Self-organizing systems research in the social sciences: Reconciling the metaphors and the models

Noshir S. Contractor
Departments of Speech Communication & Psychology
University of Illinois at Urbana-Champaign
244 Lincoln Hall
702 South Wright Street
Urbana IL 61801
nosh@uiuc.edu

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Abstract

The advent of self-organizing systems perspectives – a pan-disciplinary metatheory – has brought with it a burgeoning interest in appropriating new theoretical concepts and mechanisms into domains far removed from their original intellectual crucible. With a few exceptions, most of the initial conceptual and theoretical developments in self-organizing systems occurred in the physical and life sciences. Today there is a growing interest in applying these concepts and mechanisms in the social sciences and humanities. Social scientists and humanists have been intrigued by concepts such as auto-catalysis, autopoeisis, bifurcation, and fractals. This paper argues for the need to reconcile the desire to capture (and perhaps extend) the metaphorical richness of these concepts, while preserving their operational rigor, as well as the logical requirements of the theoretical mechanisms underlying self-organizing processes. In the absence of a deliberative discussion on this reconciliation, research on self-organizing systems in the social sciences runs the risk of being either (i) overwhelmingly metaphorical (some would argue "hand waving"), or (ii) an unenlightened and inappropriate attempt at importing models and theories from the physical and life sciences to the study of social phenomena. Both of these outcomes were evidenced in the arguably unsuccessful attempt by scholars in an earlier era to appropriate open systems theory into the social domain.

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This paper seeks to engage in a dialogue about the appropriate role of metaphors and models in the development of a communication research program based on a self-organizing systems perspective. The paper begins by reviewing recent literature that argues for conceptualizing organizations as self-organizing systems. It notes that this literature has contributed significantly to sensitizing organizational researchers and practitioners to the salience and currency of a set of novel concepts. Next, the paper argues that much of this work focuses on identifying surface manifestations that can arguably result from a self-organizing system. The use of a self-organizing systems perspective in this literature as a metaphor is richly evocative but stops short of identifying the underlying generative mechanisms, and hence realizing the nonlinear implications, offered by self-organizing systems theory. To respond to this deficiency, the paper argues for a more systematic effort to move up the operational hierarchy by specifying models of the phenomena being studied. The paper reviews several such models highlighting their relative appropriateness for studying different self-organizing processes. The paper concludes by outlining an analytic framework that dovetails an iterative process of theory construction, computational modeling and empirical validation.

Self-organizing systems as metaphor

Since the 1980s there have been several well-articulated, and well-received, books in the organizational literature that advocate the study of organizations from a self-organizing systems perspective. In his book, *Images of Organizations*, Morgan (1986, p. 233) proposed that the metaphor of organizations as a self-organizing, self-producing system offered a powerful suite of conceptual tools to examine “organizations as flux and transformation.” In *The Fifth Discipline*, Senge (1990, pp. 57-67) offered an early attempt at familiarizing organizational researchers and practitioners with key features of nonlinear dynamic systems using the following eleven aphorisms:

(i) today’s problems come from yesterday’s solutions,
(ii) the harder you push, the harder the system pushes back,
(iii) behavior grows better before it grows worse,
(iv) the easy way out usually leads back in,
(v) the cure can be worse than the disease,
(vi) faster is slower,
(vii) cause and effect are not closely related in time and space,
(viii) small changes can produce big results – but the areas of highest leverage are often the least obvious,
(ix) you can have your cake and eat it too – but not at once,
(x) dividing an elephant in half does not produce two small elephants, and
(xi) there is no blame

Senge (1990) proposes a model of the organization as a complex nonlinear system directed by the vision of a charismatic leader who can control the system by identifying leverage points at which key interventions can be implemented.

Wheatley (1992, p. 6-7) continued this advocacy about organizations as self-organizing systems by conveying via her book, "the pleasure of sensing those first glimmers of a new way of thinking about the world and its organizations. …. Here there are scientists who write about natural phenomena with a poetry and a lucidity that speaks to dilemmas we find in organizations. Here there are new images and metaphors for thinking about our own organizational experiences." She acknowledges that "some believe that there is a danger in playing with science and abstracting its metaphors because, after a certain amount of stretch, the metaphors lose their relationship to the tight scientific theories that gave rise to them." But, she continues, "others would argue that all of science is metaphor – a hopeful description of how to think of a reality we can never fully know." Following an introduction of the concept of strange attractors in self-organizing systems, Wheatley (1992, p. 133-134, 136) writes, "Ever since my imagination was captured by the phrase 'strange attractor,' I have wondered if we could identify such a force in organizations. … My current belief is that we *do* have such attractors at work in organizations and that one of the most potent shapes of behavior in organizations, and in life, is *meaning*. … When a meaning attractor is in place in an organization, employees can be trusted to move freely, drawn in many directions by their energy and creativity."

