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FROM FACTORS TO ACTORS: Computational Sociology and Agent-Based Modeling

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■ **Abstract** Sociologists often model social processes as interactions among variables. We review an alternative approach that models social life as interactions among adaptive agents who influence one another in response to the influence they receive. These agent-based models (ABMs) show how simple and predictable local interactions can generate familiar but enigmatic global patterns, such as the diffusion of information, emergence of norms, coordination of conventions, or participation in collective action. Emergent social patterns can also appear unexpectedly and then just as dramatically transform or disappear, as happens in revolutions, market crashes, fads, and feeding frenzies. ABMs provide theoretical leverage where the global patterns of interest are more than the aggregation of individual attributes, but at the same time, the emergent pattern cannot be understood without a bottom up dynamical model of the microfoundations at the relational level. We begin with a brief historical sketch of the shift from "factors" to "actors" in computational sociology that shows how agent-based modeling differs fundamentally from earlier sociological uses of computer simulation. We then review recent contributions focused on the emergence of social structure and social order out of local interaction. Although sociology has lagged behind other social sciences in appreciating this new methodology, a distinctive sociological contribution is evident in the papers we review. First, theoretical interest focuses on dynamic social networks that shape and are shaped by agent interaction. Second, ABMs are used to perform virtual experiments that test macrosociological theories by manipulating structural factors like network topology, social stratification, or spatial mobility. We conclude our review with a series of recommendations for realizing the rich sociological potential of this approach.

INTRODUCTION: AGENT-BASED MODELS AND SELF-ORGANIZING GROUP PROCESSES

Consider a flock of geese flying in tight formation. Collectively they form the image of a giant delta-shaped bird that moves as purposively as if it were a single organism. Yet the flock has no "group mind" nor is there a "leader bird" choreographing the formation (Resnick 1997). Rather, each bird reacts to the movement

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of its immediate neighbors who in turn react to it. The result is the graceful dance-like movement of the flock whose hypnotic rhythm is clearly patterned yet also highly nonlinear.

If we tried to model the elegance of the flock at the global[1] level, the effort would be misleading because the flock is not governed by a system-wide program. Moreover, the task would be immensely difficult because of the extreme complexity of a nonlinear system. Yet the task turns out to be remarkably easy if instead we model the flock as the aggregation of local interactions. This was demonstrated by Craig Reynolds (1987) when he modeled the movement of a population of artificial "boids" based on three simple rules:

- Separation: Don't get too close to any object, including other boids.
- Alignment: Try to match the speed and direction of nearby boids.
- Cohesion: Head for the perceived center of mass of the boids in your immediate neighborhood.

Reynolds' computational method is called agent-based modeling. Had Reynolds chosen instead to write a top-down program for the global behavior of the flock, he might still be working on it. By choosing instead to model the flock from the bottom up, based on agent-level interaction, he was able to produce highly realistic flight formations using very simple rules.[2] Note that Reynolds did not model the flock, nor did he model isolated birds. He modeled their *interaction*, at the relational level.

Agent-based models (hereafter ABMs) of human social interaction are based on this same theory-building strategy. Sociologists have traditionally understood social life as a hierarchical system of institutions and norms that shape individual behavior from the top down. Interest in ABMs reflects growing interest in the possibility that human groups, like flocks of birds, may be highly complex, nonlinear, path-dependent, and self-organizing. We may be able to understand these dynamics much better by trying to model them, not at the global level but instead as emergent properties of local interaction among adaptive agents who influence one another in response to the influence they receive.

Despite growing interest in relational modeling and computational methods, sociologists have not fully appreciated the potential for ABMs as tools for theoretical research. This review of recent developments is intended to demonstrate how this technique can provide sociologists with a more rigorous method for specifying the microfoundations of global patterns at the relational level. We begin with a brief historical sketch of the shift from "factors" to "actors" in computational sociology

[1]"Global" refers to population-level dynamics that determine the macro behavior of the flock, while "local" refers to micro processes at the level of individuals interacting with neighbors.

[2]Reynold's boids were so realistic that they provided the starting point for bat swarms in the movies *Batman Returns* and *Cliffhanger*. You can see the boids in action at www.discovery.com/area/science/life/life.1.3.html

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that shows how agent-based modeling differs fundamentally from earlier sociological uses of computer simulation. We then review recent contributions focused on the emergence of social structure and social order out of local interaction.

Although sociology has lagged behind other social sciences in appreciating this new methodology, a distinctive sociological contribution is evident in the papers we review. First, theoretical interest focuses on dynamic social networks that shape and are shaped by agent interaction. Second, ABMs are used to perform virtual experiments that test macrosociological theories by manipulating structural factors such as network topology, social stratification, or spatial mobility.

HISTORICAL DEVELOPMENT OF AGENT-BASED MODELS

Computer simulation is more tractable (but less generalizable) than mathematical modeling and more rigorous (but less nuanced) than natural language (Hanneman et al. 1995). Gilbert & Troitzsch (1999) identify three periods in the development of social simulation over the past half-century: macrosimulation, microsimulation, and agent-based models. In the 1960s, the first wave of innovation used computers to simulate control and feedback processes in organizations, industries, cities, and even global populations. With roots in structural-functionalism, macrosimulation models typically consist of sets of differential equations that predict population distributions as a holistic function of other systemic factors. Applications include the flow of raw materials in a factory, inventory control in a warehouse, state legitimacy and imperialist policy, urban traffic, migration, disease transmission, demographic changes in a world system, and ecological limits to growth (Forrester 1971, Meadows et al. 1974, Hanneman et al. 1995).

Beginning in the 1970s, computer modelers introduced the use of individuals as the units of analysis but retained the earlier emphasis on empirically based macro-level forecasting. In striking contrast to the holistic approach in models of dynamical systems, as Caldwell (1997) points out, "microsimulation is a 'bottom-up' strategy for modeling the interacting behavior of decision makers (such as individuals, families and firms) within a larger system. This modeling strategy utilizes data on representative samples of decision makers, along with equations and algorithms representing behavioral processes, to simulate the evolution through time of each decision maker, and hence of the entire population of decision makers." Microsimulation models use observed population distributions to estimate parameters for models of household characteristics (e.g., marital status, number of children, labor force status, income, etc.). The models then age the population at the individual (or household) level by updating these characteristics. Microsimulation models thus resemble the earlier generation of macrosimulation models, but they model changes to each element of the population distribution rather than changes to the distribution at the population level. However, the models, do not permit individuals to directly interact or to adapt. Nor are the models designed or used for basic theoretical research. As with macrosimulation, the primary

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orientation is toward applied research, mainly forecasting macro effects of public policies that alter individual behavior.

