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Agent-Based Modeling in the Social and Behavioral Sciences

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Scholars in recent years applying the sciences of complexity to social and behavioral phenomena have suffered from two distinct problems. One group of studies focused on the production of revealing metaphors at the cost of analytical rigor. Another set of studies developed mathematical models and techniques that remained remote to even sophisticated students of the sciences of complexity.

During the 1990s, however, a growing number of social scientists interested in complex phenomena, and dissatisfied with traditional research methodologies, sought new approaches for exploring the complexities of social dynamics. One of the developments emerging from this period was the use of agent-based modeling (ABM) and simulation to examine how social phenomena are created, maintained and even dissolved. These models, although diverse in their applications and approaches, generally attempt to create "microworlds" or "would-be worlds" in a computer with the goal of determining how the interactions and varied behaviors of individual agents produce structure and pattern (Casti, 1997). These models can be seen as a middle ground between the metaphor of many complex systems studies and the remote mathematics of many studies in the 1980s.

ABM is essentially the application of autonomous agents programmed to behave in different ways when interacting with adjacent agents or different aspects of their environment on a dimensional grid. An agent, say "red", may be programmed to exhibit one behavior, when, for example in contact with "blue" and "green", and another when in contact with another "red" and "yellow". The important point is that

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ABM illustrates the importance of emergence, whereby seemingly simple rules and protocol problems may generate highly complex, unexpected behavior. And, consistent with the evolutionary dynamics of complex adaptive systems (CAS), small changes in the initial start values may produce dramatically differing results.

Agent-based modeling (ABM) relies on a novel view of the creation of structure in social systems. Traditional social science generally assumes that social facts such as markets or cooperative behavior exist, and it is they that produce various forms of social organization and structure. ABM, on the other hand, assumes that both social structure and social facts such as markets or cooperative behavior are created from the bottom up via the interactions of individual agents. Rather than examining how social structure shapes behavior, ABM focuses, as noted above, on how local interactions among agents serve to create larger and perhaps global social structures and patterns of behavior (Berry, Kiel, & Elliott, 2002). Epstein and Axtell (1996) have described this approach as “social science from the bottom-up” as previously assumed social facts are now viewed as generated by the interactions of multiple local agents.

Modeling and simulation approaches used in ABM or computational modeling allow us to create new worlds from scratch, modifying various conditions and parameters as the need arises. Agent-based modeling thus examines “emergent” behavior as a structure and pattern that develops from numerous micro-level interactions. These models ask questions such as “how do markets and cooperative behavior among agents emerge”? It can be seen as “generative” social science because the goal is to identify the behavioral and environmental mechanisms that create organization and structure in the human realm.

Epstein (1999) has identified five general elements of agent-based models. These elements are heterogeneity, autonomy, explicit space, local interactions, and bounded rationality. Heterogeneity refers to the fact that agents differ in the “preference sets” or “rules” that guide their behavior during the simulation. It is this heterogeneity that is not only used to simulate human volition but also serves to create unique and surprising interactions between agents. The notion of autonomous agents means that there is no top down control in the model. Order or control is not imposed on the model, order may exist in the rules of the agents, but larger overarching schemas are not imposed. Evolution thus accrues from the bottom-up. Epstein’s third element of explicit space simply reinforces the notion that the evolution of the model occurs on some defined landscape or n-dimensional lattice.

Agent-based or computational models are also typified by local interactions. This means that agents interact with their neighbors rather than some distant agent far removed from the relevant landscape. The concept of local interactions thus promotes a simulation akin to actual human interaction within a defined geographic or cultural space. Finally, agents are subject to bounded rationality. In short, agents are driven by simple rules and respond to the local information generated from their contact with other agents. Agent-based modeling thus assumes the limits to rationality evidenced by a growing body of research in cognitive psychology.

What we have described above reveals that agent-based models can be viewed as a means for exploring the behavior of CAS. CAS are self-organizing entities consisting of a number of individual elements that behave on the basis of often very simple rules. Dooley has described the evolution of complex adaptive systems in a manner that also exhibits the characteristics of agent-based model. Dooley notes, “A CAS behaves/evolves according to three key principles: order is emergent as opposed to predetermined, the system’s history is irreversible, and the systems’ future is often unpredictable”(1997, p. 83). These comments reveal the capacity for agent-based models to incorporate the critical behavioral components of complex adaptive systems of unpredictability, irreversibility and emergent behavior.

Computational modeling as we have described offers not only a new approach to understanding a wide range of phenomena, it may be an indispensable tool that allows a researchers to answer questions about a range of political, economic and social dynamics that are consistent with CAS that would otherwise be inaccessible using traditional methodologies. The often contingent, nonlinear and unexpected behavior of complex systems means that agent-based or computational modeling provides unique opportunities for researchers who might otherwise be stymied by the nature of the phenomena they seek to understand.

