Intra-organizational Computation and Complexity

Kathleen M. Carley
Social and Decision Sciences
and
H. J. Heinz III School of Policy and Management
Carnegie Mellon University

Running Head: Intra-organizational Computation and Complexity

Direct all correspondence to:

Prof. Kathleen M. Carley

Dept. of Social and Decision Sciences

Carnegie Mellon University

Pittsburgh, PA 15213

Email: kcarley@ece.cmu.edu

Tel: 1-412-268-3225

Fax: 1-412-268-6938

Intra-organizational Computation and Complexity

Kathleen M. Carley

Abstract

Organizations are complex systems. They are also information processing systems comprised of a large number of agents such as human beings. Combining these perspectives and recognizing the essential non-linear dynamics that are at work leads to the standard non-linear multi-agent system conclusions such as: history matters, organizational behavior and form is path dependent, complex behavior emerges from individual interaction, and change is inevitable. Such a view while descriptive, is still far from the level of specificity and predictive richness that is necessary for organizational theory. To increase the specificity and value of our theories we will need to take into account more of the actual attributes of tasks, resources, knowledge and human cognition. In doing so, it will be possible to achieve a more adequate description of organizations as complex computational systems. More importantly, we will also achieve a greater ability to theorize about the complexity of organizational behavior.

This paper describes complexity theory and computational organization theory. Then a description of organizations as complex computational systems is presented and operationalized as a computational model. Within this perspective, organizational behavior results form the actions of heterogeneous actors, the boundaries between agents, tasks, and resources are permeable, organizational roles emerge, organizational groups are networks, and information technology plays a key role as an interactive agents.

Intra-organizational Computation and Complexity

Organizations are complex systems. They are also information processing systems comprised of a large number of agents such as human beings. Combining these perspectives and recognizing the essential non-linear dynamics that are at work leads to the standard non-linear multi-agent system conclusions such as: history matters, organizational behavior and form is path dependent, complex behavior emerges from individual interaction, and change is inevitable. Such a view while descriptive, is still far from the level of specificity and predictive richness that is necessary for organizational theory. To increase the specificity and value of our theories we will need to take into account more of the actual attributes of tasks, resources, knowledge and human cognition. In doing so, it will be possible to achieve a more adequate description of organizations as complex computational systems. More importantly, we will also achieve a greater ability to theorize about the complexity of organizational behavior.

Intra-organizational computation and complexity is concerned with discovering, modeling, theorizing, and analyzing the fundamental nature of organizations as complex adaptive systems composed of intelligent but constrained adaptive agents. Within computational organization science researchers search for fundamental organizational objects and the mathematical formalism with which to describe their behavior and interactions. In physics, researchers search for laws governing gravitational, electromagnetic, and other fields of force. In both cases, the aim is to discover the most reasonable basis from which, at least in principle, theories of all other processes and behaviors can be derived. A complex process, is typically one in which there are many interacting objects (e.g. people or procedures in an organization of particles in physics) and for which it is rarely possible to proceed to a complete mathematical solution. Computational analysis, e.g., simulation or enumeration, can be used to track and analyze the detailed behavior

within and among these objects (people or particles). Whether we are modeling the behavior of people, robots, organizations or atoms – computer modeling at the quantum level becomes extremely complicated as soon as more than a few of these objects are involved. Computational complexity increases and the length of time for the system to be "solved" or "simulated" on the computer increases.

Such work is carried out via formal methods – mathematical and computational reasoning. This paper describes complexity theory and computational organization theory. Then a description of organizations as complex computational systems is presented. Specific attention is paid to the role of knowledge management, network theory, computational theory, and the study of the impacts of information and tele-communication technology within organizations. Implications, limitations, and directions relative to this perspective are discussed. References are summarized in Table 1.

*** Place Table 1 About Here ***

Literature review, summary and evaluation

Essentially, complex systems are non-linear systems, one sub-class of which may exhibit chaotic behavior.[i] The study of non-linear dynamics has a long history and many books at varying level of theoretical and methodological rigor exist. Complexity theory, is actually not a theory, but a paradigm, set of procedures and techniques, and an approach to complex systems. Classic introductions to complexity include Kauffman (1993), Holland (1995), and Bak (1996). Of particular value to social and organizational theorists with little background in this area is Anderson (1999) and Morel and Ramanujam (1999) in which the relation between complexity

and organization theory is described. The edited volume by Kiel and Elliot (1996) provides base models and measures and the review by (Mathews, White and Long, 1999). Standard information on the nature of chaos, dynamical systems and approaches for measuring the Lyapunov exponent are also provided. The mathematics aside, a number of books and articles have appeared in the last decade exploring the role of complexity in the social and organizational sciences (see for example, Eve, Horsfall, and Lee, 1997; International Symposium in Economic Theory and Econometrics, 1996; Pines, Cowan, Meltzer, 1999). Much of this work looks at complexity simply in terms of the metaphor – thus the vocabulary of emergence, holism, chaos, self-organizing, criticality, bifurcation, path dependence, etc. is used to describe organizations and the behaviors within and among them with little attention to the mathematical meaning behind those concepts. There are also a number of very useful websites in this area.[ii]

Within organization theory, complexity and the study of complex or adaptive systems has taken on three identities – (area 1) complex systems, (area 2) metaphor, and (area 3) computational theory building. Each of these will be described in turn and differences in the perspectives highlighted. The point here is not to gainsay the value of either the complex systems or the metaphorically based work or to exclusively laud the value of the computational work. To be sure, much can be learned via the relation between complexity and design (area 1), via reasoning from metaphors (area 2), and via reasoning from formal theory (area 3). It may well be that some of the empirical finding about complexity and design (area 1) are useful in validating the computational models (area 3). It may be that some of the "new doors" opened through metaphorical reasoning (area 2) will result in simulations being constructed to do theory development (area 3) relative to that topic. However, just because the terms of complexity theory and non-linear dynamics are used does not mean that the findings or claims have a solid

underlying mathematical base. Moreover, empirical results that are based on constructs derived from a metaphorical interpretation of words such as emergence, chaos, etc. may not be appropriate for testing, validating, or extending the formal theories. In order to link empirical data to computational models the same construct, e.g., complexity and all related constructs, must be measured in the model and the real world in exactly the same way. With this being said, let us consider the three areas.

