Social Psychology and Complexity Theory *

Barry Markovsky
University of Iowa

* Transcript of presentation at the Pacific Sociological Association, Portland, OR, 1999. Please do not cite or quote without permission of the author. Contact information: Department of Sociology, University of Iowa, Iowa City, IA, 52242. E-mail barry-markovsky@uiowa.edu

Whatever our specific substantive interests, I think that most of us in and around social psychology are continually intrigued by some of the almost magical phenomena that occur within our theoretical purview. Take “emergence,” for example. It still interests me, and sometimes amazes me, how individual behaviors emerge from the substrate of neurological and cognitive processing; how interpersonal patterns emerge from a substrate of social perceptions and repeated interactions; how small group structures and processes emerge from the activities of their members; and how larger structures maintain their integrity and evolve through time based on *something* having to do with the actions of their sub-parts. My amazement is shared by many in other fields of research.

“Evolution” is another kind of magical phenomenon. I can dissect a computer program that illustrates the evolution of intelligence in a population of simulated entities. I can see the entire menu of behavioral and decision-making contingencies laid out before me, I can understand perfectly how the pieces all fit together, how the dynamics unfold, how the selection processes are implemented, and how the entities adapt to environmental contingencies after iterating the simulation for generations. But it all still has a magical quality. Social psychology as a discipline has not been especially interested in evolutionary processes, but there is a place for such work.

Still another magical process, related to emergence and evolution, is feedback. It would be nice if social behavior proceeded step-by-step, actors behaving according to predetermined scripts. Knowing the scripts would be sufficient to explain and predict the ensuing patterns and structures. Fortunately for those who make their living trying to understand human social behavior, it’s not this simple. If we have scripts, they are fluid and dynamic things. As behavioral sequences proceed, feedback is received continuously and steers the behavioral sequence down another of its infinite possible paths. The fact that the feedback itself emanates from other behavioral units also engaged in the dynamic sequence, also altering their actions based on feedback, ensures that the ensuing process will be a complex one. What’s really interesting is that the array of individual behaviors and contingencies can be relatively simple. But when you throw feedback into the mix, all hell can break loose.

I like social networks, too, for their tenuous balances of freedom and constraint at different levels of analysis. Under laboratory control, we can construct simple networks, populate them with human subjects, explain the rules of social engagement, and let them rip. At the micro level, there is a seemingly chaotic flurry of activity as information and interaction flows along the network’s pipelines. In time, patterns settle out and stabilize and, in most cases, conform almost perfectly to theoretically-derived predictions.

At the same time, however, as we begin to study slightly larger networks under the same experimental constraints, new kinds of dynamics appear and the old analytic models fail to work quite so well. With even larger networks, I’m quite certain the models will break down altogether. For example, we have run line-shaped networks in the lab at Iowa, ranging in length from two to seven positions. Based on theory, simulations and testing in the past, we believed that lines with an even number of positions would produce at most small advantages and disadvantages across connected positions. In contrast, odd-lines should present large differentiations in profits earned from negotiation and exchange for alternating positions.

As we started to look at six- and seven-actor lines, however, it was clear that more was going on, and results with human subjects were not nearly so clean. Some were able to acquire greater power advantages than expected in the 6-line, and in the 7-line, most did not achieve the advantages theoretically expected of them (Lucas et al. 1998). When we step out of the theory and consider what’s happening in the reality of the laboratory, it’s not hard to understand what’s going on. In all the networks we’ve studied, there is always some wiggle-room within which actors can poke around and explore options. In general, the nature of our experimental settings and smaller network structures have constrained the advantages that might accrue from such explorations, and so they generally do not stray far from the predicted path. But with structures only as large as 6-actor lines, there is more wiggle-room, and more opportunities for stable, localized patterns to emerge. While the theory makes sense of these local patterns, it cannot predict where the local patterns will pop up. What can happen is that during the initial stages of interaction when negotiations are not yet constrained by what has transpired previously, local, temporary anomalies occur virtually at random, and with trivial short-run consequences. For instance, a subject in what eventually should emerge as a higher-power network position may, for a variety of possible reasons, permit those adjacent to her to receive a slightly favorable exchange outcome. Relative to what she earned the last time around, the decrement may be trivial. However, the effect may be to shift the subsequent course of interaction down a new path. A subset of positions is isolated from the rest of the network, thus changing the larger structure irreversibly, and taking the results further and further from the predicted.

Knowing that this can happen opens up new avenues for theorizing. For example, instead of predicting a single pattern of exchange outcomes for a network, we’ll need to understand the different anomalous sub-structures that can emerge and their likelihoods, and then the current modeling procedure can be applied under these various contingencies.