ABM has in recent years been applied to a wide range of subjects and research questions, ranging from understanding patterns of cooperative behavior to the behavior of organizations (Patrick, Dorman, & Marsh, 1999; Prietula, Carley & Gasser 1998), modeling of policy (Bankes, 2002), the dynamics of financial markets (LeBaron, 2002) or the formation of international alliances (Cederman, 1997), among others.

THE METHODOLOGICAL RATIONALE FOR AGENT-BASED MODELING

Two questions that surround the application of agent-based modeling concern why these models should be employed and under what circumstances ABM adds improved insight relative to other analytical techniques. Given the basic assumption of complexity studies that nonlinearity is inherent in complex systems one would assume that capturing and enacting nonlinearity is an essential element of ABM. In ABM it is the interactions of adaptive agents that typically generate nonlinear effects. ABM is thus helpful because these nonlinear effects are generally not amenable to the deductive tools of formal mathematics. Yet, incorporating interactions that produce nonlinear behavior into agent models does not alone inform the analyst as to the robustness of the model.

Axtell (2000, p.i) has identified three “distinct” reasons for using agent-based models. The first case involves those situations in which mathematical equations are employed that completely describe some social phenomenon or process. Agent-based models in this case simply serve as a classical mode of simulation founded on verifying known relationships and outcomes. Another use of ABM within the confines of classical simulation are those cases in which stochastic elements are introduced into the model, resulting in a solution representing some probability distribution. Instances of this include Monte Carlo simulation as used in traditional operations research problems such as those employed in queuing models.

A second major use of ABM involves the simulation of phenomena in which relevant equations are only partially solvable. An extension of this logic concerns those circumstances in which the solution set results in equilibria that are either uncomputable or unstable. In the case of the existence of multiple equilibria, ABM can also be of value by providing a means for exploring the divergent paths to the varied equilibria. This point also emphasizes that even when equilibria do exist the network of interactions that lead to particular outcomes may generate multiple paths. For organizational analysts this is particularly important because it provides a means for assessing how agents get to the endgame. For example, if the desired organizational state is some improved level of performance, the interactions of agents and how the agents achieve that end state is, analytically and managerially, more important than the end state itself (Kiel, in press).

The final case for the application of ABM involves those instances in which the mathematics of the phenomenon are intractable. Instances in which the closed form of differential equations are insoluble typify this rationale for employing agent-based models. Consider the organizational case in which a manager seeks to achieve some desired state of change. The wise manager would have to assume some degree of nonlinearity as organizational agents interacted in an effort to achieve the desired changed state. Yet, an equation for such a complex series of events does not exist. Here then is an example where using agent based modeling makes sense simply due to the fact that a mathematical equation does not exist for the phenomenon. This understanding also suggests that in these “complex” situations ABM may be the first and natural analytical tool.

These reasons for employing ABM however do not resolve the problems of the robustness of ABM. One run of an agent-based model, given the built-in risk and uncertainty of outcomes due to varying interactions in each model run, cannot serve as a definitive solution. If definitive solutions are desired then multiple runs of the model are necessary. The results of these multiple runs can then be assessed using comparative statistics to define the stability of the solution, or at least the stability of the multiple equilibria that may exist. The results of these analyses are probability distributions of the expected outcomes of model runs regardless of the initial conditions.

Traditional hypothesis testing also serves as another goal of ABM. Hypotheses concerning the emergence of structure or the success of varying agent strategies may serve to confirm or negate many theories of social behavior. ABM may also serve as a platform for theory testing across a wide variety of social phenomena. This notion generates the realization that agent-based models may become the “experimental laboratory” that has generally been absent in social science research.

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As with any emerging field, there is considerable diversity in the approaches that can be labeled as agent-based modeling. Some approaches take an evolutionary strategy, while others use a more learning-theoretic paradigm. At the core of all such models, however, is a focus on agents interacting on "landscapes" consisting of a two dimensional grid. Agents are energized by rules that direct their behavior in these landscapes, which potentially can represent the diversity of social environments in which humans interact, bridging the "micro-macro" divide and provide insights into how seemingly simple rules governing agent behavior can produce surprising and unexpected results.

This special issue of *Nonlinear Dynamics, Psychology, and Life Sciences* is organized in a fashion that reflects the ability of agent-based modeling to bridge the so-called "micro-macro" divide. In other words, ABM can be exploited to model processes at very fundamental, micro levels of analysis such as cooperation among individuals to intermediate levels such as organizational behavior in firms or other entities, all the way to "macro" phenomena such as the behavior of states or global economic processes. Therefore, the articles are presented in a sequence that moves from more micro-level applications of ABM to increasingly macro-level applications. Two of the most micro-level analyses examine non-human systems, specifically the behavior of ant colonies and ovarian cycle variability in research rats. These articles help illustrate the highly impressive search of agent-based methodologies.