Area 1: Complex Systems. Within organization theory more generally, the study of organizations as complex systems has a long history. Throughout the past 50 years, researchers have examined organizational complexity, in terms of the level of detail, number of objects, or degree of interconnections in the organizational or task design. This work, on organizations as complex systems, which is largely empirical, reasons about complexity using an understanding of organizational, task and process design. In many empirical studies, the complexity of the organization is measured in terms of perceived coupling among sub-groups, tasks, or procedures, the length of the process needed to go through to make a decision, or the number of people, resources, or constraints involved. Much of the research has looked at the relation between complexity and size, coordination (Klutzy, 1970) and formalization (Hall, Haas and Johnson, 1967). Much of this work resulted in, or advanced, structural theory and contingency theory. This work is independent of the work on complexity theory – although there are notable analogies. One of the major limitations in linking this work to complexity theory is the lack of agreement on how to measure complexity. Rarely is complexity measured using the metrics of complexity theory; e.g., rarely is the Lyapunov exponent calculated nor are tests for non-linear determinism run. Definitions aside, one of the key differences is that this body of work often looks at perceived complexity, which may or may not be systematically related to actual

complexity. Another difference is that the goal of this work is to understand the relation between the elements of organizational design and performance.

Area 2: Complexity as Metaphor. Recently, within organization science, metaphor and myth have outrun formal theory building and empirical analysis of complex systems. Most of the work in this area takes the language of complexity theory, treats it as metaphor and builds on that. For example, a complexity analogy has been used to create a revision and extension of contingency theory (Dow and Earl, 1999). The distinction between this metaphorical approach and the empirical study of organizations as complex systems just described is subtle. Both approaches are similar in that they characterize complexity in terms such as number of objects, or number of interconnections, or number of steps.   One difference, however, has to do with goal and intent. The complexity theory as metaphor work seeks to open up new avenues of research, develop new theory, using analogical reasoning from complexity theory (Dow and Earl, 1999), chaos theory (Thietart and Forgues, 1995), or biological adaptation (White, Marin, Brazeal, and Friedman, 1997). A second difference is that it is less empirical. A third difference is that the research building on the complexity theory metaphor moves beyond the level of complexity and its relation to organizational design and performance to talk about the processes within such a system and the effects of complexity – e.g. self-organization, bifurcation, and chaos.

Area 3: Computational Theory Building about Complex Systems. Computational approaches are particularly useful in examining complex adaptive systems in general and organizations in particular. Computational approaches have been used successfully to look at the dynamics of change and complexity in a number of organizational areas: design (Jin and Levitt, 1996; Burton and Obel, 1998), innovation and evolution (March, 1996; Gibson, 1999), adaptation and change

(Sastry, 1997), coordination (Carley and Prietula, 1994), emergence of hierarchy (Hummon, 1990), cooperation (Macy, 1991), organizational learning (Lant, 1994), and knowledge management (Carley and Hill, forthcoming). Over the past 25 years, on average, the models have become increasingly sophisticated from an algorithms perspective, increasingly grounded in empirical data, increasingly used to augment other methodological approaches, and increasingly tied to theory development. In addition, there has been an increase in the effort to link models to each other and to build on previous work.

Computation is the methodology of choice in these and related areas for a variety of reasons. First, there is a general recognition that the non-linear dynamics that characterize the system are not mathematically tractable; hence, simulation is needed. Second, there is a desire to develop empirically grounded theory – but the data with sufficient detail is ethnographic in nature and therefor consistent with the computational approach. Third, there is an interest in exploring both the short and long term implications of the theory as learning, adaptation, and evolution occur and computational analysis is particularly amenable to the study of emergent behavior. Finally, there is a growing concern with issues of scalability – that is, do behaviors remain the same, do our theories hold, as we move from groups of 2 or 3 to thousands? Again, through simulation, we can gain some insight into whether scale matters to the non-linear dynamics that underlie fundamental organizational processes. This is particularly important as we move into a world where technology is making organizations of unprecedented size and distribution possible and giving people unprecedented access to larger numbers of others, ideas, technologies, and resources.

Contemporary issues and debates

The interest in computation as it relates to organizations and complexity is profound. Work in this area has generated a number of findings and is currently being used within some corporations. This work has led to a new perspective or paradigm in the organizations area. An important initiative in this area is the linkage of multi-agent models and network methodology. One of the core issues is how to represent technology, particularly information and tele-communication or computational technology in these models. New methodologies, centered on understanding algorithmic complexity, are being developed that may enable us to better handle network data. Further, advances have been made in how to analyze, compare, and contrast these models and associated data.

Paradigm Development

The movement in computational organization theory is slowly leading to a new perspective on organizations. The evolving paradigm sees organizations as complex structures of agents, tasks, knowledge, and resources composed of intelligent adaptive agents (Carley and Gasser, 1999) operating under context and historical constraints, the structure of which can be designed and the behavior predicted (Burton and Obel, 1998). Through a process of synthetic adaptation, groups and organizations become more than the simple aggregate of the constituent personnel and become complex, computational and adaptive agents in their own right (Carley, forthcoming). Organizations are thus intelligent, adaptive and computational agents in which learning and knowledge are distributed (Hutchins, 1995) and where ecologies of skill and strategy (Padgett, 1997) and complex social properties emerge (Epstein and Axtell, 1997). The organization and the agents within it are not simply boundedly rational information processors (March and Simon, 1958), but are cognitive agents (Carley and Newell, 1994) limited both

structurally, cognitively, and emotionally. Within organizations, agents, resources, knowledge and tasks are connected by, and embedded in, an ecology of evolving networks (Carley and Prietula, 1994; Carley, 1991; Krackhardt and Carley, 1998) all of which change dynamically through an ecology of learning mechanisms (Carley and Svoboda, 1996) and change processes (Sastry, 1997).

Networks

One of the linking pins that brings computational organization theory together is network analysis. As researchers in this area have moved to modeling processes - the role of networks in affecting the hiring, firing, mobility, decision making, etc. processes has come to the fore. As researchers in this area have moved to modeling organizations as collections of agents, the role of networks in structuring and being structured by the interactions among these agents becomes critical. As researchers model inter-organizational alliances, the links between organizations and the processes by which they form again become central. Networks, whether between agents, or between agents and resources or knowledge or tasks, has become the glue that needs to be examined in order for computational theorizing to move beyond simple statements about individuals or dyads. The network approach has also led to common representation schemes which are allowing data to be transferred between computational models and is enabling experiment and field data collected as networks to be treated as input to the computational models.[iii] For example, VDT (Jin and Levitt, 1996) and ORGAHEAD (Carley and Svoboda, 1996) use essentially the same network based representation scheme for the organization's authority network and knowledge network (who knows what or has access to what resources). Since much of the computational organization theory work derives from the information processing tradition, where organizational structure and cognition constrain individual and

organizational decisions, it was a natural leap to use network methodology and representation, so amenable to describing the flow of information, to describe and measure snapshots of the organization through time.