Thought experiments and computer simulations have suggested other interesting phenomena that can occur in these networks. For example, when actors in certain positions act out of line—that is, for instance, they take a hard bargaining stance despite being at a structural disadvantage, the impact on neighbors is immediate. Even if the deviant actor quickly returns to “normal” behavior, however, the local effect of the disruption would be expected to travel down the line in either direction, in a wave-like fashion. Depending on the length of the line and on the state of the process along the way, positions many steps removed from the deviant may eventually experience his effect in the form of an unexpected windfall or loss. It would seem to be short step from this type of network-wave phenomenon to distinguishing structures that would promote or "amplify" such waves from those that would dampen them.

Everything I've discussed thus far is connected in some way to complexity theory. This is a relatively new approach to studying certain kinds of systems that previously defied understanding. One of the most striking qualities of the approach lies in the simplicity and generality of its models. Its adherence to scientific norms of parsimony, even while generating complex and dynamic outputs, partly accounts for its popularity across numerous disciplines.

"Complexity theory" is not actually a theory *per se,* but rather a loose set of concepts, heuristics and analytic tools. These components emerged gradually from independent, sometimes isolated scholars in numerous disciplines. In every case, these theorists and researchers had come up against unpredictable, dynamic phenomena as they strained to discern patterns amidst the chaos (Gleick 1987; Waldrop 1992). Applications include artificial intelligence, economic modeling, evolutionary ecology, physics and much more. The common problematics helped to coalesce sets of disparate and sometimes marginalized scholars. All had discovered an absence of existing theories or models that could be applied in their respective fields. And all shared a firm commitment to the language and methods of science as the means to address their questions—as opposed to giving up or falling back on metaphysics and nebulous theories.

Perhaps the most obvious of the commonalities is that all of the questions refer to systems that, relative to those which we already understand fairly well, seem very complex. They have **large numbers of components** coupled with even **larger numbers of interactions** among components. A second commonality is that **self-organization** occurs at some stages. Generally speaking, people do not consciously build exchange structures or belief systems in their totality, just as systems of atoms and neurons, cells and mammals, solar systems and galaxies are not designed and constructed in the forms that we find them. They self-organize, and the new science of complexity is unlocking the principles of self-organization.

Complex systems also **adapt** to their environments over time. They change their behaviors and properties, contingent on external and internal perturbations or threats. Generally, but not always, brains, species, economies and ecosystems enact changes that appear to be responsive and beneficial, not just mechanically reactive.

Complex systems are **dynamic**. More than being merely complicated by having lots of members or appendages or nooks and crannies, complex systems have a kind of patterned liveliness to them. New behaviors and structural forms **emerge**. Sometimes what emerges appears to go far beyond what seems possible when considering just the constituent elements. In a literal sense, the parts of complex systems don't sum. They are **non-linear**: interactions and feedback among elements produce higher-level emergent phenomena. **Feedback** allows transformations of system processes into new system structures.

This image of complexity stands in clear distinction to that of *chaos,* a predecessor of complexity theory. Chaotic processes have been described as generating "weirdly unpredictable gyrations" (Waldrop 1992:12). Think of turbulence or the famous Mandelbrot set graphics. The dynamism of a complex system resides at the margin between order and chaos.

So the edge of chaos is where complexity begins. There it's possible for little revolutions and innovations to emerge and ripple out into the system without toppling it. Consider biological evolution, the immune system, or the organization of scientific fields. Also, *social* systems.

Some of the social sciences, economics in particular, jumped on the complexity bandwagon around 20 years ago when "chaos theory" was the label coming into use. Sociology has been slower to adapt these concepts and perspectives to its problems, but that is changing. In recent social science collections on the subject, around one in twenty contributors are sociologists. There is a recent collection *Chaos, Complexity and Sociology,* edited by Raymond Eve, Sara Horsfall and Mary Lee (1994). Most of the volume is "sensitizing" and informal, however, and does not actually involve empirical or simulation research. Still, the relevance for social psychology is evident. Topics included dynamic approaches to parent-child attachment, friendship formation, and information processing in organizational contexts.

In contrast, social psychology may now have a leg up on sociology with the recent publication of the very sophisticated *Connectionist Models of Social Reasoning and Social Behavior,* edited by Stephen J. Read and Lynn C. Miller (1998). Nearly the entire volume is in the vein of what we would call psychological social psychology. That is, most of the chapters are concerned with individual cognitive outcomes that are conditioned by social stimuli: person perception, stereotyping, categorization, causal attribution, and attitude-formation. Shoe-horned in the last section are two chapters on social influence and group interaction.

In my remaining time, I'll review a few of the more sociological examples of the recent social psychological research in this genre.