Stacey (1996) extends this approach, arguing that organizations are complex adaptive systems (p. 23), with "dissipative structures" (p. 47) and "self-organizing learning systems at the edge of chaos" (p. 72). Stacey (p. 265) concludes, "perhaps the science of complexity adds most value because it provides new analogies and metaphors for those in the research community who are inclined to play in that community's recessive schema, in tension with the dominant schema, to produce creative change in our understanding of organizations."

Others, such as Goldstein (1994) and Warneke (1993) use self-organizing systems metaphors to describe *The Unshackled Organization* and *The Fractal Company* respectively. All of these authors illustrate the power of metaphorically re-conceptualizing organizations as dynamic, chaotic, non-linear systems, with self-similar structures, given to sudden disruptive changes, often triggered by small actions that may be random. The authors offer several illustrative anecdotes of organizational activities and structures that appear to bear out these characteristics. However, the plural of anecdote is not empirical data. Instead, these anecdotes are intended -- and must be construed -- as metaphorical attempts to "imaginize" organizations. Morgan (1993, p. 289-291) argues that using such metaphors to "imaginize" organizations have at least six payoffs:

(i) metaphors always involve a sense of paradox and the absurd, because it invites users to think about themselves or their situations in ways that are patently false;
(ii) metaphors requires its user to find and create meaning … and also helps to create *ownership* of the insights;
(iii) when different people generate different metaphors that have a great deal in common, one knows that one is dealing with highly resonant insights;
(iv) resonant metaphors can energize a group and "take hold;"
(v) metaphors invite a conversational style where meaning and significance emerge through dialogue; and
(vi) the tentative nature of metaphorical insights mean that they cannot be taken too seriously or made too concrete.

While these authors have succeeded in popularizing the self-organizing systems metaphor, their expositions raise two issues that are likely to hinder the intellectual durability and longevity of this perspective: the intellectual value added by these metaphors and the conflict between the metaphorical and technical interpretations of the concepts used in self-organizing systems.

First, in a dialog sponsored by the Santa Fe Institute and moderated by Jen (1994, p. 559), Stevens wonders if these perspectives are "a restatement of things we already know in a different language and there's no new result. Sometimes this can be useful but it's not a theory. I would be interested to hear the extent to which people think that complex systems theory has been a restatement or the extent to which, in all the various areas, there are results where we know something we didn't know before." Stevens' questions about the intellectual insights derived from complexity theory invoke memories of a trenchant critique made twenty years ago by Lilienfeld (1978, pp. 191-192) in his book, *The Rise of Systems Theory*:

> Systems thinkers exhibit a fascination for definitions, conceptualizations, and programmatic statements of a vaguely benevolent, vaguely moralizing nature … They collect analogies between the phenomena of one field and those of another … the description of which seems to offer them an esthetic delight that is its own justification … no evidence that systems theory has been used to achieve the solution of any substantive problem in any field whatsoever has appeared.

In the context of studying organizations from a self-organizing systems perspective, what new insights can be gleaned by metaphorically describing "meaning" in organizations as a "strange attractor?" Perhaps, we can better appreciate that "meaning" in the organization is not constant (in which case it would be a point attractor), or changing in cycles (in which case it would be a periodic attractor), but appears to change randomly within certain bounded realms. But even this conjecture begs several questions: What components in the system influence the trajectory of "meaning?" Under what conditions is "meaning" likely to become a point attractor, a periodic attractor, or a different strange attractor?