One area in which the relation between complexity, computation, and networks is emerging is in the area of power laws. Complex systems, differ from random system, in that they display surprising, although sometimes subtle, regularities. One that has often been referred to is the tendency of the products of complex process to follow a power law distribution. A commonly touted example is the distribution of firm sizes, which is approximately $1/f$ - i.e., a power law. Recent research is suggesting that the topology of human networks also have regularities, which can be described by power laws. For example, Faloutsos, Faloutsos and Faloutsos (1999) found that despite the apparent randomness of the Internet, there are some surprisingly simple power-laws that describe the topology of the Internet. The power-laws they discover describe concisely skewed distributions of graph properties such as the out-degree associated with sites. For a complex system, the discovery of power laws is important. The power laws can be used to estimate important parameters such as the average neighborhood size. Power-laws can be used to generate and select realistic topologies for computational theorizing purposes, thus enabling the development of grounded theory.

Information Technology

A growing recognition in this community is that we cannot adequately explain, predict, or understand organizational behavior without also taking into account the information technology (IT) environment within and around the organization. From a computational perspective a number of questions have emerged. The primary question is what is the fundamental nature of

IT?   How   do   we   represent   IT   in   these   models?   Research,   both   field,   simulation,   and

experimental, has demonstrated that IT is both an agent and an agent enhancer.

Most research on the social or organizational impacts of technology assume that IT is an

enhancer. Therefor, the reason that IT does or does not effect change is because it augments or

changes the information processing capabilities of humans. For example, email is seen to effect

differences in communication because it enables asynchronous, high speed communication, and

is archivable. Researchers who view IT as an enhancer many often predict that one of the core

effects of email, the web, and various other IT will be that they will simply scale up current

organizations leading to larger, more distributed, organizations and more knowledgeable, more

connected individuals.

Nevertheless, new technologies have the ability to create and communicate information,

make decisions and take action. In other words, modern IT, is intelligent and the work in

computer engineering is making it more so. Many of the databases and webbots of the future

will be agents. Theories of social change in which IT is characterized as an agent have been

successfully employed to explain the effect of previous communication technologies; e.g.,

Kaufer and Carley (1993) use this approach to explain the impacts of print. Moreover, IT as

agent computational theories have led to important new findings about the limitation of IT in

effecting a unified and educated mass. In particular, this work suggests that IT is not a panacea

equally facilitating all individuals decreasing the socio-economic distance between disparate

groups. Rather, this research suggests that since individuals who know more or no more people

have more ability to learn new information, and will gravitate to IT agents, IT has the possibility

of increasing the socio-economic distance between the intellectual haves and have nots (Carley,

1995; Allstyne and Brynjolfsson, 1995). Finally, the IT as agent approach can be used to

accurately model and predict the behavior of organizations in which humans, webbots, smart databases, robots, avatars, and so forth all work together to perform organizational and social tasks (Kaplan, 1999).

Algorithmic Complexity

Algorithmic complexity is concerned with the length of the algorithm; loosely speaking, for two algorithms the one with more steps is more complex. Knowing the algorithmic complexity needed to do some task, to model some process, or to generate some organizational structure is valuable. The degree of algorithmic complexity can be used to guide development, suggest procedures for ruling out certain data as sufficient for testing certain models, determine the need for heuristic search procedures and tractability of data analysis, and enable more precise theorization. A variety of measures of algorithmic complexity, e.g., Kolmogorov-Chaitin, and a variety of proxies exist (which are often turned to for pragmatic reasons) (Lempel and Ziv ,1976). For the most part, social and organizational theorists have not attended to the role of algorithmic complexity. One advance in this area is the application of algorithmic complexity to determining the complexity of social and organizational networks (Butts, forthcoming).   Butts argues that there is a precise correspondence between the equivalence and the structure of the social network, and the use of reduced models. More precisely, the structure of a network is algorithmically complex to the extent that a long program is required to regenerate the structure. Thus, highly compressible structures that can be succinctly described by a set of equivalency classes of nodes and relations among the classes, are algorithmically simple. For example, if a social network can be accurately characterized in terms of sets of structurally equivalent nodes and the relations among the node sets, then it is algorithmically simple.   Social networks, which cannot be described in this way, are algorithmically complex.   Knowing the algorithmic

complexity of a network provides a mathematics for reasoning about fundamental organizational constructs such as roles, power, and groups.

Algorithmic complexity can also be applied to theories of organizations that are realized in terms of grammars. A grammar can produce a series of statements or sequences describing behavior. The algorithmic complexity of these statements is related to the complexity of the grammar from which they were generated (Nordahl, 1988). We can take any organizational theory, or general theoretical statements, and express the theory or specific statements as a sequence. The degree complexity in these statements provides a guideline for the complexity of the grammar, which will be required to represent real-world organizational behavior. This in turn provides guidance in ruling out or in various proposed grammars (and associated theorem provers) purported to be adequate for the organizational behaviors they describe.

As we move into the realm of large scale data analysis, algorithmic complexity plays another role. With large scale data bases, or data with high levels of inter-connectivity, such as network or spatial data, there is a need to answer questions such as how do points cluster and how do regions compare. Answering these questions typically requires looking at all points at least once. In this case the complexity is at least proportional to the number of points (N). When all dyads are considered it is at least proportional to N^2. Advances in data-mining, machine learning, and algorithms are enabling organizational researchers to address new and important organizational questions.

Comparison of Models

The art of analyzing complex systems is that of finding the means to extract from the computational theory no more information than one needs. This means that the researcher is

called upon develop and use virtual experiments to assess core findings. The non-linearities inherent in the underlying processes when coupled with the large number of processes, agents and variables leads to a system about which it is difficult for humans, unassisted by computation, to effectively reason about the consequences of any one action or change. Computational analysis, both enumeration and simulation, becomes an important tool for generating hypotheses about the behavior of these systems that can then be tested in the lab and field (Carley, 1999).

Computational models of organizations need to be built at varying levels. It is common in organizations to talk about micro and macro behavior. Computational models are often heralded as the means for linking the micro to the macro. To an extent, this is true. In addition, different computational models and methods can be used at multiple levels and used to reason across levels if the organization community would create a more detailed hierarchical structure for analysis – similar to what has been developed in physics. An approach, drawn from physics, is for the research community to develop a hierarchical structure of simple models each of whose function is to make possible and practical the analysis of the system being studied at that particular level of complexity. Each successive level gains in complexity. The logical relationship between contiguous levels needs to be established so that the researcher knows that the methods used at any one level are supported by the body of fact and theory that have been gathered across all levels. This hierarchical approach can be applied at the micro level, the macro level, or both. To an extent this is being done, albeit not systematically in the area of organizational culture. Carrol and Harrison's (1991) single factor model of organizational culture and Carley's (1991) construct model of culture formation are both consistent with the body of findings regarding culture and enculturation but operate at different levels of complexity.