Stephen Guerin's study exploits the analysis of insect behavior as an instance of the important overarching principle of self-organization. While self-organization is critical to the phenomenon we refer to as complex adaptive systems, the theoretical foundation of self-organization requires, as Guerin notes, further study. "Emergence of Constraint in Self-Organizing Systems" demonstrates measures of order creation and constraint production, then uses these measures to evaluate several important questions involving the nature of complex systems, including the relationship of constraints to entropy-producing processes, the role of positive feedback loops in structure formation and the extent to which constraint decay plays a role in self-organizing dynamics. The role of ABM in helping answer these questions yields some potentially crucial theoretical insights that may lead to important advances in the modeling of social behavior.

Jeffrey Schanks' article, "Avoiding Synchrony: Ovarian Cycle Length as a Strategy for Mate Choice" is another impressive micro level application of computational modeling on display in this special issue. Schanks incorporates both formal mathematical models with agent-based approaches to explore ovarian cycle variability in Norway rats. Schanks' work is based on the somewhat counter-intuitive finding that female mammals do not necessarily synchronize ovarian cycles, unlike the common belief that high degrees of synchronization occur when female mammals are in close proximity to each other. The simulation results yield interesting findings concerning the behavior of mammals in ecologically simulated contexts, which may have important implications for our understanding of population dynamics and ecosystem stability.

Steven Phelan's contribution, "Using Agent-Based Simulation to Examine the Robustness of Up-or-Out Promotion Systems at Universities" examines the robustness of an "up-or-out" system to various labor supply contingencies, demonstrating that (we denizens of academe perhaps suspected this for a long time!) up-or-out promotion is not always optimal when compared to serenity and merit based promotion systems.

A related interest in organizational behavior is seen in Dal Fourno and Merlone's article entitled "Personal Turnover in Organizations: an Agent-Based Simulation Model". They use a heterogeneous agent approach to explore important dynamics, specifically effort level within the organization. The paper combines both a theoretical treatment of this issue as well as offering a simulation approach as complexity is added to the model. The findings offer important insights into the development of hiring and firing policies and the role of incentives within organizations.

At the most "macro" level of analysis we have Jasmina Arifovic and Paul Masson's "Evolutionary Models of Exchange Rate Behavior". The authors note the persistent fluctuations in exchange rates since the adoption of flexible exchange rates in 1972 following the collapse of the Bretton Woods frameworks. But, as they point out, various methodological approaches have failed to explain the substantial variation in rates over time. Using a computational model in which boundedly rational agents' beliefs are allowed to evolve over time appears to best capture exchange rate dynamics. Arifovic also shows how such dynamics are consistent with the behavior of human experimental subjection. This paper adds important knowledge to our understanding of evolutionary forces governing economic change.

Steven Bankes and Robert Lampert's contribution, "Robust Reasoning with Agent-Based Modeling" offers important insights into the use of ABM by policymakers. Drawing upon a series of macro-level policy relevant phenomena, Bankes and Lempert make a crucially important point. Essentially, the authors want to show that, given the probabilistic and contingent nature of ABM outcomes in any given simulation (i.e. the same simulation that is repeated with the same values and specifications may produce a different outcome), the future of ABM in the policy context requires an appreciation of the importance that ensembles of models may play. Ensembles allow us to judge the invariant properties of different models, and thus help to establish plausible conclusions about various types of policy interventions.

Even though the application of agent-based modeling to the social and behavioral sciences is quite recent given the substantial computing requirements, it is nonetheless important to appreciate that ABM is really one facet of the much larger arena of research in complex nonlinear systems. Leslie Henrickson's "Trends in Complexity Theory and Computation in the Social Sciences" offers a citation analysis of the use of chaos and complexity theory and computational simulation in the published literature over the 1971-1999 time period. Her analyses reveal interesting insights into the evaluation of the growing field of complex adaptive systems and the more recent application of computational simulation top furthering our understanding of complex systems.

Complex system frameworks have offered tantalizing insights into a wide range of multilevel phenomena such as patterns of cooperation and non-cooperation (Axelrod, 1997), to the dynamics of macroeconomic processes (Brock, 1988; Holland, 1988), electoral dynamics and political realignments (Brunk, 2001) or the collapse of entire political and social systems (Tainter, 1998). A very practical means for accessing the knowledge produced by agent-based models is presented in Holland's notion of agent-based models as policy flight simulators. Given that the parameters of agent-based models can be altered leading to divergent outcomes such models would seem to excellent tools for policy makers. While only the naïve would think that such tools would serve to override ideology in political debates in may lead to the enhanced recognition that public policy can lead to multiple possible outcomes and to a greater recognition of likely yet unintended consequences.

Perhaps most importantly, though, agent-based modeling may be the method and the tool that brings a level of acceptance and functionality to the sciences of complexity that has heretofore been missing. Consider the recent article in the *Harvard Business Review* by Bonabeau and Meyer (2001) on agent-based modeling and its application to phenomena from scheduling factory equipment to business strategy.

With an entry into this informational venue and considering the readership of such a journal, it may be that agent-based modeling may be the tool that moves the complexity sciences from the somewhat arcane to the profoundly practical.

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