik, Dodds, and Watts (2006) simulated an online music marketplace where more than 14,000 teenagers were asked to listen to a list of obscure rock songs and download the most preferred ones. By making available information on the previous choices of others only to a treatment group of subjects (namely the number of downloads by previous participants), the outcomes in terms of songs' success could be shown to be dramatically and unpredictably affected by such knowledge (even when taking into account the different preferences of the subjects). This confirms classical studies on social influence on consumer behavior (e.g., Burnkrant & Cousineau, 1975). Bond et al. (2012) performed a large-scale experiment concerning political mobilization on Facebook on November 2, 2010, which involved more than 60 million users. They compared three groups: (a) a group where a message was shown at the top of their news feed that encouraged people to vote as well as providing a link to information on local polling places, (b) a group where this was accompanied with a "I Voted" button, which, once clicked, made visible the faces of people on the provided link, and (c) a control group with users not receiving any messages. They found that the exposure to social information, group (b), dramatically influenced voter's behavior (e.g., information seeking and voting) and this extended to friends of friends and people in their off-line networks. More recently, Muchnik, Aral, and Taylor (2013) performed a large-scale experiment on a social news aggregation website to study biases in the rating behavior of users. Results showed that social influence substantially biases individual judgment and that a positive herding effect can be easily caused by positive social influence, such as in case of rating bubbles.

These simple, "in vitro" examples indicate that different social influence mechanisms, contents, and channels might differ greatly in terms of their effects. These can range from a single occasion such as reading a web review of an anonymous expert on a particular product to the daily interactions with parents and friends on a wide variety of activities and opinions. Additionally, individuals are likely to discuss different issues with different groups of people on different topics. From a network perspective, this implies that people are separately linked to a variety of different groups (such as family, work, sports clubs, and the like), where each group is unlikely to be connected to the others. Hence, a friend you play music with in a band is more likely to be connected to other people you know in the local music scene than with your colleagues at work. Next, it is obvious that asymmetries exist in the influence that people exert on each other. The social forces that go in and out may differ significantly, and literature shows that early adopters/innovators, market mavens, and opinion leaders often have more influence (e.g., Van Eck, Jager, & Leeflang, 2011). This influential position may translate into a network position, and hence it can easily be understood that some highly influential people have an impact on large numbers of people, whereas their ingoing influences may be confined to just a few, for example, Warren Buffet in stock trading and Jeremy Clarkson in car markets. To further complicate things, networks are dynamic, so that new links are being formed, other links forgotten or fallen into disuse, still others dormant with little activity but can be activated at a later date (old but not forgotten friends). This suggests that an important aspect of networks is not only whether nodes are connected but also the frequency of interactions between nodes (e.g., Jager & Amblard, 2008).

Since social interaction is the main complexity driver of social systems, understanding the link between social networks and social influence mechanisms is essential. Here, the social simulation literature has recently proliferated by touching upon issues such as the diffusion of binge drinking, obesity, depression, and other social and health problems (e.g., Christakis & Fowler, 2007; Giabbanelli & Crutzen, 2013; Ormerod & Wiltshire, 2009; Rosenquist, Fowler, & Christakis 2009). Basically, two network approaches can be distinguished: (1) models that test stylized network architectures and (2) models based on specific networks built for the empirical case or domain of interest, with more or less dynamical aspects involved.

Under the heading of (1) different types of networks can be identified. The most basic ones are spatial grids where agents can interact exclusively with their neighbors (either four in the Von Neumann neighborhood, excluding diagonal contacts and eight in the Moore neighborhood) versus a condition where everybody is connected with everybody (complete network). When it is assumed that agents have a limited number of contacts, one can distinguish between purely local contacts (which reflect more of a spatial grid type of network) and a fully randomized network. The observation that most contacts in a network are usually local (strong ties), but that also *some* more distant connections exist (weak links), is important in the spreading of information through a network translated in the development of the "small-world" network (Watts, 1999). Here one starts with a regular network of local links (such as a spatial grid) and then, with a given probability randomly rewires some of those links. By increasing the probability of rewiring from 0 to 1, a variety of small-world networks can be implemented, with the local network and fully random networks as extremes in this continuum. The observation that in many networks people differ concerning the number of links they have gave rise to the development of the scale-free network (Barabási & Albert, 1999). Here the principle of preferential attachment is used to create networks of agents with a variable number of contacts each. Starting with an unconnected network a random link is made, but after that links are made with a bias toward connecting with nodes with more links. The stronger the preference to link with agents having already a lot of contacts, the more likely it is only a few hubs emerge that absorb most of the links, and the more skewed the distribution of contacts in the so-called scale-free networks will be. Amaral, Scala, Barthemely, and Stanley (2000) suggested that the number of contacts a person can process is limited and hence proposed preferential attachment with a limitation of the number of links one can have.