The third wave in social simulation, agent-based modeling, coincided with the advent of the personal computer in the 1980s. Like microsimulation, these bottom-up models explored the microfoundations of global patterns. The difference is that, unlike the socially isolated actors in microanalytical simulation, the agents now interact interdependently. More precisely, ABMs impose four key assumptions:

1. *Agents are autonomous.* The system is not directly modeled as a globally integrated entity. Systemic patterns emerge from the bottom up, coordinated not by centralized authorities or institutions (although these may exist as environmental constraints) but by local interactions among autonomous decision-makers. This process is known as "self-organization" (Kaufman 1996).
2. *Agents are interdependent.* Interdependence may involve processes like persuasion, sanctioning, and imitation, in which agents influence others in response to the influence that they receive. Interdependence may also be indirect, as when agents' behaviors change some aspect of the environment, which in turn affects the behavior of other agents, such that the consequences of each agent's decisions depend in part on the choices of others.
3. *Agents follow simple rules.* Global complexity does not necessarily reflect the cognitive complexity of individuals. "Human beings," Simon contends (1998, p. 53), "viewed as behaving systems, are quite simple." We follow rules, in the form of norms, conventions, protocols, moral and social habits, and heuristics. Although the rules may be quite simple, they can produce global patterns that may not be at all obvious and are very difficult to understand (like Reynolds' "boids"). Hence, Simon continues, "the apparent complexity of our behavior is largely a reflection of the complexity of the environment." ABMs explore the simplest set of behavioral assumptions required to generate a macro pattern of explanatory interest.
4. *Agents are adaptive and backward-looking.* When interdependent agents are also adaptive, their interaction can generate a "complex adaptive system" (Holland 1995, p. 10). Agents adapt by moving, imitating, replicating, or learning, but not by calculating the most efficient action (Holland 1995, p. 43). They can adapt at two levels, the individual and the population. Individuals learn through processes like reinforcement, Bayesian updating, or the back-propagation of error in artificial neural networks. Learning alters the probability distribution of behaviors competing for attention within each individual. Populations learn through evolutionary processes of selection, imitation, and social influence. Evolution alters the frequency distribution of agent-types competing for reproduction within a population.

From Forecasts to Thought Experiments

Unlike earlier approaches to computer simulation, whose value depends largely on predictive accuracy, agent-based models are "much more concerned with

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theoretical development and explanation than with prediction" (Gilbert 1997, p. 2.1). They are used to perform highly abstract thought experiments that explore plausible mechanisms that may underlie observed patterns. As such, these models do not necessarily "... aim to provide an accurate representation of a particular empirical application. Instead, the goal of agent-based modeling is to enrich our understanding of fundamental processes that may appear in a variety of applications" (Axelrod 1997, p. 25). When simulation is used to make predictions or for training personnel (e.g., flight simulators), the assumptions need to be highly realistic, which usually means they will also be highly complicated. "But if the goal is to deepen our understanding of some fundamental process," Axelrod continues, "then simplicity of the assumptions is important and realistic representation of all the details of a particular setting is not." On the contrary, making these models more realistic inevitably adds complexity that undermines their usefulness as tools for theoretical research if we can no longer figure out how the model produces a given result.

Nevertheless, many sociologists remain highly skeptical about the validity of simulation results when computational models are used for theoretical exploration rather than empirical prediction. As noted (and lamented) by Sawyer (2001), recent survey articles on sociological simulation neglect agent-based modeling and focus primarily on the earlier equation-based methods of social forecasting—macrosimulation and microsimulation (e.g., Halpin 1999, Hanneman et al. 1995, Meeker & Leik 1997).

Equation-based models can approximate ABMs by operating on population attributes and their distribution. The difference, however, is best captured by Coleman's methodological "boat" (1990, p. 8). Holistic models represent the deck of the boat, in which one macrosocial factor influences another. Coleman advocated a more circuitous route (via the bottom of the boat), in which initial macro conditions constrain and motivate the behavior of individual actors whose interactions then aggregate as a new macrosocial outcome. This explanatory method searches for the causal mechanisms at the level of human action that underlie the association between social factors.

ABMs implement Coleman's critical realist epistemology but with an additional caveat: The macrosocial outcome is also more than the sum of its parts. This concept, known as *emergence*, was anticipated by Durkheim: "The hardness of bronze lies neither in the copper, nor the tin, nor in the lead which have been used to form it, which are all soft or malleable bodies. The hardness arises from the mixing of them" (Durkheim [1901] 1982, pp. 39–40). The principle applies as well to sociology, he continued: "[Social] facts reside in the society itself that produces them and not in its parts—namely its members."

Here Durkheim oversteps. Whereas the principles of emergence and self-organization imply that properties of the larger system are not properties of the components—and may not resemble nor be intended by any of the constituent actors—these principles also incorporate an essential insight of methodological individualism, the idea that societal patterns emerge from purposive choices and not from social facts external to individuals. Global properties are sui generis, but they also emerge from the bottom up, through local interactions. Without a model of

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the microfoundations of emergent properties, path-dependent self-organizing processes (such as informal social control) are likely to be mistaken for institutions that are globally coordinated (such as bureaucratic controls in formal organizations). In short, ABMs defy classification as either micro or macro but instead provide a theoretical bridge between levels (Saam 1999). It is thus ironic that sociological interest in ABMs has lagged behind that of the other social sciences, for sociology may be the discipline best equipped to develop a methodology that bridges Schumpeter's (1909) methodological individualism and Durkheim's rules of a nonreductionist method.

Clearly, not all problems can be usefully viewed from the bottom up. ABMs are most appropriate for studying processes that lack central coordination, including the emergence of organizations that, once established, impose order from the top down. The models focus on how simple and predictable local interactions generate familiar but highly intricate and enigmatic global patterns, such as the diffusion of information, emergence of norms, coordination of conventions, or participation in collective action. Emergent social patterns can also appear unexpectedly and then just as dramatically transform or disappear, as happens in revolutions, market crashes, fads, and feeding frenzies. ABMs provide theoretical leverage where the global patterns of interest are more than the aggregation of individual attributes, but at the same time, the emergent pattern cannot be understood without a bottom-up dynamical model.

In surveying recent applications, we found that most congregated around two problems, (*a*) the self-organization of social structure and (*b*) the emergence of social order. The two problems are highly complementary. In one case, the clustering of social ties is the explanandum and in the other it is the explanans.

1. *Emergent structure*. In these models, agents and agent-behaviors move through social and physical space in response to social influences and selection pressures. Agents may start out undifferentiated and then change location or behavior so as to avoid becoming different or isolated (or in some cases, overcrowded). Rather than producing homogeneity, however, these conformist decisions may aggregate to produce global patterns of cultural differentiation, stratification, and homophilous clustering in social networks. Other studies reverse the process, starting with a heterogeneous population and ending in convergence: the coordination, diffusion, and sudden collapse of norms, institutions, beliefs, innovations, standards, etc.
2. *Emergent social order*. These studies show how egoistic adaptation can lead to successful collective action without either altruism or global (top-down) imposition of control. A key finding across numerous studies is that the viability of trust, cooperation, and collective action depends decisively on the social embeddedness of interaction.

Despite a common focus on two central problems, there has been little effort to provide a meta-analysis of how results differ depending on the model designs. To

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that end, we have grouped studies by substantive application in order to highlight methodological differences that may explain conflicting results. These differences emerge through a series of interrogations about model design:

1. Is interaction global or local, that is, is the population fully connected or is interaction constrained by the structure of social ties?
2. If interaction is local, are the constraints on tie formation spatial or social?
3. Are ties elective (formed and broken through movement, exit, or assortative mating) or is interaction forced?
4. Is adaptation based on learning (which modifies the probability distribution of behaviors in each agent's repertoire) or evolution (which modifies the frequency distribution of behaviors across the population of agents)?
5. If evolution, does reproduction involve competition for survival or social influence?
6. If influence, is this limited to external states of the agent (e.g., behavior) or do agents copy other agents' internal programming, even though this cannot be directly observed?
7. Is influence based on attainment (success, fitness, payoffs, status) or familiarity (proximity, frequency)?
8. Is the model used as an experiment (parameters are manipulated to test for predicted differences) or a demonstration (parameters are manipulated to test for predicted robustness)?
9. If used experimentally, are the manipulations mainly of agent-level parameters (to test a micro theory about the global implications of behavioral assumptions) or system-level parameters (to test a macro theory about the dynamical implications of environmental assumptions)?