Second, there is considerable misunderstanding surrounding the terminology used in the self-organizing systems perspective. Goldstein (1992, p. 40) an organizational researcher and consultant on self-organizing systems, confesses that, "I often have had the experience of not quite understanding what others are talking about, as well as the sense of being misunderstood myself." He argues that one source for this misunderstanding is when the terminology is used metaphorically. "For example," Goldstein (1992, p. 42) notes:

> I have said, on occasion, and I have heard a number of people in organizational appropriations of chaos theory say that to facilitate organizational transformation we need to add some chaos into organizations. What exactly is being referred to here as chaos? Most likely, it is not any kind of behavior in a system that could be typified by a chaotic attractor. And even if it did fit such a technical definition, how does one add this kind of chaos to an organization? Isn't chaos per se a matter of deterministic evolution following some simple nonlinear rules? How exactly is such a thing added to an organization?

Goldstein (1992) notes that this confusion is created because it is not always clear when scholars use the terms metaphorically. Hence, in order to build intellectually on the evocative power of metaphors, it is imperative to move up the operational hierarchy of these concepts. That next step in the hierarchy is the specification of models, which Barbour (1974) citing the philosopher of science Max Black, describes as *systematically developed metaphors*.

Self-organizing systems as model

Before discussing the challenges posed in specifying models based on a self-organizing systems perspective, it is worthwhile to review earlier attempts at creating formal models in the social sciences. One of the earliest attempts was by Kurt Lewin (1936, 1951) who introduced new mathematical terminology to study human action and interpersonal interaction. He called his approach topological psychology and field theory. Back (1997) notes that Lewin "favored formulas over verbal explanation, using the cachet of mathematics without its rules of procedure. Thus his most popular formula, $B = f(P, E)$, says that behavior is a function of the person and the environment, without specifying how any of these are to be measured or what the functional relationship could be. Even more, the formula is supposed to say that P and E are interdependent and have joint effects, contrary to what it really does indicate. ….. (F)ield theory, postpones the technical problems of mathematics for future solutions and stresses the appeal of its intuitive insights."

In their influential monograph on Information Theory, Shannon and Weaver (1949) described two sets of mathematical concepts: entropy and information, with the expectation that the latter would appeal to those interested in applying information theory to study communication in social systems. However, as Back (1997) notes, "these general ideas spread into many realms of thought … but it did not humanize social research as Shannon had hoped."

Sociometry (Moreno, 1934), while offering a new mathematical representation of social systems, is now viewed by all but a small clique within the intellectual community as a method (network analysis) rather than a paradigm, thus dashing the messianic claims by its founder Moreno. Similar trajectories can be traced for the introduction of Game Theory (von Neumann & Morgenstern, 1947), Catastrophe Theory (Thom, 1975), and Fuzzy Sets Theory (Zadeh, 1975).

Back (1997, p. 43-44) recognizes a pattern in the fate of these new techniques following their introduction:

(i) the application of this procedure to unresolved questions in social science;
(ii) a skeptical reception in the established science with claims of faddism and similar reactions;
(iii) the formation of a following for this mathematics;
(iv) the claim for a new science resolving many previous problems;
(v) the diffusion into popular – non-scientific culture;
(vi) reaction and disillusionment;
(vii) the adaptation of the technique to the established model.

The recent surge of interest in self-organizing systems perspective is precariously poised at stage 5, threatening to lurch on to stage 6 on this trajectory. The history of, and reaction to, earlier mathematical theories described above suggest that disillusionment sets in when the public tires of the metaphor and the research community fails to see formalized intellectual advances. This time around, the advent of computational modeling holds out the promise that disillusionment can be pre-empted, or at least delayed. Turner (1997) argues that the theoretical machinery of complexity theory combined with the exponential increase in computational power, recommends modeling as a critical fifth tool in addition to the four tools used by classical science: observation, logical/mathematical analysis, hypothesis, and experiment. Turner (1997, p. xxv) concedes that "in a sense any logical/mathematical analysis of data is a sort of passive model, based on a particular type of math such as statistics or topology; a hypothesis is a static model in the scientist's mind, and the questions a given experiment is designed to presuppose a model of a desired answer. But such models have until now been fixed and inflexible, and based as they are on a linear conception of cause and consequence, they are confirmed or deconfirmed in an all-or-nothing way." Today, the computer serves as an exploratorium permitting researchers in a variety of disciplines to examine with a relatively small effort and at a high speed the aggregate, dynamic, and emergent implications of multiple nonlinear generative mechanisms. These new sub-areas in a variety of disciplines are collectively referred to as computational sciences (Carley & Prietula, 1994). The potential of computational modeling prompted Pagel (1988) to observe that just as microscopes revealed new frontiers of knowledge in the seventeenth century, today the frontiers of knowledge are being revealed via the "macroscope" of computers.