Computational organization theory models vary dramatically in the level of detail used to describe and represent the agent, resources, knowledge, task, organizational structure, culture and technology. The more detailed, the more veridical these underlying models the more precise the predictions possible from the model, the more useful the model as a managerial tool. The classic simple abstract model is the Garbage Can Model (Cohen, March and Olsen, 1972) in which organizations are represented by personnel with energy and a salience rating of various problems and a set of decision, problems, and solutions flow through the organization. In contrast, two of the most detailed and tested models of organizational behavior are VDT (Jin and Levitt, 1996) and the organizational consultant (Burton and Obel, 1998). The simpler more abstract models are typically referred to as intellective models. For these models, a central research goal is theory building: to discover general principles underlying organizational behavior. The more detailed models may allow the researcher to use the model to emulate specific organizations by entering specific authority structures and/or procedures. For these models a key research goal is organizational engineering: to examine whether or not the performance of a specific organization will be affected by making some specific change such as re-engineering the task in a particular way or adding a new technology.

For each scientific method, methodologists work to develop procedures for overcoming the limitations of that methodology. In survey analysis, for example, specialized sampling procedures can be employed to increase the generalizability of the results. In computational research, one of the limitations has to do with the extent to which model specifications are driving the outcome. The assumptions made in constructing the computational model and the way in which the basic processes are characterized may, but need not, affect the generalizability of the outcomes. To address this issue, a variety of techniques are used by computational

theorists; such as, sensitivity analysis, parameter space exploration, and docking. For example, Monte Carlo techniques are used to average out assumptions about parameter values (Balci, 1994), empirical data is used to calibrate the model (Carley, 1999) and docking (Axtell, Axelrod, Epstein, and Cohen, 1996) is to used to understand the match between two models with different core processes.

Central Questions That Remain Unanswered

The past decade has witnessed important recent advances in machine learning, social and organizational networks, and toolkits for computer modeling. These advances, together with the ubiquity of computing, and the growing recognition of the inherent complexity and dynamics of organizations has increased the general interest in computational modeling and theory building. As more work in this venue has appeared a series of questions have emerged that need to be attended to for major advances in this area to occur.

Issue 1: Representation. As the field of artificial intelligence matured researchers came to recognize the criticality of representation; i.e., how should core elements of the model be represented. This recognition led to a greater understanding that representation is not an art. Rather, research on how to represent model elements such as tasks, process, knowledge, resources, goals is central to the scientific enterprise. Appropriate representation schemes affect the algorithmic complexity of the model and speed of processing. They also affect the types of hypotheses and findings that can be derived from the model and the type of data needed to validate, calibrate or develop the model. As research in this area matures, common representation will be key to sharing and integrating models.

Issue 2: Relative Impact of Task. Within the computational organization area a number of tasks are emerging as canonical. These include: the sugar production task, the binary-choice task (or its variant the radar detection task), the maze task, and the warehouse task (or its variant the web search tasks). This set does not span the space the tasks. Research using these tasks underscores the lesson from contingency theory and operations management that the nature of the task determines the effectiveness of the organizational structure and procedures. Both in the field and in virtual experiments many critical parameters have been found to affect the value of various organizational designs. These include at least task complexity, degree of coupling or interdependence, knowledge intensity, the degree of routinization, whether resources are consumed, the speed with which the task must be completed, and the allowable error margin. Nevertheless, we do not have a comprehensive understanding of the space of tasks, how to represent tasks in general, and exactly how the various aspects of task interface with organizational goals and constraints to determine the way in which organizations are and should be designed for effective performance.

Issue 3: Learning. Organizational researchers have turned with increasing interest to the area of organizational learning. This work has highlighted that learning does occur at the organizational level and that within the organization there are multiple types of learning. Three types of learning commonly referred to include: experiential (learning by doing), expectation based (learning by planning), and imitation (learning from others). Each of these types of learning becomes embedded in the minds of individuals, in data bases, and in routines. The computational work has highlighted another type of learning – structural. Structural learning is concerned with the embedding of knowledge in the relations connecting personnel, or organizations, or tasks. Core issues center around the relative effectiveness of the different types

of learning, the interaction between learning and organizational memory, the role of IT in retaining organizational memory and enhancing learning, and the relation between learning and adaptation.

Issue 4: Detail. Perhaps the hardest issue being faced in the computational organization area is how detailed do the models need to be. Current models run from simple intellective models like the garbage can model (Cohen, March and Olsen, 1972) to emulative models like VDT (Jin and Levitt, 1996). A basic answer is the level of detail depends on the purpose of the model. However, this answer does not address the core concerns, many of which have to do with the philosophy of science. On the one extreme, high predictability is expected; e.g., the results from engineering models often correlate .9 or better with the behavior of the systems they emulate. On the other extreme, extremely simple models are the most easily understood and replicable. At issue then is a fundamental tradeoff in the way in which research is conducted. However, the effects of detail may be more pernicious than expected. A recent study examined the impact of organizational structure on performance – while varying the level of detail (or veridicality) in the model of the agent. A key result was that the observed performance of the simulated organizations varied with structure and the level of detail in the agent model. In other words, one must carefully consider the impact of detail on the theoretical propositions derivable from the model.

Issue 5: Emergence and Constraint. Organizations often show an intelligence and a set of capabilities that are distinct from the intelligence and capabilities of the agents within them, or the average behavior of those agents (Epstein and Axtell, 1997; Padgett, 1997 Kauffman, 1993; Macy, 1991). Organizational behavior cannot be predicted by looking at the average behavior, or even the range of behaviors, of the ensemble members, or even that of the CEO or top

management team. Rather, it is , at least in part, an emergent property of the decisions and actions taken by the set of heterogeneous agents within the organization who are in turn constrained and enabled by both their cognitive abilities and their interactions with others (Simon, 1955, 1956). The networks linking agents, knowledge, tasks, etc. affect and are affected by these agents. This web of interconnections serves to constrain and enable what actions are taken when, by whom, and the efficiency of those actions. These networks, coupled with the agents' cognitive processes, dictate what changes can occur, are likely to occur, and will have what effect (Carley and Newell, 1994). Computer modeling, because it can take into account the complexities of network dynamics and cognitive processes facilitates accurate prediction and helps us to move from saying interesting complex behaviors will emerge to saying what behaviors will emerge when. As such, a great deal of research is needed on what behaviors will emerge under what conditions and on what future scenarios are likely to occur or are infeasible given the constraints of human cognition, socio-economic policies, and the way in which the extant networks change, constrain, and enable individual behavior.