Table 1 classifies representative papers we review in a typology based on answers to these nine questions. The articles we included are not intended to be exhaustive. The field of social simulation is now too large to survey in a single article. We have therefore narrowed the focus to ABMs of emergent structure (differentiation and diffusion) and emergent order (cooperation and collective action), written by sociologists or published in sociological journals[3] in the past five years.[4]

[3]Reviewed articles were published in *American Sociological Review* (5), *Computational and Mathematical Organization Theory* (5), *Journal of Artificial Societies and Social Simulation* (5), *American Journal of Sociology* (3), *Rationality and Society* (2), *Sociological Methods and Research* (1) and *Behavioral Science* (1).

[4]For an *Annual Review* of related papers published before 1996, see Bainbridge et al. (1994). For a recent review of agent-based modeling in political science, see Cederman (2001) and Johnson (1999).

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TABLE 1 Typology of representative agent-based models

Article	Substantive problem	Network[a]	Elective ties[b]	Number agents	Adaptive mechanism[c]	Adaptive criteria	Manipulation[d]
Lomi & Larsen 1998	Differentiation	Spatial	N	10000	Reproduction	Density	Macro
Mark 1998	Differentiation	Social	Y	6–100	Imitation	Familiarity	Both
Axelrod 1997	Differentiation	Spatial	Y	10^2–10^4	Imitation	Familiarity	Macro
Orbell et al. 1996	Differentiation	Social	Y	1000	Learning	Proximity	Macro
Bullnheimer et al. 1998	Diffusion	Global	N	10	Social Learning	Success	Micro
Rosenkopf & Abrahamson '99	Diffusion	Global	N	20	Imitation	Density	Macro
Strang & Macy 2001	Diffusion	Global	N	100	Social Learning	Success	Both
Eshel et al. 2000	Social Order	Spatial	N	1000	Imitation	Success	Both
Flache & Hegselmann 1999	Social Order	Spatial	Y	315	Learning	Success	Micro
Chwe 1999	Social Order	Spatial	N	30	Imitation	Density	Macro
Castelfranchi et al. 1998							
Saam & Harrer 1999	Social Order	Spatial	Y	50	Reproduction	Success	Macro
Cohen et al. 2001	Social Order	Spatial	Y	256	Imitation	Success	Macro
Takahashi 2000	Social Order	Gl & Sp	N	20–100	Reproduction	Success	Macro
Smith & Stevens 1999	Social Order	Global	N	4	Learning	Success	Both
Kim & Bearman 1997	Social Order	Social	N	100	Imitation	Success	Macro
De Vos et al. 2001	Social Order	Social	Y	10–50	Reproduction	Success	Macro
Macy & Skvoretz 1998	Social Order	Social	Y	1000	Reproduction	Success	Macro

[a]Spatial: restricted by physical distance; social: restricted by social distance; global: not restricted by distance.

[b]Is interaction forced or voluntary, based on an option to move, exit a relationship, or assortative mating?

[c]Reproduction: Successful agents replace or convert unsuccessful ones; imitation: agents copy observed behavior (but not the underlying rule); learning: agents change behavior based on direct experience; social learning: direct and vicarious experience.

[d]Macro: manipulation of global parameter; micro: manipulation of agent parameter.

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EMERGENT STRUCTURE: MODELS OF CONVERGENCE AND DIFFERENTIATION

In models of structural differentiation, interest centers on the self-organization of the population into locally dense networks (or clusters) based on simple rules of local interaction. Applications include residential segregation, density-dependent organizational survival, group formation, and cultural differentiation.

These models often study clustering within spatial networks, using cellular automata (CA), a technique first proposed by Stanislaw Ulam (Coveney & Highfield 1995, pp. 94–96). Hegselmann & Flache (1998) provide a lucid introduction to and history of CA in the social sciences. The agents usually live on a checkerboard (either flat or a donut-like torus), and the state of each agent depends on the states of its neighbors. Simple rules of local influence or spatial movement sometimes generate surprising results and lead to unexpected insights. They illustrate a key advantage of the CA approach: two-dimensional visual representation of diffusion and clustering across a spatial network.

Schelling's (1971) model of neighborhood segregation is one of the earliest and best known ABMs based on movement in a spatial network. Red and green agents are randomly distributed on a lattice and move to empty locations if the number of in-group neighbors falls below a certain threshold. The model shows how extreme segregation tends to arise even in a population that prefers diversity, as agents relocate to avoid being in the minority.

One criticism of many spatial networks is that they preclude both structural equivalence (no two nodes can have identical sets of interactants) and relational heterogeneity (every node has an isomorphic relational pattern). Flache & Hegselmann (2001) relaxed the latter constraint by using irregular grids that allow the number and strength of social ties to vary randomly over the population. However, the model still permits the population to self-organize into clusters through spatial movement. Although they find that key results are robust over variation in relational heterogeneity, irregular grids also yield new implications that could not be identified with the conventional rectangular structures.

Other CA models generate spatial dynamics through ecological[5] competition for survival rather than movement. The classic in this genre is Conway's "Game of Life" in which the survival of each agent depends on the density of its neighborhood.[6] Although Conway was not a sociologist, his design has immediate application to problems in organizational ecology, in which the agents are

[5]Ecological models are those in which the spatial or frequency distribution of agents depends on rules that govern survival and reproduction. These models are often characterized as "evolutionary," but strictly speaking, the latter requires the possibility for entirely new types of agents to appear that were not present at the outset.

[6]Like Schelling's, Conway's model was originally created without a computer, using a game board. The model is now implemented in Java and interested readers can experiment online at www.math.com/students/wonders/life/life.html. However, these simple CA models are not agent based as defined above.

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supra-individual. For example, Lomi & Larsen (1998) study the interaction between network structure and the lagged effects of population density on organizational survival. They use a cellular network in which the survival of each cell depends on the number of occupied cells in its Moore neighborhood (the eight adjacent cells). The model is very simple: Agents live, replicate, and die, based on local density. Lomi & Larsen then explore the implications for organizational survival of alternative hypotheses about the effects of density delay based on simple rules that regulate the appearance, survival, and demise of individual organizations. Using event history analysis, they identify structural features that can generate organizational life histories that are qualitatively consistent with those observed in empirical organizational populations.

Some models incorporate both spatial movement and ecological competition. In Epstein & Axtell's (1996) "Sugarscape," a spatially distributed population of simple rule-based agents develops a culture, an economy, and a class structure. Agents move around on a grid and exchange with others to gain access to valued resources on which their survival and reproduction depend.

Social Influence and the Paradox of Mimetic Divergence

The ecological assumption that adaptation occurs through a struggle for survival is appropriate if the agents are organizations competing for resources or members. If the agents are individuals in a modern welfare state, however, a more broadly applicable assumption is that adaptation occurs through imitation of the fittest. Agents are not replaced by better performers; they simply copy their observed behavior. This in turn relaxes the assumption that selection pressures are performance driven. Although some influence models continue to posit selection of role models based on relative success, others assume that influence is density dependent, based on familiarity, popularity, or spatial proximity. For example, Latané's (1996) Social Impact Model uses a rule to mimic one's neighbors in a two-dimensional lattice. From a random start, a population of mimics might be expected to converge inexorably on a single profile, leading to the conclusion that cultural diversity is imposed by factors that counteract the effects of conformist tendencies. However, the surprising result was that "the system achieved stable diversity. The minority was able to survive, contrary to the belief that social influence inexorably leads to uniformity" (Latané 1996, p. 294).