The idea of dynamic modeling of organizations is not a late 20th century innovation. Early examples include Forrester's "system dynamics" and Stafford Beer's "management cybernetics." Early attempts at modeling relied on specifying dynamics in terms of differential equations (ordinary, partial, or stochastic) for continuous-time processes and difference equations for discrete time processes. Hence, for a system with 10 components each of which had time dependencies with, say, 5 other components, the model would need to specify 50 equations. If these components were being operated on ten independent actors, the number of equations would jump to 500. Further, if the actors were interdependently connected in a network (where some components of one actor could impact components of other actors) the number of equations would rise exponentially. Fortunately, object oriented programming environments make it possible to specify these models for a fraction of the effort. Further, re-specifying the model is also considerably easier in an object-oriented environment.

Clearly, many of the technical obstacles to computational modeling that stood in the way of earlier generations of researchers have been overcome. The opportunity to engage in extensive computational modeling entails addressing more specifically a set of theoretical and methodological issues. Self-organizing systems refer to a family of more specific complex systems, with many *genres of theoretical generative mechanisms*: auto-catalysis, mutual causality, deviation amplifying feedback, self-referencing (for a systematic review, see Contractor, 1994; Contractor & Grant, 1996). Several distinctions have been proposed in the generative mechanisms for modeling complex chemical systems (such as BZ reaction), physical systems (such as lasers), living systems (such as cells), and social systems (such as organizations). There is general agreement that unlike physical or chemical systems, living systems must include mechanisms that specify self-referencing, self-producing, and/or self-renewing. Maturana and Varela (1980) refer to these as autopoietic systems. However, as others (Capra, 1996; Staubmann, 1997) have noted, there is considerable disagreement on whether the generative mechanisms for living systems can also be applied to social systems. Maturana (1988) and Varela (1981) have expressed varying degrees of ambivalence about the viability of studying social systems as autopoietic. However, Luhmann (1990, p.3) argues for the study of social systems as an autopoietic system that "use communication as their particular mode of autopoietic reproduction. Their elements are communications that are recursively produced and reproduced by a network of communications and that cannot exist outside of such a network." Debates, such as the one between Luhmann (1990), Maturana (1988), and Varela (1981), are a critical step in the specification of models appropriate to social systems. It pre-empts the blind appropriation of models from the "hard" sciences – a problem that has plagued earlier generations of social scientists.

Self-organizing systems theory is explicitly concerned with understanding the emergent pattern of organization, that bridges micro and macro features of the complex system (Smith, 1997). Capra (1996, p. 82-83) notes that the "most important property is that it is a network pattern. … The pattern of life, we might say, is a network pattern capable of self-organization. This is a simple definition, yet it is based on recent discoveries at the very forefront of science." While Capra (1996) makes this argument in the context of living systems, the network framework can also be applied to studying self-organization in the organizational context. However, due to its meta-theoretical status, self-organizing systems theory does not offer *content-specific generative mechanisms* for organizational networks. These must be derived from existing social scientific theories or by extending these theories. Monge and Contractor (in press) identify ten families of such theoretical mechanisms that have been used to explain the emergence of communication networks in organizational research. These include: (a) theories of self-interest (social capital theory and transaction cost economics), (b) theories of mutual self-interest and collective action, (c) exchange and dependency theories (social exchange, resource dependency, and network organizational forms), (d) contagion theories, (social information processing, social cognitive theory, institutional theory, structural theory of action), (e) cognitive theories (semantic networks, knowledge structures, cognitive social structures, cognitive consistency), (f) theories of homophily (social comparison theory, social identity theory), (g) theories of proximity (physical and electronic propinquity), (h) uncertainty reduction and contingency theories, (i) social support theories, and (j) evolutionary theories.

These ten families of generative mechanisms for the creation, maintenance, and dissolution of organizational networks are illustrative of the need to ground the modeling of systems in domain specific social scientific theories. One of the mechanisms enumerated above, cognitive social structures (Krackhardt, 1987), is of particular importance from a self-organizing systems perspective. Consistent with the view of those scholars who argue that self-organizing systems must be modeled as observed by the participants in the network (rather than an outside observer), cognitive social structures model actors' behaviors on the bases of their perceptions of the overall communication network, even if these perceptions are at variance with the observed communication network.