Issue 6. Training tools: One of the major difficulties in this area is the lack of adequate educational material. First, there is a lack of textbooks. The only textbooks in the area are focused just on simulation. An important exception here is Gerhard Weiss (1999)*Distributed Artificial Intelligence*. which is an upper-division or Ph.D. level text. Nevertheless, what is needed is a text focused more specifically on organizations. Second, there is not an educational computational testbed filled with multiple models that students can easily use, compare, contrast, adapt etc. in order to learn how build models and evaluate them. Third, most small intellective models have not been archived together with their results and post-processing algorithms. This makes the task of re-implementing those models and replicating earlier results non-trivial.

Additional educational material are critical for the advancement of the field. Major advances in organizational research were made when statistical packages and text books became available. We can expect similar levels of advance when comparable educational material become available for computational modeling, analysis and theorizing.

New and Emerging Directions

A number of exciting and important research directions are emerging in this field. Several that promise to have sweeping consequences include — the extension of the network approach, the focus on IT, the study of emotions, and the development of intelligent analysis tools. In all cases, the advances are being made possible by linking computational modeling of complex systems to other areas. The extension of the network approach is facilitated by linking work on mental models and cognitive agents to work on social networks and task management. The IT work is enabled by linking work on information diffusion, learning, and discovery to work on networks, and technology. Emotions based research is facilitated by linking work in cognitive psychology with that on learning, structural embeddedness, procedures and task performance. The new approaches to computational analysis rely on machine learning, intelligent search, and data mining techniques.

As organizational theorists address issues of dynamics, increasing attention is paid to the link between knowledge, memory, procedures, learning, on the one hand and networks, tasks, personnel, technology on the other. This growing concern with the link between knowledge and interaction plays out in a number of venues — knowledge management, organizational decision making, change management, transactive memory, etc. Across the board is a growing need to understand how agents and knowledge link within and among organizations. This is leading to

new studies of learning, adaptation, impact of technology, and so forth. This work is facilitated by a network perspective. More precisely, traditional social network techniques, which have heretofore been concerned with just the relations among people, or just the relations among organizations, are being extended to look at any and all relations including the relations among information (mental models). Krackhardt and Carley (1998) suggested a meta-network scheme, PCANS, that uses networks of relations among individuals, resources, and tasks to derive organizational propositions. A similar approach in the area of knowledge management was proposed by Carley and Hill, forthcoming. A generalization of these schemes to include knowledge management issues and strategic inter-organizational issues is described in table 2. The core concept is that webs of affiliation link agents, knowledge, resources, tasks and organizations into a giant meta-network. Changes in policy, procedures, IT, and institutional arrangements; new discoveries, organizational births, mergers, and deaths, and personnel turnover and promotions all effect changes in this meta-network by altering the nodes and or relations. To understand such changes and to facilitate the ease of such transitions one needs to understand the impact of those changes on the meta-network. Tracking these changes, tracking this meta-network, lies at the core of being able to predict and manage such changes; i.e., it lies at the heart of knowledge management and strategic decision making.

*** Place Table 2 About Here ***

The advantage of a meta-network approach to knowledge management, organizational analysis, etc. is that it enables the researcher to employ the well developed network methodology in the study of other organizational topics. Another advantage is that it enables both models and data collection to proceed from the same representation base, thus facilitating docking, calibration, and validation. As more data is collected from firms using this representation

scheme and stored in a common space (such as the web), it can be employed by multiple computational models. Such data archiving using a common meta-network representation enables not only more grounded theories, but it also enables the models to serve as virtual laboratories drawing on web-accessible data in which practitioners and scientists can conduct what-if analysis on the potential impact of policy changes, new procedures, new institutional arrangements and new IT. Research needs to proceed on how to automatically collect and maintain such data and on the level of detail at which the data needs to be collected.

The rapid development of new forms of information technology (IT) create the promise of new ways of organizing and doing work. As we have moved into the realm of e-commerce organizational researchers in general, and computational organizational theorists in particular, have begun to examine the relationship between IT and fundamental organizational processes and forms. One of the most promising areas is the use of computational models to understand the impact of information technology within and among organizations. Modeling modern IT also requires modeling learning, as the IT itself is becoming intelligent and capable of learning and because organizational learning and search affect the organization's technological competence (Stuart and Podolny, 1996 Computational work on organizations and IT is facilitated by the emergent neo-information processing paradigm. The information processing paradigm centered on the recognition that what information is available to whom when determines organizational outcomes. The neo-information processing paradigm uses recent findings from a variety of areas, including cognitive science, social networks, and distributed artificial intelligence to provide precision and specific underlying models to the general claims of information processing. Thus, the general notion of a boundedly rational agent has been replaces with exact specifications of a cognitive agent, often embodied in a general empirically grounded cognitive

model such as Soar. The general notion of structural limitations on access to information has been replaced with the way in which the agents and organizations are embedded in networks influences access to information, the rate of information diffusion, and the relative power of structural positions. Collectively, the result provide a more precise understanding of the nature of information, the way in which different types of information are affected by learning processes and affect decision processes, the mechanisms for controlling the flow of information, the impact of information enablers and constraints, and so forth.

One interesting notion that has emerged in the neo-information processing area is the that of mutable boundaries. In most organizational research, individuals, organizations, tasks, resources, etc. are treated as entities with concrete and immutable boundaries. Thus, a task or resource moved from firm to firm remains essentially the same. However, from a neo-information processing perspective, the characteristics of these entities depends on the information available and their information processing capabilities. Since the information available depends on the exact position of the entity in the meta-network, moving it about changes its' characteristics. Thus, the boundaries around agents, task, etc. are to an extent mutable, particularly for composite agents such as workgroups and organizations. A configuration is a particular combination of agents, resources, knowledge, tasks, etc. organized to meet some objective. Consider the objective of refilling stock in a store. The individual with pen, ink, whiteout, paper, ledger and inventory list writing a note is one configuration, and another is the web-bot sending automated email orders when a sensor in the inventory system indicates depletion is near. Advances in emergent agents and intelligent systems are enabling organizational theorists to rethink the basic nature of organizing.