Kathleen Carley's "ORGAHEAD" model (Carley and Svoboda 1996; Carley and Lee 1998) conceptualizes organizational decision making as occurring in networks of intelligent agents. Her computer-simulated organization consists of several layers of personnel, each member having one or more ties to other individuals in other layers, each member capable of learning from feedback but constrained by human-like information processing limitations. Ties among agents determine patterns of authority and access to resources. The organization has tasks to perform, and performance depends on the organization's success at adapting to complex contingencies. A computational algorithm called *simulated annealing* explores different configurations of network ties and agents' beliefs, while emergent behaviors and processes are checked against organizational performance goals. Gradually, the better configurations are frozen in place. Functional organizational structures and pragmatic individual beliefs and actions self-organize and emerge with no higher-level guidance.

Recent work by Michael Macy and John Skvoretz (1998) looks at the emergence of trust among strangers with no assurance of future interaction. They set up a computer simulation with a thousand actors engaged in pair-wise interactions. Pairs of actors may or may not be in each others' neighborhoods, operationalized as likelihoods of mutual encounters. Macrostructural properties such as numbers and sizes of neighborhoods can be varied. In each encounter, actors choose to cooperate, defect, or not to play, with fixed payoffs creating prisoner's dilemmas. Actors acquiring higher payoffs are by definition more "fit" in this computational world. How actors respond to one another in interactions depends upon an array of characteristics that may or may not signal trustworthiness, and which change in response to successes and failures in interactions.

Then one can examine the population-wide distributions of individual characteristics, and even the impact of structural constraints on interpersonal encounters.

Andrzej Nowak and Robin Vallacher (1998) used a different method to approach a somewhat similar problem. They were interested in how opinions change at the individual level based on the opinions held by virtual neighbors, and how interpersonal dynamics of opinion change generate emergent patterns in the larger group. The model assumes that in formulating their opinions, individuals sample the opinions of others socially close to them to determine social support, with greatest weight given to the opinions of the most proximate others. The process is iterated repeatedly until opinions group-wide achieve stability.

A variety of computational algorithms have been used in the studies I just mentioned, and in other work in the complexity theory genre. The best known you may have heard of: cellular automata, simulated annealing, genetic algorithms and neural networks. Although these appear very different from each other on the surface, they share a set of common properties that make them well-suited to the task of driving simulations of complex phenomena. In general, they go from a set of inputs to a set of outputs using fairly simple transformation rules. What makes complex phenomena emerge—such as macro-patterns that seemingly have nothing to do with micro-activities—is the sheer number of units involved, the sheer number of iterations over which the process operates, some mechanism for trial-and-error-correction, and the feeding back of information among the units of the system. What emerges is a kind of artificial intelligence, not at the micro-level of interacting units, but in the higher-order patterns that are produced—the colony rather than the ants (Hofstadter 1980).

At this stage, I think it is important for social psychologists to become familiar with these new tools, at least at a metaphorical level. Complexity theory directs our attention to important aspects of interactions and their outcomes which we may not have thought about otherwise. Dynamics, emergence, nonlinearity, parts and wholes—these old terms take on new, specific, highly-integrated meanings in the complexity tool kit. They direct us to look for the *edges* of structures and status quo's, to the uncertainty, exploration and innovation from which evolved the phenomena we have been accustomed to studying.

References

Carley, Kathleen and Ju-Sung Lee. 1998. "Dynamic organizations: organizational adaptation in a changing environment." *Advances in Strategic Management* 15:269-297.

Carley, Kathleen and David M. Svoboda. 1996. "Modeling organizational adaptation as a simulated annealing process." *Sociological Methods and Research* 25(1):138-168.

Eve, Raymond A., Sara Horsfall and Mary E. Lee (Eds.). 1994. *Chaos, Complexity and Sociology: Myths, Models, and Theories.* Thousand Oaks, CA: Sage Publications.

Gleik, James. 1987. *Chaos: Making a New Science.* New York: Viking.

Hofstadter, Douglas R. 1980. *Gödel, Escher, Bach.* New York: Vintage.

Lucas, Jeffrey, C. Wesley Younts, Michael J. Lovaglia, and Barry Markovsky. 1998. "Lines of power development in exchange networks." Annual Meetings of the American Sociological Association, San Francisco.

Macy, Michael W. and John Skvoretz. 1998. "The evolution of trust and cooperation between strangers: a computational model." *American Sociological Review* 63:638-60.

Nowak, Andrzej and Robin R. Vallacher. 1998. "Toward computational social psychology: cellular automata and neural network models of interpersonal dynamics. In Stephen J. Read and Lynn C. Miller (Eds.), *Connectionist Models of Social Reasoning and Social Behavior.* Mahwah, NJ: Lawrence Erlbaum Associates.

Read, Stephen J. and Lynn C. Miller (Eds.). 1998. *Connectionist Models of Social Reasoning and Social Behavior.* Mahwah, NJ: Lawrence Erlbaum Associates.

Waldrop, M. Mitchell. 1992. *Complexity.* New York: Simon & Schuster.