Further, from a *methodological* standpoint, complexity theory has spawned several modeling techniques: such as cellular automata, neural networks, fractals, catastrophe models, and binary nets (or Boolean nets). The selection of an appropriate modeling technique must be guided by decisions about the genre of mechanisms and the nature of the variables being specified in the model. For instance, fractals are more useful to specify models of nested entities, while neural networks are more appropriate for modeling networked entities. Likewise, cellular automata models are most appropriate for studying actors whose attributes are influenced by the attributes of those in their immediate network "neighborhood" (of four other actors). On the other hand, binary nets (or Boolean nets) are more appropriate when the attributes of actors (which must be considered binary in nature, i.e. present or absent) are influenced by others actors in the network, including those not in their immediate neighborhood. For instance, Varela, Maturana and Uribe (1974) were exploring the most appropriate modeling environment to simulate autopoiesis in cells. They sought to model a network of processes in which components of the cell and its boundary helps produce, transform, and maintain other components of the cell and its boundary. After reviewing several models, they decided that cellular automata models were more appropriate than binary network models.

Examples of self-organizing systems models

In the past decade there have been several examples of modeling self-organizing social systems. Just in the past four years, four books have served as important compilations of studies of social systems from a self-organizing systems perspective. Cowan, Pines, and Meltzer's (1994) edited volume from the Santa Fe Institute, *Complexity: Metaphors, Models, and Reality*, Guastello's (1995) *Chaos, Catastrophe, and Human Affairs*, Robertson and Combs' (1995) edited volume, *Chaos Theory in Psychology and the Life Sciences*, and Eve, Horsfall, and Lee's (1997) edited volume, *Chaos, Complexity, and Sociology* present several nonlinear models of phenomena including human decision making, organizational motivation and conflict, stress and human performance, disaster relief, organizational adaptation, and innovation and creativity.

Further, there are several examples of social science research focusing attention specifically on the self-organization of networks (Stokman & Doreian, 1996). These studies use computational models that incorporate network mechanisms that both influence and are influenced by actors in the social network. It extends recent work in object-oriented modeling, cellular automata (CA), and neural networks to capture the ongoing, recursive and nonlinear mechanisms by which organizational networks evolve over time (Banks & Carley, 1996; Carley, 1997; Corman, 1996; McKelvey, 1997; Stokman & Zeggelink, 1996; Woelfel, 1993). Banks and Carley (1996) compared three mathematical models of network evolution based on social comparison theory (Heider, 1958), exchange theory (Blau, 1964) and constructuralism (Carley, 1990, 1991). They noted that the pattern of network evolution associated with the three models were not always distinct, thereby making it difficult to empirically validate one model over the other. They offer statistical tests that, at the very least, allow for the falsification of a particular model. Corman (1996) suggested that multidimensional CA models offer insights into the unanticipated consequences of collective communication behavior. His computer simulations of a simplified CA model based, in part, on Giddens' structuration theory suggested that integrationist strategies by individuals were, unintentionally and perversely, most responsible for segregation in communication structures. Zeggelink, Stokman, and Van de Bunt (1996) modeled the likelihood of various configurations of friendship networks that may emerge among an initial set of mutual strangers. Their stochastic model deployed network mechanisms of selection and contagion to explain the creation, maintenance and dissolution of friendship ties among the individuals. Stokman and Zeggelink (1996) developed simulations and then empirically tested the network configuration of policy makers charged with determining the fate of a large farming cooperative in the Netherlands.

The use of computer simulations to study the self-organization of networks requires considerable programming knowledge by researchers. In order to make these efforts more accessible to a larger community of researchers, Hyatt, Contractor, and Jones (1996) have developed an object-oriented simulation environment, *Blanche*, that provides an easy user-interface to support the specification of mathematical network models, executing simulations, and the dynamic analysis of the network evolution. Using *Blanche*, Contractor, Whitbred, Fonti, Hyatt, O'Keefe, and Jones (1998) modeled and empirically validated the self-organizing processes of a communication network at a public works department over a two year period. They found that two network generative mechanisms -- transitivity and group cohesion – played a statistically significant role in the self-organizing process.