From the general work on complex systems and from decades of work from a contingency theory perspective, a number of classic findings have emerged; such as, there are multiple configurations to achieve any organizational objective, different organizational objectives require different configurations, history and order effects are critical (i., path dependence exists), and overall system behavior is highly non-linear. The recent work which suggests that the boundaries between agents, tasks, etc. are mutable, also suggests that there are an ecology of learning mechanisms which collectively lead the organization to engage in meta-learning. Through such meta-learning the organization develops norms and procedures which in turn become institutionalized. Such meta-learning also leads to the emergence of diversification and heterogeneous behavior at the organizational level. The line between intra- and inter-organizational behavior blurs as research on he processes underlying meta-learning and institutionalization of behaviors progresses.

Most of the work in complexity and in computational organization theory, when the agents has been the focus of concern, has treated the agent as an intelligent adaptive being. However, recent work in cognitive psychology has moved beyond this to consider the role of emotions relative to cognition. Similarly, some organizational theorists are beginning to look at emotions, and in particular trust, particularly distributed work settings or between groups or organizations. One of the motivations is that emotions in general, and trust in particular, may play a greater role in the organizations of the future where personnel are more distributed. Essentially, there has been an implicit assumption that in organizations, since personnel know each other, see each other, etc. trust existed and emotions were kept under control or were irrelevant. However, as work is out-sourced, as more temporary workers are employed, as work is distributed geographically and temporally and as work proceeds at a faster pace (and presumably under

more stress, the role of emotions may be more critical. While a model of the emotional-organizational agent does not exist, recent work points to the potential value of emotions as a coordination mechanism, and the factors that may make the play of emotions important or irrelevant.

Promising avenues also exist at the methodological level. If we look back at the computational organization models of the 1970's we find that those models tended to be exceedingly simple – only a few lines of codes, a few agents, etc. Today, many models are more complex (even algorithmically). With the models of the 1970's it was possible to run a comprehensive analysis of the impact of all parameters built into the model. The space of outcomes could be completely simulated. Today, this is no longer possible for all models. Many models are sufficiently detailed that a complete sensitivity analysis across all parameters cannot be done in a feasible amount of time; rather, researchers often use response surface mapping techniques, experimental designs and statistical techniques to examine key aspects of the models. Indeed, one of the key areas of research is how to validate and test these highly complex models. Another key research area is how to use intelligent agents to automatically navigate the parameter space and run virtual experiments.

Computational analysis and theorizing is playing an increasingly important role in the development of organizational theory. In part this is due to the growing recognition that social and organizational processes are complex, dynamic, adaptive, and non-linear, that organizational and social behavior emerges from interactions within and between ecologies of agents, resources, knowledge, tasks, and other organizations and that the relationships among and within these entities are critical constraints on, and enablers of individual and organizational decision making and action. In part, the computational movement is due to the recognition that

organizations are inherently computational since they have a need to scan and observe their environment, store information and procedures, communicate, and transform information through human or artificial agents. Computational theories are providing the organizational research with both a new toolkit for examining organizations and new insights into the fundamental nature of organizations. Computational models have value beyond theory building. They can also be used for experimental and survey refinement, the comprehension and visualization of dynamics, and the comprehension and visualization of complexity.

Bibliography

Alstyne, M. v. and Brynjolfsson, E., 1995. Communication Networks and the Rise of an Information Elite -- Does Communication Help the Rich get Richer? Paper presented at the International Conference on Information Systems, Amsterdam.

Anderson, Phil. 1999. *Organizational Science*.

Axtell, R., R. Axelrod, J.M. Epstein, and M.D. Cohen, 1996. "Aligning Simulation Models: A Case Study and Results." *Computational and Mathematical Organization Theory*, 1(2): 123-142.

Bak, P., 1996. *How Nature Works: The Science of Self-organized Criticality*, Copernicus.

Balci, O., 1994. Validation, Verification, and Testing Techniques Throughout the Life Cycle of a Simulation Study. *Annals of Operations Research* 53: 121-173.

Burton, Richard M. and Borge Obel. 1998. *Strategic Organizational Design: Developing Theory for Application*, Norwell, MA: Kluwer Academic Publishers.

Butts, Carter, forthcoming. *Social Networks*.

Carley, K. and A. Newell, 1994. "The Nature of the Social Agent." *Journal of Mathematical Sociology*, 19(4): 221-262.

Carley, K. and M. Prietula, 1994. "ACTS Theory: Extending the Model of Bounded Rationality," Pp. 55-87 in Kathleen M. Carley & Michael Prietula (Eds.), *Computational Organization Theory*. Hillsdale, NJ: Lawrence Earlbaum Associates.

Carley, K., and A. Newell. 1994. "The Nature of the Social Agent." Journal of Mathematical Sociology , 19(4): 221-262.

Carley, K.1991. "A Theory of Group Stability." *American Sociological Review* , 56(3): 331-354.

Carley, K.M. and D.M. Svoboda, 1996. "Modeling Organizational Adaptation as a Simulated Annealing Process." *Sociological Methods and Research*, 25(1): 138-168.

Carley, K.M. and V. Hill, forthcoming. "Structural Change and Learning within Organizations. " . In Anne Miner (Ed.) %%%. JAI Press

Carley, K.M. forthcoming. "On the Evolution of Social and Organizational Networks." In D. Knoke (Ed) Research in the Sociology of Organizations volume on Networks In and Around Organizations. JAI Press.

Carley, Kathleen and Allen Newell, 1994, "The Nature of the Social Agent." *Journal of Mathematical Sociology* , 19(4): 221-262.

Carley, Kathleen M. and Les Gasser, 1999. "Computational Organization Theory." Ch. 7 in Gerhard Weiss (Ed.) *Distributed Artificial Intelligence*. Cambridge, MA: MIT Press.

Carley, Kathleen M., 1999. "On Generating Hypotheses Using Computer Simulations. " *Systems Engineering*, 2(2): 69-77.

Carley, Kathleen M., 1999. Validating Computational Models. CASOS Working Paper, CMU

Carley, Kathleen, 1995, "Communication Technologies and Their Effect on Cultural Homogeneity, Consensus, and the Diffusion of New Ideas." *Sociological Perspectives* , 38(4): 547-571.

Cohen, M.D., J.G. March and J.P.Olsen. 1972. "A Garbage Can Model of Organizational Choice." *Administrative Sciences Quarterly*, 17(1), 1-25.

Dow and Earl (Eds.) 1999. Contingency, complexity and the theory of the firm. Cheltenham : Edward Elgar.

Epstein, Joshua and Rob Axtell. 1997. *Growing Artificial Societies.* Boston, MA: MIT Press.