Following an earlier study by Carley (1991), Axelrod (1997; see also Axtell et al. 1996) makes the paradox of mimetic divergence even more compelling. Carley's and Axelrod's models couple local influence (the tendency for people who interact frequently to become more similar over time) and homophily (the tendency to interact more frequently with similar agents). This closes the loop—the more agents interact, the more similar they become, and the more similar they become, the more likely they are to interact. More precisely, neighboring agents on a two-dimensional lattice interact with a likelihood determined by the similarity of their cultural traits (given by a simple, randomly assigned string of numbers). Interaction, in turn, reduces remaining differences. Axelrod expected this self-reinforcing

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dynamic would lead inexorably to cultural convergence and homogeneity. Again the result was surprising. He found that "local convergence can lead to global polarization" and that unique subcultures can survive in the face of a seemingly relentless march toward cultural conformity. Stable minority subcultures persist because of the protection of structural holes created by cultural differences that preclude interaction, thereby insulating agents from homogenizing tendencies.

Axelrod's model also reveals a surprising effect of population size. Intuitively, one might expect larger numbers of stable subcultures to emerge in larger populations. However, Axelrod found a nonlinear effect, in which the number of minority cultures first increases with population size but then decreases. This counter-intuitive result illustrates the principle of "gambler's ruin." Large populations allow for larger cultural movements that can survive random fluctuations in membership better than smaller competitors. As the big get bigger, the number of minority subcultures diminishes.

Axelrod begins with a heterogeneous population and shows that heterogeneity persists. But how does the initial heterogeneity arise? Axelrod also assumes spatial networks that restrict interaction to nearby neighbors. Will differentiation persist if the spatial restriction is removed and interaction is based only on similarity?

Mark (1998) addresses these questions in a paper that explains social differentiation "from first principles," starting from homogeneity and without spatial constraints on interaction. Agents can interact with anyone in the population (not just neighbors), with a probability determined by cultural similarity. Starting from perfect cultural homogeneity, interactions are initially random, but not for long. Mark finds that a self-reinforcing dynamic based on homophily and creation of new bits of culture, is sufficient to create an emergent network with local patterns of interaction among distinctive subcultures. Contrary to Axelrod, Mark also finds that population size decreases cultural homogeneity, due to the absence of spatial restrictions on interaction in the model.

One limitation in most social influence models is the assumption that influence is only positive. However, social relations can also have negative valence, such that the state of an agent tends toward maximal distinctiveness rather than similarity. Contrary to theories of homophily, dissimilarity does not always weaken the social tie; rather, it may sometimes strengthen the negative relation (or enmity). Structural differentiation based on positive and negative influence has been studied using attractor neural networks, a cognitive modeling technique developed by Hopfield (1982) and applied to social influence by Nowak & Vallacher (1998; see also Kitts, et al. 1999).

Artificial neural networks are a simple type of self-programmable learning device based on parallel distributed processing (Rummelhart & McClelland 1988) and modeled after the nerve systems of living organisms. In elementary form, the device consists of a web of neuron-like units (or neurodes) that fire when triggered by impulses of sufficient strength, and in turn stimulate or inhibit other units when fired. The effect of an impulse (as stimulus or inhibitor) depends on the sign and strength of the synaptic connection between two neurodes. The network learns by modifying these path coefficients. In feed-forward networks, learning is

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based on environmental feedback that propagates backward through the network. In attractor networks, the path coefficients are updated based on the similarity between the states of adjacent connected nodes. While feed-forward networks can be used to model agent cognition, attractor networks provide a dynamic alternative to static network models of social interaction.

Feed-forward devices have been used to model cognitive social differentiation, based on self-affirming stereotypes. Vakas-Duong & Reilley (1995; see also Bainbridge 1995) study the emergence of irrational racial hiring preferences that are less profitable than purely meritocratic selection. In their model, employers learn to make intuitive hiring decisions based on what connotations come to be associated with the traits exhibited by job applicants, while applicants associate traits with relative success. The simulation results showed how false beliefs can easily become self-sustaining following an early accident of association that sows the seeds of racial preference in an employer's mind. This in turn makes it difficult for talented members of the same race to gain employment and diminishes that race's access to emerging status symbols.

Other cognitive models of social differentiation focus on the self-reinforcing dynamics created by stereotypical beliefs that change the behaviors on which the beliefs are based. Orbell et al. (1996) model self-organizing stereotypes in a population of 1000 adaptive agents playing Prisoner's Dilemma games with an option to exit. Prisoner's Dilemma is a two-person game in which the best move is to defect (e.g., cheat), no matter what the partner is expected to do, but when each defects, the outcome is deficient for both. However, the authors' interest is focused not on the problem of cooperation but the formation of groups and group stereotypes. Agents are assigned a tag that indicates their membership in one of two groups. Agents update their tag-specific expectations of cooperative behavior based on the outcomes of interactions. Agents also become more likely to cooperate with members of groups they expect to cooperate. They find that agents from both groups converge on an increasingly strong preference for interaction with members of an initially preferred group (when groups are of equal size) or a larger group (when initial preferences are equal). The mechanism is straightforward: If you interact with one group more than the other (due either to differences in initial expectations or group size), you update your expectations for this group more than for the other. Since both groups are relatively cooperative, the updating always causes expectations of cooperation to increase, leading to more cooperative treatment, which induces the expected cooperative behavior, thereby affirming the expectation on which the preferential interaction is based.

Diffusion of Innovation

The models considered so far explore emergent networks based on structural differentiation. However, social influence models can also be used to study self-reinforcing dynamics that lead to convergence. Applications include the spread of innovations, coordination of conventions, emergent norms, and cultural diffusion.

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These models start with some distribution of practices and a rule by which agents decide whether to abandon current practice in favor of one used by another agent. Rosenkopf & Abrahamson (1999) studied diffusion where influence derives from popularity, without regard to prior interaction history or relative success. This creates a "positive feedback loop where adoptions by some actors increase the pressure to adopt for other actors" (Rosenkopf & Abrahamson 1999, p. 361). However, influence was weighted by reputations (which were exogenous to the model) and combined with information about the unprofitability of innovations. The network was fully connected, that is, each agent had access to the decisions and reputations of all other agents in the population. They found that "bandwagons occur even when potential adopters receive information about others' unprofitable experiences with the innovation" (1999, p. 361). Their model shows how agents can converge on inefficient practices but not how conformity collapses.

Bullnheimer et al. (1998) studied the diffusion of innovation among firms based on the assumption that managers evaluate the relative performance of alternative technologies based on their own experience with a technology as well as with the performance of others. They assume that firms have knowledge of the adoptions and performance of all other firms. They found that firms who combine imitation with their own experience outperform "both pure imitators and nonimitators in production efficiency as well as in profits" (1998, p. 267). Like Rosenkopf & Abrahamson, they explain stable homogeneity but not how conformity might then collapse.

In contrast, Strang & Macy (2001) generate the punctuated cascades associated with fad-like behavior. Their diffusion model bridges these earlier studies by showing how a decision rule similar to those Bullnheimer et al. found to be highly efficient can nevertheless trap firms in a bandwagon of adoption and abandonment of innovations that are worthless or nearly so. They assume firms evaluate current practice based on their balance sheets, and if dissatisfied, turn to "best practices" for new ideas. In a series of computational experiments, they manipulate the intrinsic value of innovations, the stratification of the market, and the skepticism of managers to see how these affect the fad-like pattern. Results show that fads are most likely in stratified markets where innovations have a modest effect on performance and managers are not so skeptical that they cannot see the performance differences.