Critique of self-organizing systems models

While the computational modeling research reviewed above has led to several important insights into the dynamic implications of social scientific theories, it has been plagued with many of the problems endemic to past research using simulations. There is a growing sense within the research community that individual studies within this area can arguably be indicted based on one or more of the following seven criteria. The modeling techniques and programs used to study nonlinear systems are frequently:

(i) not logically consistent (i.e., the model specification among the variables allowed for some logical inconsistencies),
(ii) not theoretically grounded (i.e., the models while perhaps being intuitively appealing were not contributing to cumulative theory building);
(iii) not sufficiently complex (i.e., the models did not include variables which substantively were critical);
(iv) based on simulation programming environments that do not have a good user interface and are not well documented;
(v) not easily replicable by a third party using different simulation programming environments;
(vi) not comprehensible to scholars interested in the substantive domain who are not quite as familiar with computational modeling; and finally
(vii) not validated using empirical data collected from field or experimental studies, hence leaving their substantive validity and import in question. Unfortunately, this indictment can be leveled against the overwhelming proportion of research reviewed above.

Methodology for the study of self-organizing systems

The response to the critique offered above is best framed as a case of Ashby's Principle of Requisite Variety. Complex modeling efforts, such as those proposed here, require the assembly of complex heterogeneous teams of researchers. This assembly represents both a “vertical” and a “horizontal” integration of research expertise. In terms of “vertical integration,” a coherent research program draws upon expertise in mathematical modeling, formal logic, organizational and communication theory, expertise in designing field and experimental studies, sophisticated statistical techniques, visualization, user-interface, computer programming, domain expertise, and end-user cooperation. These skills are typically distributed across multiple people, institutions and even disciplines. There is insight in the aphorism that "Computers are wonderful at turning good scientists into lousy programmers”; to which one may add, "Experiments and field studies are wonderful at turning good programmers into lousy empiricists."

Assembling a research team with the requisite variety, enables a comprehensive analytic approach to the study of self-organizing systems in the social sciences. Figure 1 below provides a schematic outline of this approach (Contractor, et al., 1998).