Whereas the networks mentioned under (1) are generally easy to implement, and it is relatively easy to conduct experiments, comparing outcomes resulting from different settings, the question remains what network type best fits the problem one is modeling. Ideally one would have data concerning key properties of social network for the situations being modeled, such as density, size, average degree, shortest and average path length, and clustering coefficient. To obtain such properties, full data of network interactions have to be available. Having such data would allow for the construction of specific networks as mentioned under (2). In the past years, this culminated in a number of studies using data obtained from social network sites, most notably Facebook (Aral & Walker, 2012), Twitter (Toubia & Stephen, 2013), and telecommunication systems (e.g., Haenlein, 2013; Nitzan & Libai, 2011; Risselada, 2012). Whereas this resulted in more knowledge of the structure of real networks, the problem is that these data only address a single channel, but in practice people use many channels simultaneously and probably use different channels for different people and for different purposes. For example, the daily conversations you have with people you meet in your neighborhood or at work are not captured in such data. Additionally, such data do not usually address the type of information and influence that is being exerted. As a result, these data sets only provide a partial perspective on people's patterns of communication.

A different approach is based on dynamically constructing networks on the basis of the likeliness that people connect. It has been observed that the similarity between people, or homophily, increases that chance that people talk (Brown & Reingen, 1987), and highly similar people are more likely to connect than those who are very different (Kossinets & Watts, 2009). Similarity is often measured in terms of attributes such as age, gender, education, or lifestyle (Rogers, 1983). Greater similarity between people seems to also increase trust, understanding, and attraction between them, creating a stronger relationship (Ruef, Aldrich, & Carter, 2003). This introduces the possibility of using social simulation models to look at networks built up based on individual preferences and characteristics rather than having to collect full network data. As such it is possible to use survey data of people that are in reality not connected to construct a network that more or less matches their preferences. A first step in this direction is to make the chance of two agents being connected proportional to the similarity they have on a number of (weighted) key attributes (e.g., Van Eck, 2013). This also opens an interesting venue for modeling dynamic networks, since if the key attributes of agents are changeable (such as income and location) this may affect the chances of interaction and hence the structure of the network as the simulation progresses.

An example of this approach is given by Speelman et al. (in press), where a farmer's chance of interaction is based on location, crop type, and wealth. In this context, a farmer agent losing money due to experimenting with a different crop is more likely to lose contacts due to a decrease in similarity. A more advanced approach becomes possible if data are collected concerning who communicates with whom, for example, whether a person interacted with another on a certain issue, the influence was ingoing and/or outgoing, and whether the influence was normative or informative. In Van Eck (2013), a methodology is tested to construct networks by using such data in matching respondents on the basis of these profiles. This implies that not only does similarity play a role but also complementarity is being used in network construction. Hence, an agent with a strong outgoing informational influence will be coupled to an agent having a strong ingoing informational influence. The algorithm to construct such a network can be designed to deal with any number of variables that are relevant in this context. Whereas in the current application, the resulting network was used in experiments where the network remained static, dynamic implementations can also be envisaged. This would imply that cross-sectional data could be used to construct the network using such an approach and that simulated changes in these variables would translate into adaptations in the network that might be checkable using longitudinal evidence.