Etzioni Amatai. (Ed.) 1961.*Complex Organizations: A Sociological Reader.* New York: Holt, Rinehart & Winston

Eve, Raymond A., Sara Horsfall, and Mary E. Lee (Eds.), 1997. *Chaos, complexity, and sociology : myths, models, and theories*. Thousand Oaks, Calif. : Sage Publications.

Faloutsos, Michalis, Petros Faloutsos and Christos Faloutsos, 1999. On Power-Law Relationships of the Internet Topology, SIGCOMM 1999.

Gibson, David, 1999. Mapping the dynamics of change : a complexity theory analysis of innovation in five Vermont high schools: Ph.D. dissertation, University of Vermont. 1999.

Hall, Richard, Haas, J. Eugene, Johnson, Norman J., 1967. Organizational Size, Complexity, and Formalization. *American Sociological Review*, 32(6): 903-912.

Harrison J.R. and G.R. Carrol. 1991. Keeping the Faith: A Model of Cultural Transmission in Formal Organizations. *Administrative Science Quarterly*, 36, 552-582.

Holland, John, 1995. *Hidden Order: How Adaptation Builds Complexity*. Helix Books.

Hummon, Norman P., 1990. Organizational Structures and Network Processes. *The Journal of Mathematical Sociology*, 15(2): 149-161.

Hutchins, E., 1995. *Cognition in the Wild*. Cambridge, MA: MIT Press.

International Symposium in Economic Theory and Econometrics, 1996. Commerce, complexity, and evolution : topics in economics, finance, marketing, and management : proceedings of the Twelfth International Symposium in Economic Theory and Econometrics . University of New South Wales.

Jin Y. and R. Levitt, 1996. The Virtual Design Team: A computational model of project organizations. Computational & Mathematical Organization Theory, 2(3): 171-196.

Kaplan, David, 1999. The STAR System: A Unified Multi-Agent Simulation Model of Structure, Task, Agent, and Resource. Unpublished Ph.D. Thesis, Heinz School of Public Policy and Management, Carnegie Mellon University

Kaufer, David S. and Kathleen M. Carley, 1993, *Communication at a Distance: The Effect of Print on Socio-Cultural Organization and Change,* Hillsdale, NJ: Lawrence Erlbaum Associates.

Kauffman, Stuart, 1993. "At Home in the Universe: The Search for Laws of Self Organization and Complexity",

Kiel, Douglas and Euel Elliott (Eds.), 1996. *Chaos theory in the social sciences : foundations and applications*. Ann Arbor, MI : University of Michigan Press,

Klatzky, S.R., 1970. Relationship of Organizational Size to Complexity and Coordination. *Administrative Science Quarterly*, 15(4): 428-438.

Krackhardt, David and Kathleen M. Carley, 1998. "A PCANS Model of Structure in Organization" Pp. 113-119 in *Proceedings of the 1998 International Symposium on Command and Control Research and Technology*. June. Monterray, CA.

Lant, T., 1994. Computer Simulations of Organizations as Experiential Learning Systems: Implications for Organizational Theory. Ch 9 in *Computational Organization Theory*, edited by K.M. Carley and M.Prietula, Hillsdale, NJ: Lawrence Erlbaum Associates.

Lempel, A. and Ziv, J., 1976. ``On the Complexity of Finite Sequences." IEEE Transactions on Information Theory, 22, 75.

Lindgren, K. and Nordahl, M., 1988. "Complexity Measures and Cellular Automata." Complex Systems, 2, 409-440.

Macy, Michael W., 1991. Chains of Cooperation: Threshold Effects in Collective Action. *American Sociological Review*, 56(6): 730-747.

March, J.G. and H.A. Simon, 1958. *Organizations*. New York, NY: Wiley.

March, James G. 1996. "Exploration and Exploitation in Organizational Learning." In *Organizational Learning*, edited by M. D. Cohen and L. S. Sproull. Thousand Oaks, CA: Sage.

Mathews, K. Michael; White, Michael C.; Long, Rebecca G., 1999. Why Study the Complexity Sciences in the Social Sciences? *Human Relations*, 52(4): 439-462.

Morel, Benoit and Rangaraj Ramanujam, 1999, Through the Looking Glass of Complexity: The Dynamics of Organizations as Adaptive and Evolving Systems. *Organization Science*.

Padgett, John F. 1997. "The Emergence of Simple Ecologies of Skill." Pp. 199-222 in *The Economy as an Evolving Complex System II* Vol. XXVII, edited by B. Arthur, S. Durlauf and D. Lane. Reading MA: Addison-Wesley.

Pines, David. Cowan, George. Meltzer, David (eds.), 1999. Complexity : metaphors, models, and reality. Addison-Wesley, Santa Fe Institute series.

Sastry, M. Anjali, 1997. Problems and Paradoxes in a Model of Punctuated Organizational Change. : Administrative Science Quarterly, 1997, 42, 2, June, 237-275.

Simon, Herbert. 1955. "A Behavioral Model of Rational Choice." Quarterly Journal of Economics, 69: 99-118.

Simon, Herbert. 1956. "Rational Choice and the Structure of the Environment." Psychological Review, 63: 129-138.

Stuart, Toby E. and Joel M. Podolny. 1996. "Local search and the evolution of technological capabilities." Strategic Management Journal, 17: 21-38.

Thietart, R.A. and B.Forgues, 1995. "Chaos Theory and Organization." *Organization Science* , 6: 19-31.

White, Michael C., Marin, Daniel B., Brazeal, Deborah V. and Friedman, William H., 1997. The Evolution of Organizations: Suggestions from Complexity Theory about the Interplay between Natural Selection and Adaptation. *Human Relations*, 50(11): 1383-1401.

Table 1: Summary of references				
Reference	**Area**	**Key Concepts**	**Key Contribution**	**Approach**
Alstyne, Brynjolfsson, 1995	Computational Social Science	Networks Communication IT	Impact of IT on information diffusion	Computational theorizing
Anderson, 1999	Complexity Theory	Organizations	Organization Theory	Overview
Bak, 1996	Complexity Theory	Physics	Self Organized Criticality	Introduction
Burton and Obel. 1998	Computational Organization Theory	Design Strategy	Expert System integrating the findings of contingency theory into a unified system for designing organizations	Computational analysis
Butts, Carter forthcoming	Complexity	Networks	Relation of complexity to networks	Computational theorizing
Carley and Gasser, 1999	Computational Organization Theory	Agents Tasks Learning Models	The nature, assumptions, and basic models in the field	Introduction
Carley and Hill, forthcoming	Computational Organization Theory	Knowledge Networks Organizations Culture	Combines information processing and networks to provide a perspective on knowledge management and culture	Computational theorizing
Carley and Newell, 1994	Computational Organization Theory	Agents Cognition Knowledge	The Social Agent Social Turing Test	Theory
Carley and Newell, 1994	Computational Social Science	Agents Knowledge Cognition	The model social agent	Formal argument
Carley and Svoboda, 1996	Computational Organization Theory	Agents Knowledge Task	Organizational adaptation Strategic response as annealing process	Computational theorizing
Carley and. Prietula, 1994	Computational Organization Theory	Agents Cognition Tasks Social Networks	ACTS Theory	Computational theorizing
Carley, 1991	Computational Social Science	Construct Agents Knowledge Groups Culture	Socio-cognitive model of information diffusion and the co-evolution of social networks and culture	Computational theorizing