EMERGENT ORDER: MODELS OF COLLECTIVE ACTION, TRUST, AND COOPERATION

In models of structural differentiation, agents influence others in response to the influence they receive, leading to spatial or social clustering, such as Reynold's flocks of "boids." Interest centers on the self-organization of dynamic structural configurations, and not on their consequences. Models of emergent order, in contrast, focus attention on the ways in which network structures affect the viability of

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prosocial behavior. Four network properties have been shown to promote/inhibit cooperation and participation in collective action:

- *Relational stability*: On-going relationships lengthen the "shadow of the future" (Axelrod 1984).
- *Network density*: The coordination complexity of cooperation increases with the number of social ties (Macy & Skvoretz 1998).
- *Homophily*: Agents tend to interact with partners who use similar strategies (Cohen et al. 2001).
- *Transitivity*: An agent's partners tend to interact with each other. This in turn affects:
  - Diffusion of reputations (Takahashi 2000).
  - Bandwagons caused by threshold effects (Chwe 1999).
  - Monitoring and enforcement of conformity to prosocial norms (Kim & Bearman 1997).

Relational Stability

The classic study of emergent order is Axelrod's (1984) *Evolution of Cooperation.* Although defection is the dominant strategy in a single play of Prisoner's Dilemma, that is not true when the game is played repeatedly in an ongoing relationship. However, this does not guarantee cooperation. In fact, there is no dominant strategy in endlessly repeated play, and game theory cannot predict whether cooperation is likely to evolve. To find out, Axelrod organized a computer tournament in which agents played a round robin iterated Prisoner's Dilemma. He invited leading game theorists to submit strategies, and each submission was assigned to one of the agents. The winner was the simplest contestant, Anatol Rapaport's Tit for Tat, a strategy that always cooperates unless provoked, and then always retaliates, but only once and then forgives.

Variations on Tit for Tat use less-strict accounting. De Vos et al. (2001) compare the evolutionary viability of two types of reciprocity, based on strict vs. loose accounting. Payoffs determine whether an agent survives, and strategies reproduce in proportion to the survival rate. Agents ask for help when it is needed and decide to whom to give it (if anyone), based on past exchanges. Some agents insist on keeping the books strictly balanced, while others favor commitment to old partners, even if they are in arrears. In a population that includes nongivers, simulations demonstrate the importance of committing oneself to an ongoing relationship. Ironically, the results suggest that a looser commitment strategy, based on long-term balancing of the books, is superior to a strategy of strict reciprocity that is less vulnerable to being cheated, a result similar to that reported by Kollock (1993) based on a similar ecological competition. However, Kollock's agents were paired randomly, without the option to select their partners. He also found that loose accounting is superior, but only if the environment is noisy (with occasional mistakes

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and misinformation). Strict reciprocity is then prone to needless recrimination that can be avoided by looser accounting systems.

One problem with this modeling strategy is that the outcome of an evolutionary tournament may be an artifact of a theoretically arbitrary set of initial contestants. This led Axelrod to use a genetic algorithm (GA) to see if Tit for Tat would evolve in an open-ended population in which strategies could evolve from a random start (1997, pp. 14–29). Working with John Holland, Axelrod found several strategies similar to Tit for Tat that proved to be highly robust.

GAs are strings of computer code that can mate with other strings to produce entirely new and superior programs by building on partial solutions. Each strategy in a population consists of a string of symbols that code behavioral instructions. These symbols are often binary digits (or bits) with values of 0 or 1. A string of symbols is analogous to a chromosome containing multiple genes. A set of one or more bits that contains a specific instruction is analogous to a single gene. The values of the bits and bit combinations are analogous to the alleles of the gene. A gene's instructions, when followed, produce an outcome (or payoff) that affects the agent's reproductive fitness relative to other players in the computational ecology. Relative fitness determines the probability that each strategy will propagate. Propagation occurs when two mated strategies recombine. If two different rules are both effective, but in different ways, recombination allows them to create an entirely new strategy that may integrate the best abilities of each "parent," making the new strategy superior to either contributor. If so, then the new rule may go on to eventually displace both parent rules in the population of strategies. In addition, the new strings may contain random copying errors. These mutations restore the heterogeneity of the population, counteracting selection pressures that tend to reduce it.

The GA can be used to discover both optimal and likely solutions. Where the aim is to discover what agents should do to optimize performance, the models typically assume global search. This means every agent has complete knowledge of the strategies and fitness of every member of the population and plays against every member of the population with equal probability. Where the aim is to find what agents are likely to do, models often assume local rather than global interaction and knowledge (Klos 1999). Local search can be implemented by embedding the GA in a spatial or social network.

Network Density

Macy & Skvoretz (1998) embed the GA in a social network to investigate Weber's theory that Protestant sects in colonial America provided cultural markers needed for trusting strangers in physically dispersed markets. The problem in Weber's argument is that the need for economic growth does not guarantee the evolution of the means for its realization. Macy & Skvoretz's simulations show that a system of telltale signs is highly fragile, even with unrealistically generous assumptions about cultural diffusion. However, the robustness can be greatly improved when

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exchanges are embedded in social structures comprised of a large number of small communities, precisely the conditions that Weber identified in colonial America.

Homophily

Smith & Stevens (1999) model the formation of psychological support networks in which agents seek out relationships with others that will help them manage anxiety. In their model, agents decide with whom to form relationships through a process of assortative mating. They find that agents form relationships with partners who are similar to themselves in their ability to manage stress, creating homophilous clusters. In needy populations, support networks form with stronger attachments but lower transitivity than in populations with less need for social support.

Several other recent studies also suggest that the viability of cooperation is greatly improved when populations can self-organize into locally homogeneous clusters (Lomborg 1996). For example, Pedone & Parisi (1997) use socially embedded artificial neural networks to show how altruistic behavior can arise among similar agents, and they conclude that similarity conveyed by culture may be what allows altruism to evolve in natural settings.

Other studies explore the effects of homophilous clustering in spatial networks. Eshel et al. (2000) use spatial clustering on a one-dimensional array where agents play Prisoner's Dilemma. Their agents have only two possible strategies—cooperate or defect. Agents interact strategically with nearest neighbors and imitate those (in a somewhat larger neighborhood) who are most successful. Because they cannot reciprocate, there is no advantage to cooperating even in an ongoing relationship. Nevertheless, when the game is spatially embedded, they find that cooperation is "a stable strategy that cannot easily be eliminated from the population" (2000, p. 341).

Flache & Hegselmann (1999) explore the macro implications of alternative assumptions about agent cognition in a social support game played on a torus. Rational agents make the choices prescribed by analytical game theory, while adaptive agents respond to experience through reinforcement learning. In each case, agents migrate on the grid, selecting neighbors from whom to request help and deciding whether to service the requests of others in an asymmetric Prisoner's Dilemma, where payoff asymmetry reflects difference among agents in the need for and ability to help. The forward-looking model makes strong assumptions about information: Each agent knows all players' locations, their payoffs, and their level of need. Flache & Hegselmann find that both forward- and backward-looking agents self-organize into mutually supportive relationships with those in similar class positions. However, the stratification structure differs under most conditions. Rational egoists tend to form an "onion-shaped structure of solidarity" (1999, p. 110), with the wealthiest at the center of a large heterogeneous cluster, surrounded by rings of increasingly needy agents. In contrast, backward-looking agents migrate into distinct homogeneous clusters with much greater class segregation than found among rational egoists.