In the same line, recent examples exist that have investigated dynamic social network models based on empirically verified individual preferences (e.g., Fehl, van der Post, & Semmann, 2011; Zschache, 2012). For example, by combining experimental and computational work on coordination games within dynamic networks, Corten and Buskens (2010) showed that any stability in the set of applicable social norms can be extremely sensitive to social influence. This was due to the fact that individuals were influenced by their social contacts and used the observed behavior of neighbors to predict (often erroneously) the behavior of unknown partners. Results showed that, while less efficient norms persisted especially in case of dense networks under conformity pressures, more efficient norms tended to emerge when social networks were endogenously developed by individual agents, actively creating and breaking their links. By calibrating an agent-based model on experimental data on behavior of real subjects in a repeated trust game, Bravo, Squazzoni, and Boero (2012) found that cooperation was not influenced by the initial network configurations (e.g., scale-free, small worlds, or random networks) but that it did significantly increase in case of dynamic networks based on partner selection. When individuals were allowed to create or break links according to a simple happiness function, norm abiders benefited from more interactions, more social ties, and were more profitable by ensuring in turn higher profitability for their partners. While in contrast the "bad apples" tended to be isolated over time. In short, the social structure dynamically adapted to the positive outcomes of social interaction which, by increasing the density of contacts between norm abiders, strengthened the functional configuration achieved over time. Interestingly, although certain standard network statistics were similar across simulation scenarios that differed from each other by adding dynamics networks and partner selection, significant differences did exist in terms of the resulting network topology and cooperation outcomes (see also Santos, Pacheco, & Lenaerts, 2006).

These results indicate that looking at heterogeneity only at the level of individual behavior without considering the social structure the individuals are embedded within might lead to inaccurate conclusions. Not only is it the case that the same individual behavior can have different implications for social outcomes depending on network structural properties of the system but also the network structural properties can change as a consequence of individual behavior and so give rise to complex causal relations between the micro and macro levels. It is difficult to look at these types of level interconnections without models capable of simulating this complex interplay (e.g., Edmonds, Norling, & Hales, 2009).

Although we might hope that big data might help us to better empirically link individual choices and network effects, significant progress has been made on empirically driven social network models. However, at the present stage, the social processes that are channeled within the varying and overlapping networks in which people are embedded cannot be captured in sufficient richness. For this purpose, it is critical to realize what kind of social influences plays a role in any specific case before selecting a particular network formalization. Critical questions for social simulation here concern the type and quality of empirical data on social networks, the type and quality of data about the individuals (e.g., profiles, tastes, and choices) to be used for network dynamics (formation, maintenance, and breaking up), and the evidence about the kind of dynamics and interplay between individual choices (ties creation and breaking) and network structures that could lead us to revise estimates as to the static influence of the topology of such networks on their own.

Conclusion: Prospects and Challenges

This article provided an overview of the social simulation approach in the social science, concentrating on some areas in which its contribution is clearest. Thus, it focused upon the importance of behavior and network heterogeneity and the interplay of individual choices and network structures to understand complex social systems. Next, we would like to briefly discuss a few prospects and challenges, looking at relationships between social simulation and other interesting fields, such as neurocognitive sciences and network medicine.

First, recent neuroscience and experimental cognitive science discoveries on the role of empathy and social emotions in understanding human behavior (e.g., Adolphs, 2009; Edmonds, Declerck, Boone, Vandervliet, & Parizel, 2011; Hsu, Anen, & Quartz, 2008) call for reconsideration of the theoretical, "rational," strategic foundations that inform the micro foundations of many social simulation models. These new studies could even influence the dominant cognitive science approach to social simulation (e.g., Sun, 2006), by inducing to reconsider cognitive accounts of individual behavior based on complex symbolic reasoning or economic rationality. Here, one of the most important challenges is to better understand the role of the social and institutional environment in triggering particular social emotions and exploring social network effects on cognition and behavior. Given its strongly transdisciplinary inspiration, social simulation could play a fundamental role in strengthening a more constructive alliance between all the difference disciplines concerned with understanding social behavior, for example, the neurosciences, cognitive, and behavioral science as well as the social sciences.