Carley, 1995	Computational Social Science	Agents Knowledge Networks IT	Impact of IT on information diffusion	Computational theorizing
Carley, 1999	Computational Organization Theory	Hypothesis generation	Approach to generating hypotheses from simulations using virtual experiments.	Introduction
Carley,. forthcoming	Computational Organization Theory	Agents Knowledge Learning	Network evolution	Computational theorizing
Cohen, March and Olsen, 1972	Computational Organization Theory	Decisions Agents Access Salience	Garbage Can Model	Computational theorizing
Dow and Earl, 1999	Complex Systems	Performance Environment	Recasts contingency theory in terms of complexity	Metaphor
Epstein and Axtell, 1997	Computational Social Science	Agents Adaptation	A-life models of emergent social behavior	Computational theorizing
Etzioni, 1961	Complex Systems	Organizations Environment	Nature of organizations	Overview
Eve, Horsfall, and Lee, 1997	Complexity	Organizations Society	Discussion of role of complexity in social sciences	Mixed
Faloutsos, Faloutsos and Faloutsos, 1999	Computer Science	Complexity Networks	Power laws in internet topology.	Computational analysis
Gibson, 1999	Complexity	Educational systems	Innovation and education	Computational analysis
Hall, Haas and Johnson, 1967	Complex Systems	Size formalization	Organizational design	Empirical
Harrison and Carrol, 1991	Computational Organization Theory	Culture Evolution	Emergence and maintenance of distinct cultural forms in organizations	Computational theorizing
Holland, 1995	Complexity Theory	Biology	Adaptive Systems	Introduction
Hummon, 1990	Computational Social Science	Networks Hierarchy Emergence	Division of labor & hierarchy evolve out of network processes.	Computational theorizing
Hutchins, 1995	Complex Systems	Cognition	Learning and Decision Making	Empirical
International Symposium	Complexity	Economics	Discussion of role of complexity in economics	Mixed

in Economic Theory and Econometrics, 1996				
Jin and Levitt, 1996	Computational Organization Theory	Design Teams Skills Agents Tasks	The virtual design team	Computational analysis
Kaplan, David	Computational Organization Theory	Agents Knowledge IT Networks	STAR system	Computational theorizing
Kaufer and Carley, 1993	Computational Social Science	Agents Knowledge Print	Impact of print on information diffusion	Computational theorizing
Kauffman, 1993	Complexity Theory	General Science	Order	Introduction
Kiel and Elliot, 1996	Complexity	Measures	Introduction	Measures and applications
Klatzky, 1970	Complex Systems	Size coordination	Organizational design	Empirical
Krackhardt and Carley, 1998	Computational Organization Theory	Agents Tasks Resources	A network approach to formal organizational theory	Formal argument
Lant, 1994	Computational Organization Theory	Organization Learning	Multiple approaches to learning	Review
Lempel and Ziv ,1976	Complexity	Measures	Measures of complexity	Formal argument
Lindgren and Nordahl, 1988	Complexity	Logic	Relation of complexity to logic	Measures
Macy 1991	Computational Social Science	Cooperation Collective action	Social Theory	Computational theorizing
March and Simon, 1958.	Computational Organization Theory	Organizations	Bounded Rationality	Theory
March, 1996	Computational Organization Theory	Innovation Search Exploitation Organizational longevity	Relative value of exploration and exploitation	Computational theorizing
Matthews,	Complexity	Social	Role of complexity in social	Review

White and Long, 1999		Science	sciences	
Morel and Ramanujam, 1999	Complexity Theory	Organizations Social Networks	Organization Theory	Review
Padgett, 1997	Computational Social Science	Agents Skill Emergence	Patterns of behavior emerge from local conditions	Computational theorizing
Pines, Cowan and Meltzer, 1999	Complexity	Economics	Examines relation between metaphors, models and reality, largely in economics	Mixed
Sastry, 1998	Computational Organization Theory	Change Environment Timing	Mechanisms supporting punctuated organizational change	Computational theorizing
Simon, 1955	Computational Social Science	Agents	Boundedly rational agents	Theory
Simon, 1956	Computational Social Science	Agents Environment	Boundedly rational agents and environments	Theory
Thietart and Forgues, 1995	Chaos Theory	Chaos Organization	Application of general chaos theory to organizational performance.	Metaphor
White, Marin, Brazeal, and Friedman, 1997.	Complexity Theory	Complexity Adaption Organizational evolution	Application of general complexity findings to organizational success and failure	Metaphor

Table 2. A Meta-Network Approach to Organizational Representation					
	People	Knowledge	Resources	Tasks	Organizations
People Relation	**Social Network** *Who knows who*	**Knowledge Network** *Who knows what*	**Capabilities Network** *Who has what resource*	**Assignment Network** *Who does what*	**Work Network** *Who works where*
Knowledge Relation		**Information Network** *What informs what*	**Skills Network** *What knowledge is needed to use what resource*	**Needs Network** *What knowledge is needed to do that task*	**Competency Network** *What knowledge is where*
Resources Relation			**Substitution Network** *What resources can be substituted for which*	**Requirements Network** *What resources are needed to do that task*	**Capital Network** *What resources are where*
Tasks Relation				**Precedence Network** *Which tasks must be done before which*	**Market Network** *What tasks are done where*
Organizations Relation					**Inter-Organizational Network** *Which organizations link with which*

---

[i] Actually, the term chaos does not refer to a class of systems, but to the dynamic behavior of many non-linear systems. The behavior of concern is high sensitivity to initial conditions. Complex systems need not be chaotic and "chaos cannot explain complexity" (Bak 1996, p.31).

[ii]

http://www.calresco.force9.co.uk/sos/sosfaq.htm
http://views.vcu.edu/complex/
http://views.vcu.edu/~mikuleck/ON%20COMPLEXITY.html
http://www.ices.cmu.edu/casos
http://www.santafe.edu/projects/swarm/
http://www.soc.surrey.ac.uk/research/simsoc/simsoc.html