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In sum, numerous studies converge on the conclusion that prosocial strategies thrive on both spatial and social embeddedness, due to the tendency to interact with similar strategies while avoiding contact with predators. However, Cohen et al. (2001) point out that what appears to be the effect of homophily may actually be due to the effects of relational stability and transitivity. Transitivity (or clustering) means that "paired agents have neighbors who are themselves paired" (Cohen et al. 2001, p. 11). For example, in a Moore neighborhood, each of an agent's eight neighbors interacts with two of the other seven. Relational stability (which they call "context preservation") means that agents continue to interact with the same partners across many periods, creating a "shadow of the adaptive future" (2001, p. 13). The smaller the neighborhood, the greater the chance of interacting with a previous partner. In short, the effect of embeddedness may not be due to the tendency for local interactions to be with partners who are similar, as most studies have assumed, but the tendency for partners to be correlated (due to network transitivity) or familiar (due to local pairing).

The authors tease apart these effects by manipulating network structure in a population of 256 agents who play a four-iteration Prisoner's Dilemma game with each of four different partners in each period, for 2500 periods. Agents are programmed with three (initially random) probabilities for cooperating under three conditions: the first move of the game, after the partner cooperates, and after the partner defects. Between periods, agents adopt the strategy used by the most successful of their four partners, based on the payoffs accumulated during that period. In this model, many different strategies can produce identical behavior under given conditions, and the authors do not explain how agents know which of these was actually responsible for the behavior they observe, but somehow the agents guess correctly about 90% of the time.

Using controlled computational experiments, the authors observe the independent effects of homophily, ongoing relations, and transitivity. They find that ongoing relations greatly improve the viability of cooperation, whereas transitivity alone has little effect. However, the effect of relational continuity is not due to the prudence of being nice to those one expects to meet again. Because agents imitate their partners, ongoing relations increase the chances that an agent will interact with a partner using a similar (if not identical) strategy. They conclude that friendly strategies do well so long as they can generally avoid those that are not.

Diffusion of Reputations

Takahashi (2000) uses an evolutionary model to study the emergence of generalized exchange, in which agents give and receive help but not to one another directly (see also Nowak & Sigmund 1998). Takahashi challenges previous studies that assumed that these exchange systems require either altruism or centralized enforcement of the rules of exchange. He then uses an evolutionary model to show that exchange systems can self-organize based on norms of generalized reciprocity (giving selectively to those who give to third parties). He programs agents with two

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genes that control compliance with norms of generalized exchange and enforcement of compliance by others. The first gene controls the amount the agent gives to others, and the second gene controls reciprocity, based on the recipient's reputation for giving to others. Giving and receiving determines each agent's relative fitness or chances for reproduction. Reproduction copies the agent's genes with a small probability of mutation. However, with only two genes, there is no need for recombination, so Takahashi does not use a genetic algorithm. Simulations show that a system of generalized exchange can evolve in a population that is initially nongenerous, assuming agents have perfect information about the past behavior of other agents. Takahashi then relaxes this assumption by positioning agents on a two-dimensional grid, restricting their knowledge, interaction, and reproductive competition to their Moore neighborhood. Thus, agents continue to have perfect information about all their potential exchange partners, of whom there are now only 8 (instead of 19). Generalized exchange emerges within each of the overlapping neighborhoods, but Takahashi did not test to see if generalized exchange could evolve between members of different neighborhoods when reputational knowledge remains local.

Castelfranchi et al. (1998; see also Conte & Castelfranchi 1995) examine the effect of reputations on deterrence of aggressive behavior on a two-dimensional grid where agents compete locally for scarce resources and adaptation operates through evolutionary selection. They find that a prosocial strategy can thrive in a homogeneous population but suffers as contact with aggressors is increased. However, the aggressor's advantage is diminished if agents can exchange information on the reputations of others. Saam & Harrer (1999) used the same model to explore the interaction between normative control and power. They find that systems of informal social control can tip toward either greater equality or inequality, depending on the extent of inequality at the outset.

Bandwagons

Network transitivity becomes much more important when outcomes depend on the flow of information through the network. Chwe (1999) proposes a threshold model of collective action in which agents choose to participate depending on the number of neighbors expected to participate. Expectations of neighbors' behavior depend in turn on expectations of neighbors' neighbors' behavior, and so on. In the base condition, 30 agents are randomly assigned two partners with whom they remain attached for the duration of the simulation. Chwe then manipulates transitivity by increasing the number of partners and the bias toward selecting the partners of one's partners. High transitivity avoids an endless regress because an agent's neighbors and the neighbors' neighbors are likely to be the same people. Transitivity is especially important in populations with low thresholds that can be triggered by local knowledge about the behavior of members of densely tied but relatively small local clusters. This may explain the importance of overlapping social ties for Freedom Summer participation reported by McAdam (1988). Conversely, Chwe demonstrates the strength of weak ties in populations with high thresholds. Low transitivity facilitates the diffusion of information about participation of distant

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agents. The optimal configuration may be a small worlds network (Watts 1999), with a few ties between many small and densely tied clusters.

Social Pressure

Chwe's thresholds correspond to agents' concerns about the efficacy of participation in collective action (see also Marwell & Oliver 1993, Macy 1991). Thresholds can also represent agents' responsiveness to social pressures to conform to an emergent norm, as in bandwagon models of self-reinforcing popularity. Kim & Bearman (1997) model collective action among agents whose interest in the public good is heavily influenced by social pressure from other participants in their local network. This causes interest in the collective action to spread like a contagion through network channels. The authors find that participation spreads most effectively within densely clustered subnetworks comprising a critical mass of highly interested primary contributors.

Kim & Bearman's study reflects the conventional wisdom that social pressure to participate is needed to overcome the temptation to free ride. It follows that dependence on the group for social direction promotes compliance with group obligations, as argued by Homans (1974). Yet a number of ethnographic studies of deviant cliques have shown that conformist pressures can also undermine normative compliance, leading to badly suboptimal outcomes for all group members, including the deviants (Willis 1977, Shibutani 1978, MacLeod 1995). This led Flache & Macy (1996) to investigate the possibility that dependence on peer approval can backfire, leading to collective action failure rather than success. Kitts et al. (1999) extended this study by modeling self-organizing social relations using an attractor neural network similar to Nowak & Vallacher's (1998). In these models of dynamic networks, social influence increases with the strength of the connecting tie, and ties strengthen with the similarity of connected agents. They added the innovation that agents respond not only to social influence but also to the lessons of direct experience (similar to the back-propagation in feed-forward neural nets). Agents in a team-rewarded task group decided whether to work or shirk and whether to approve of other group members. The authors then manipulated agents' susceptibility to influence. Computer simulations revealed a surprising result—a curvilinear effect of social influence on compliance with prosocial norms. Moderate doses of influence reduce the coordination complexity of self-organized collective action and help the network achieve satisfactory levels of cooperation. High doses, however, undermine the agent-based learning required to find coöperative solutions. Increasing group size also diminished compliance due to increased complexity, with larger groups requiring more influence to overcome the coordination problem.