For example, while these studies on human behavior traditionally focus on small-scale observation, social simulation could explore large-scale, collective, and evolutionary implications of these empirically verified behaviors, so increasing the "social" aspects of these studies. In this sense, recent examples of social simulation studies that tried to test the so-called social brain hypothesis by connecting knowledge on human cognition and social networks are of great interest (e.g., Sutcliffe & Wang, 2012; Sutcliffe, Wang, & Dunbar, 2012). It may well be that such interdisciplinary ties influence those that have a tendency to study humans in isolation, as much as the neuro/psychological/cognitive approaches influencing us. Much human behavior and cognition only makes sense in its social context, and much social behavior and structures is constrained and biased from the particularities of human cognition—studying either in isolation of the other does not make much sense. Social simulations have the potential to study cognitive and social processes together and help bridge the gap between the individualist approaches and the social.

Second, the growing field of network medicine and the analysis of social networks for disease diagnosis and health problems have recently made relevant progress in understanding the complex interplay between genetics and social environment (e.g., Barabási, Gulbahce, & Loscalzo, 2011; Christakis & Fowler, 2007). By studying six available genotypes from a longitudinal study of adolescent health in the United States, Fowler, Settle, and Christakis (2011) showed that distribution of genotypes in the population depends not only on reproductive associations but also on friendship and social networks, which are largely determined by social processes. They found that genotypes are clustered in social networks so that people's friends resemble each other on a genotypic level. These results suggest that the type and feature of social networks in which people are embedded might have significant evolutionary consequences on human health by altering environmental exposures to sources of homophily and heterophily. Network medicine here is a new approach, rethinking the way we think about disease and redefining the traditional way in which diagnosis and treatments are viewed. While currently these studies are statistical studies on raw data gained from detailed surveys concerning the effects of social networks, especially at the level of topologies and structure, social simulation could play a crucial role in understanding the large-scale implications of these new discoveries and fill a gap of understanding the link between environment, network, and behavior.

While it is the fact that social simulation *formalizes* ideas about the working of social phenomena that will most strike social scientists that are new to it (e.g., Edmonds & Hales, 2005), this may not be its most important feature. They may associate it with a strong reductionist approach, often characterized by quite abstract quantitative approaches. However, social simulations are not constrained by the need for analytic mathematics and hence can be a much gentler formalization step, retaining some (but not all) of the "messiness" of what we know to occur (Edmonds, 2010). It avoids the need to ignore the variation between individuals and the particular patterns that they make in their social life for the reason that we can simply run the simulation to observe the complexity of what transpires, we do not have to solve equations to get answers (Macy & Willer, 2002). In particular, this relative expressiveness allows for social simulations to form a bridge between different areas of knowledge, giving it an integrating role (Pahl-Wostl, 2002). In the above, we have talked about how social simulation can relate the micro and macro levels of social phenomena and the relationship of social networks to both of these. It has the potential to understand better the subtle relationship between knowledge about human cognition, as being uncovered by psychology, the neurosciences and cognitive sciences. Not that human behavior can be reduced to such but that it is constrained by its propensities and limitations and, less obviously, that much of the discoveries in these fields will only make sense when put into the social context they were evolved within (Edmonds, 2013). Finally, and most importantly for social science, social simulation can help bridge the worlds of the qualitative and quantitative. Qualitative data in the form of narrative texts are an excellent source for informing the micro specification of social simulations and hence enriching overabstract conceptions (e.g., Bhawani, 2004; Taylor, 2003). Once formulated as a social simulation, it can be run and the results observed and, indeed, measured in many different ways. The simulation itself may not be easy to understand, involving a lot of behavior that only makes sense at the "microscopic" level of the agents' individual contexts, but it forms an intermediate stage in the process of abstracting, avoiding overlarge leaps of abstraction and hence facilitating the understanding of the richness of social phenomena.

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Notes

1. It is worth noting that money is a quantification of trust and so is also a psychological concept, as originally argued by certain classic sociological studies (e.g., Simmel, 1907).
2. Of course, a further step, which is the establishment of formal institutions to make punishment possible on large scale, through economies of scale, can be even more effective in this (e.g., Boyd, Gintis, & Bowles, 2010).
3. Because the experts basically share the same body of professional knowledge due to their training.
4. Of course, the reverse can be true so that forces of social conformity can lead to worse decisions than individuals might make (Ariely, 2008).

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