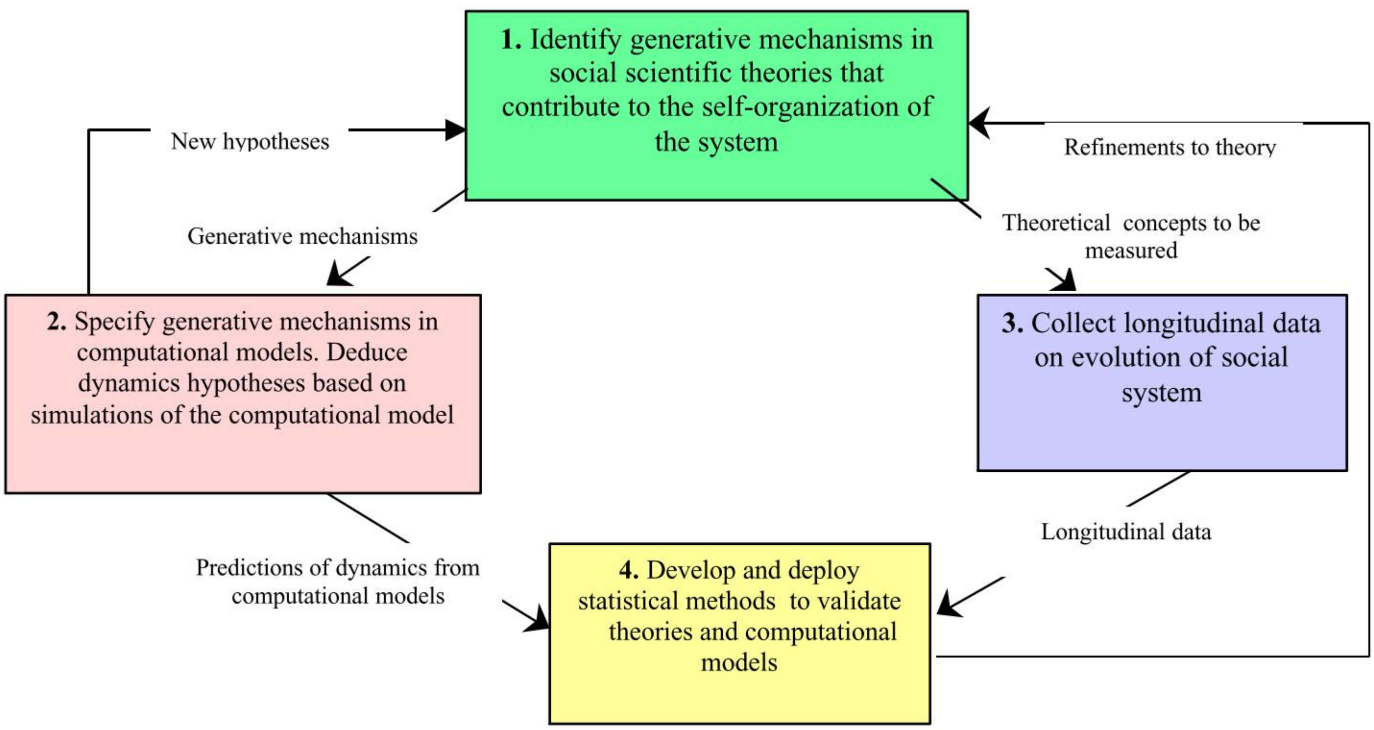

Figure 1. Analytic approach to study self-organizing systems

The first step (Box 1) begins with the identification of generative mechanisms derived from theories specific to the domain of the system being studied. The next step (Box 2) is to specify these generative mechanisms in a computational model. The genres of generative mechanisms (e.g., auto-catalysis, mutual causality, self-referencing) and the nature of variables (e.g., attributes, network relationships, binary, or continuous) should guide the selection of the appropriate computational model (e.g., cellular automata, binary nets, neural nets, fractals). Concurrent with this step (Box 3), efforts must be made to empirically collect data on the identical key variables that are being simulated in the computational model. Finally (Box 4), tests should be conducted to validate the dynamic hypotheses processes predicted by the computational models with the empirical data collected.

In some instances, validation of the dynamics predicted by the computational model may not be possible using conventional statistical techniques. For instance, computational models may generate strange attractors. The best prediction implied by a strange attractor is that the values of a certain variable fall within a certain range bounded by the "envelope" of the strange attractor. Eve (1997) argues that a strange attractor is in essence a "probability diagram" and is therefore a graphical analog of the digitally computed p-value in traditional statistics. "While one cannot say where the next point will appear on a strange attractor, it will appear somewhere on the strange attractor! Areas where the number of points are dense are areas of high probability of the appearance of the next point than are areas where preexisting points are rare" (Eve, p. 279). In addition, the Lyapunov exponent for the dimension of an attractor can also serve as a pseudo-statistic. In essence it "allows a test of the hypothesis as to whether an attractor is a fixed point or a limit cycle, and thereby nonchaotic, in which case the exponent is negative, or whether the attractor is aperiodic or chaotic, in which case the exponent is positive (Guastello, 1995, p. 64-65). Finally, the results from this validation should be used to extend and/or refine the theories examined in Box 1, an important iterative feature of computer-assisted theory building (Hanneman, 1987).

Conclusion

Prigogine and Stengers (1984, p. 55) heralding the dawn of the self-organizing systems paradigm, wrote: "Classical science, the mythical science of a simple, passive world, belongs to the past, killed not by philosophical criticism or empiricist resignation, but by the internal development of science itself." In the physical sciences, this new paradigm does not displace the majority of past research (Robertson, 1995). Rather, "the new paradigm demonstrates that knowledge gained under the old paradigm is true *under specific boundary conditions*" (Eve, 1997, p. 275). The boundary conditions refer to situations in the physical sciences where making simplifying linearizing assumptions of non-linear phenomena are defensible. However, in social systems, which are far more non-linear than their physical counterparts, there are very few instances where making linearizing assumptions are theoretically plausible or defensible. "Social science, dealing as it must with complex two-way interactions of many complex organisms, themselves feedback systems of almost unimaginable depth and complication, has until now been forced to use logical and mathematical instruments originally designed to deal with hugely simpler systems" (Turner, 1997, p. xxvi-xxvii). Hence the new self-organizing systems paradigm, with its conceptual and modeling tools particularly appropriate for studying non-linear phenomena, has an even greater potential for unleashing intellectual progress in the social sciences than it has in the physical sciences. For the better part of the 20th century, the common-sense nature of hypotheses tested by social sciences have often been chided as being the "deliberation of the obvious." A judicious use of computational modeling from a self-organizing systems perspective, holds the promise of ushering a new millenium where the world will witness a generation of social science research deliberating, explaining, and "predicting" the non-obvious.

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