CONCLUSION

Agent-based modeling is a new tool for theoretical research at the relational level, with particular relevance for sociologists as a bridge between the micro and macro levels. Nevertheless, sociology has lagged behind the other social sciences in

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recognizing and exploiting this methodology. Computational sociology has traditionally used simulation to forecast social trajectories based on statistical associations, using models that are highly realistic, empirically grounded, and holistic. In contrast, agent-based models use simulation to search for causal mechanisms that may underlie statistical associations, using models that are highly abstract and microsocial. This has led to confusion about the appropriate standards for constructing and evaluating agent-based models. We conclude our review with a series of recommendations for realizing the rich sociological potential of this approach.

1. *Start it simple.* Analysis of very simple and unrealistic models can reveal new theoretical ideas that have broad applicability, beyond the stylized models that produced them. Pressure to make models more realistic (and agents more cognitively sophisticated) is misguided if models become so complex that they are as difficult to interpret as natural phenomena. When researchers must resort to higher order statistical methods to tease apart the underlying causal processes, the value of simulation is largely undermined. Models should start out simple and complications should be added one at a time, making sure that the dynamics are fully understood before proceeding.
2. *Avoid reliance on biological metaphors.* Chattoe (1998) has raised probing questions about modeling cultural evolution as a genetic analog. What is the mechanism that eliminates poor performers from the population and allows others to propagate? Imitation of the fittest may be more applicable than starvation and reproduction, but unlike survival of the fittest, mimetic selection replicates only observed behavior and does not copy the underlying (unobservable) rules. Biological metaphors paper over the importance of this distinction. For example, in repeated Prisoner's Dilemma games, it is plausible that an agent observes and then copies the cooperative behavior of successful neighbors, but how does the agent know that this behavior is based on a rule (or supergame strategy) like Tit for Tat and not Win-Stay, Lose-Shift or Always Cooperate that generate identical behavior with cooperative partners?
3. *Experiment, don't just explore.* Agent-based modeling is an experimental tool for theoretical research. While important discoveries can be made by open-ended exploration of theoretical possibilities, researchers need to resist the temptation to become freewheeling adventurers in artificial worlds. Careful, systematic mapping of a parameter space may be less engaging, but it makes for better science. This requires theoretically motivated manipulation of parameters, based on careful review of current theoretical and empirical knowledge, and a clear statement of the hypotheses that guided the experimental design.
4. *Test robustness.* Although simulation designs should use experimental rather than post-hoc statistical controls to identify underlying causal processes, that

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does not mean researchers should avoid statistical analysis of the results. On the contrary, ABMs, especially those that include stochastic algorithms, require replications that demonstrate the stability of the results. Where possible, replications should include variation in parameters that are theoretically arbitrary or of secondary interest. Authors then need to be careful to distinguish between experimental manipulations (where results are expected to change with the parameters) and robustness tests (where they are not).

5. *Test external validity*. Virtual experiments test the internal validity of a theory, without which there is no need to test the external validity. However, this does not mean there is *never* such a need. ABMs are often used to grow familiar macrosocial patterns, as a way to identify possible causal mechanisms (Epstein & Axtell 1996). When this succeeds, researchers need to think about ways these mechanisms can be operationalized and tested in laboratory or natural conditions.
6. *Test domain validity*. Do two different models of the same phenomenon produce the same results? If they do not, find out why. Identify the assumptions that are the logical source of divergent implications by carefully aligning the models. "Without such a process of close comparison, computational modeling will never provide the clear sense of 'domain of validity' that typically can be obtained for mathematized theories" (Axtell et al. 1996, p. 123).
7. *Bring factors back in*. The bottom-up approach in ABMs might seem to imply that these models can only be used to test microsociological theories. That is a tragic misunderstanding because it precludes what is most exciting to sociologists about this methodology. An artificial world populated by computational agents is a laboratory in which researchers can manipulate structural conditions to test macrosociological theories without reifying causal factors at the macro level. Contrary to the holistic epistemology of an earlier generation of equation-based simulations, changes in population density or network structure, for example, do not directly lead to the diffusion of innovations. The causal process is effected through individual choices. Computational experiments in virtual worlds provide a rigorous methodology for studying the microfoundations of macro dynamics. However, the shift from factors to actors should not limit experimenters to manipulation of agent attributes (such as cognitive or behavioral assumptions). Bringing factors back in as experimental manipulations will realize the full potential of agent-based modeling, especially in sociology.

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LITERATURE CITED

Axelrod R. 1984. *The Evolution of Cooperation*. New York: Basic

Axelrod R. 1997. *The Complexity of Cooperation*. Princeton, NJ: Princeton Univ. Press

Axtell R, Axelrod R, Epstein JM, Cohen MD. 1996. Aligning simulation models: a case study and results. *Comput. Math. Organ. Theory*. 1(2):123–41

Bainbridge WS. 1995. Neural network models of religious belief. *Sociol. Perspect.* 38(4): 483–96

Bainbridge WS, Brent E, Carley K, Heise D, Macy M, et al. 1994. Artificial social intelligence. *Annu. Rev. Sociol.* 20:407–36

Bullnheimer B, Dawid H, Zeller R. 1998. Learning from own and foreign experience: technological adaptation by imitating firms. *Comput. Math. Organ. Theory* 4(3):267–82

Caldwell SB. 1997. *Dynamic Microsimulation and the Corsim 3.0 Model*. Ithaca, NY: Strategic Forecasting

Carley K. 1991. A theory of group stability. *Am. Sociol. Rev.* 56:331–54

Cartwright D, Harary F. 1956. Structural balance: a generalization of Heider's theory. *Psychol. Rev.* 63:277–93

Castelfranchi C, Conte R, Paolucci M. 1998. Normative reputation and the costs of compliance. *J. Artificial Soc. Soc. Simulat.* 1(3): 3.1–3.19

Cederman L-E. 2001. Agent-based modeling in the political science. *Polit. Methodol.* 10(1): xxx–xx

Chattoe E. 1998. Just how (un)realistic are evolutionary algorithms as representations of social processes? *J. Artificial Soc. Soc. Simulat.* 1(3):2.1–2.36

Chwe MS-Y. 1999. Structure and strategy in collective action. *Am. J. Sociol.* 105(1):128–56

Cohen MD, Riolo RL, Axelrod R. 2001. The role of social structure in the maintenance of cooperative regimes. *Rationality Soc.* 13(1): 5–32

Coleman JS. 1990. *Foundations of Social Theory*. Cambridge, MA: Harvard Univ. Press

Conte R, Castelfranchi C. 1995. Understanding the effects of norms in social groups through simulation. In *Artificial Societies: The Computer Simulation of Social Life*, ed. N Gilbert, R Conte, pp. 252–67. London: UCL Press

Coveney P, Highfield R. 1995. *Frontiers of Complexity*. New York: Fawcett Columbine

de Vos H, Smaniotto R, Elsas DA. 2001. Reciprocal altruism under conditions of partner selection. *Rationality Soc.* 13(2):139–83

Durkheim E. 1982 [1901]. *The Rules of the Sociological Method*. London: Macmillan.

Epstein J, Axtell R. 1996. *Growing Artificial Societies: Social Science from the Bottom Up*. Cambridge, MA: MIT Press

Eshel I, Herreiner DK, Samuelson L, Sansone E, Shaked A. 2000. Cooperation, mimesis, and local interaction. *Sociol. Methods Res.* 28(3):341–64

Flache A, Hegselmann R. 1999. Rationality vs. learning in the evolution of solidarity networks: a theoretical comparison. *Comput. Math. Organ. Theory* 5(2):97–127

Flache A, Hegselmann R. 2001. Do irregular grids make a difference? Relaxing the spatial regularity assumption in cellular models of social dynamics. *J. Artificial Soc. Soc. Simulat.* 4(4):6.1–6.27

Flache A, Macy M. 1996. The weakness of strong ties: collective action failure in highly cohesive groups. *J. Math. Sociol.* 21:3–28

Forrester JW. 1971. *World Dynamics*. Cambridge, MA: MIT Press

Gilbert N. 1997. A simulation of the structure of academic science. *Sociol. Res. Online* 2(2):3.1–3.21

Gilbert N, Troitzsch K. 1999. *Simulation for the Social Scientist*. Buckingham, UK: Open Univ. Press.

Halpin B. 1999. Simulation in sociology. *Am. Behav. Sci.* 42(10):1488–508

Hanneman RA, Collins R, Mordt G. 1995.

This content downloaded from 129.81.226.149 on Thu, 19 Sep 2013 01:47:03 AM
All use subject to JSTOR Terms and Conditions

Discovering theory dynamics by computer simulation: experiments on state legitimacy and imperialist capitalism. *Sociol. Methodol.* 25:1–46

Hegselmann R, Flache A. 1998. Understanding complex social dynamics: a plea for cellular automata based modelling. *J. Artificial Soc. Soc. Simulat.* 1(3):1.1–1.36

Holland J. 1995. *Hidden Order: How Adaptation Builds Complexity.* Reading, MA: Perseus

Homans GC. 1974. *Social Behavior: Its Elementary Forms.* New York: Harcourt, Brace, Jovanovich

Hopfield JJ. 1982. Neural networks and physical systems with emergent collective computational abilities. *Proc. Natl. Acad. Sci. USA* 79:2554–58

Johnson PE. 1999. Simulation modeling in political science. *Am. Behav. Sci.* 42:1509–30

Kaufman S. 1996. *At Home in the Universe: The Search for the Laws of Self-Organization and Complexity.* Oxford, UK: Oxford Univ. Press

Kim H, Bearman P. 1997. The structure and dynamics of movement participation. *Am. Sociol. Rev.* 62:70–93

Kitts J, Macy M, Flache A. 1999. Structural learning: attraction and conformity in task-oriented groups. *Comput. Math. Organ. Theory* 5(2):129–45

Klos TB. 1999. Decentralized interaction and co-adaptation in the repeated Prisoner's Dilemma. *Comput. Math. Organ. Theory* 5(2):147–65

Kollock P. 1993. An eye for an eye leaves everyone blind. *Am. Sociol. Rev.* 58:768–86

Latané B. 1996. Dynamic social impact: robust predictions from simple theory. In *Modeling and Simulation in the Social Sciences from a Philosophy of Science Point of View*, ed. R Hegselmann, U Mueller, KG Troitzsch, pp. 287–310. Boston: Kluwer Dorderecht

Lomborg B. 1996. Nucleus and shield: the evolution of social structure in the iterated Prisoner's Dilemma. *Am. Sociol. Rev.* 61:278–307

Lomi A, Larsen ER. 1998. Density delay and organizational survival: computational models and empirical comparisons. *Comput. Math. Organ. Theory* 3(4):219–47

Macy M. 1991. Chains of cooperation: threshold effects in collective action. *Am. Sociol. Rev.* 56:730–47

Macy M, Skvoretz J. 1998. The evolution of trust and cooperation between strangers: a computational model. *Am. Sociol. Rev.* 63: 638–60

MacLeod J. 1995. *Ain't No Makin' It.* Boulder, CO: Westview

Mark N. 1998. Beyond individual differences: social differentiation from first principles. *Am. Sociol. Rev.* 63:309–30

Marwell G, Oliver P. 1993. *The Critical Mass in Collective Action: A Micro-Social Theory.* Cambridge, UK: Cambridge Univ. Press

McAdam D. 1988. *Freedom Summer.* New York: Oxford Univ. Press.

Meadows DL, Behrens WW III, Meadows DH, Naill RF, Randers J, Zahn EK. 1974. *The Dynamics of Growth in a Finite World.* Cambridge, MA: MIT Press

Meeker B, Leik R. 1997. Use of computer simulation for theory development: an evolving component of sociological research programs. In *Status, Network, and Structure: Theory Development in Group Processes*, ed. J Szmatka, J Skvoretz, J Berger, pp. 47–70. Stanford, CA: Stanford Univ. Press

Nowak A, Sigmund K. 1998. Evolution of indirect reciprocity by image scoring. *Nature* 393:573–77

Nowak A, Vallacher RR. 1998. Toward computational social psychology: cellular automata and neural network models of interpersonal dynamics. In *Connectionist Models of Social Reasoning and Social Behavior*, ed. SJ Read, LC Miller, pp. 277–311. Mahwah, NJ: Lawrence Erlbaum

Orbell J, Zeng L, Mulford M. 1996. Individual experience and the fragmentation of societies. *Am. Sociol. Rev.* 61:1018–32

Pedone R, Parisi D. 1997. In what kind of social groups can 'altruistic' behaviors evolve? In *Simulating Social Phenomena*, ed. R Conte,

This content downloaded from 129.81.226.149 on Thu, 19 Sep 2013 01:47:03 AM
All use subject to JSTOR Terms and Conditions

R Hegselmann, P Terna, pp. 195–201. Berlin: Springer-Verlag
Resnick M. 1997. *Termites Turtles and Traffic Jams*. Cambridge, MA: MIT Press
Reynolds CW. 1987. Flocks, herds, and schools: a distributed behavioral model. *Comput. Graphics* 21:25–34
Rosenkopf L, Abrahamson E. 1999. Modeling reputational and informational influences in threshold models of bandwagon innovation diffusion. *Comput. Math. Organ. Theory* 5(4):361–84
Rummelhart D, McClelland J. 1988. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*. Cambridge, MA: MIT Press
Saam N. 1999. Simulating the micro-macro link: new approaches to an old problem and an application to military coups. *Sociol. Methodol.* 29:43–79
Saam NJ, Harrer A. 1999. Simulating norms, social inequality, and functional change in artificial societies. *J. Artificial Soc. Soc. Simulat.* 2(1):2.1–2.20
Sawyer K. 2001. Artificial societies and the micro-macro link in sociological theory. Unpublished manuscript, Washington Univ.
Schelling T. 1971. Dynamic models of segregation. *J. Math. Sociol.* 1:143–86
Schumpeter JA. 1909. On the concept of social value. *Q. J. Econ.* 23:213–32
Shibutani T. 1978. *Derelicts of Company K: A Sociological Study of Demoralization*. Berkeley: Univ. Calif. Press
Simon H. 1998. *The Sciences of the Artificial*. Cambridge, MA: MIT Press
Smith TS, Stevens GT. 1999. The architecture of small networks: strong interaction and dynamic organization in small social systems. *Am. Sociol. Rev.* 64:403–20
Strang D, Macy M. 2001. "In Search of Excellence:" fads, success stories, and adaptive emulation. *Am. J. Sociol.* 107(1):147–82
Takahashi N. 2000. The emergence of generalized exchange. *Am. J. Sociol.* 105(4):1105–34
Vakas-Duong D, Reilley K. 1995. A system of IAC neural networks as the basis for self-organization in a sociological dynamical system simulation. *Behav. Sci.* 40:275–303
Watts DJ. 1999. Networks, dynamics, and the small-world phenomenon. *Am. J. Sociol.* 105(2):493–527
Willis P. 1977. *Learning to Labor*. New York: Columbia Univ. Press

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