

Intra-organizational Computation and Complexity

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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. In a complex process there are typically many interacting objects (e.g. people or procedures in an organization or particles in physics) and it is rarely possible to proceed to a complete mathematical solution. Systems in which there are complex processes often exhibit non-linear behavior, phase changes in behavior, and often reach dramatically different end states given only minor changes in initial conditions. 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.

Table 1: Summary of references				
Reference	Area	Key Concepts	Key Contribution	Approach
Meyer and Scott, 1983.	Complex Systems	Size Institutions Environments Open Systems	Neoinstitutional theory.	Statement of theory with description. Draws on previous case studies and large scale surveys.
Perrow, 1984	Complexity as Metaphor	Design Coupling Errors Accidents	Accidents as inevitable.	Detailed theory development drawing on case studies, ethnographies, and archival data.
Epstein and Axtell, 1997	Computational Organization Theory	Agents Adaptation	A-life models of emergent social behavior.	Computational theorizing from stylized situations. Face validity. Large numbers of spatially located simple adaptive agents.
Burton and Obel. 1998	Computational Organization Theory	Design Strategy Managerial practices Processes	The Organizational Consultant. An expert System integrating the findings of contingency theory into a unified system for designing organizations.	Computational theorizing about real and hypothetical organizations. Validation from case studies. Reasoning using rules derived from contingency theory.
Harrison and Carrol, 1991	Computational Organization Theory	Culture Evolution Design Learning	Emergence and maintenance of distinct cultural forms in organizations.	Computational theorizing about organizational culture. Face validity. Single parameter model of culture.
Jin and Levitt, 1996	Computational Organization Theory	Design Teams Skills Agents Tasks Organization Chart Pert Chart Communication technology Rework	The virtual design team. A process model combining project management, agent expertise, and organizational chart information.	Computational theorizing about real world design teams faced with routine tasks. Validation from case studies. Variable number of agents varying in ability and access.
Cohen, March and Olsen, 1972	Computational Organization Theory	Decisions Agents Access Salience Problems Solutions Effort	The Garbage Can Model. A simple model of organizational decisions resulting from personnel, solutions, and problem flows.	Computational theorizing about highly stylized organizational designs. Face validity. Small number of agents varying in ability, interests and access.
Carley and Svoboda, 1996	Computational Organization Theory	Agents Knowledge Task Change strategies Access Learning	ORGAHAD. A multi-agent model of organizational adaptation where the agents are intelligent and adaptive.	Computational theorizing about real and hypothetical organizations. Strategic response as annealing process coupled with individual experiential learning. Validation from experiments and case studies. Variable number of agents varying in

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; rather, it is a paradigm, set of procedures and techniques, and an approach to complex systems. Complex systems typically have internal change, adaptation, or evolutionary mechanisms that result in behavior that on the surface might appear random but actually has an underlying order (Holland, 1995), where complex outcomes emerge from simple processes and there are multiple possible outcomes depending on input conditions and history (Kauffman, 1995), some of which may be catastrophic (McKelvey, 1999b). Complex systems have the ability to self-organize (Bak, 1996).ⁱⁱ Much of the formal work in complexity is in physics, biology and chemistry; however, complex processes also occur in organizations. Complexity analysis provides us with a means for re-thinking and extending organizational theory (McKelvey, 1999a; Morel and Ramanujam, 1999) and social theory more generally (Axelrod and Cohen, 1999). The general work on complex systems extends decades of work that took either a contingency theory or information processing perspective. The result is that a number of now classic findings have emerged both computationally and empirically such as, there are multiple configurations to achieve any organizational objective, different organizational objectives require different configurations, history and order effects are critical (i.e., path dependence exists), and overall system behavior is highly non-linear. 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; Baum and McKelvey, 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 their behaviors with little attention to the mathematical meaning behind those concepts.

Within organization theory, complexity and the study of complex or adaptive systems has taken on three identities –complex systems, metaphor, and 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, via reasoning from metaphors, and via reasoning from formal theory. Moreover, it may well be that some of the empirical finding about complexity and design are useful in validating the computational models. It may be that some of the “new doors” opened through metaphorical reasoning will result in simulations being constructed to do theory development 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. It is the case that all of the approaches tend to characterize complexity in terms such as number of personnel (or agents), resources, tasks, and/or the number of interconnections (network ties) among them, or number of

steps in the processes used to evaluate, form, move things through or modify these networks. However, if we are to link empirical data to computational models we need to move beyond common characterizations to actually using the same construct, e.g., complexity and all related constructs, and measuring these in the model and the real world in exactly the same way. Now let us consider the three areas.

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. The goal of this work is to understand the relation between the elements of organizational design, the environment and performance. 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 fundamental nature of organizations (Etzioni, 1961), and the relation between complexity and size (Scott and Meyer, 1994), coordination (Klutzy, 1970) and formalization (Hall, Haas and Johnson, 1967). Much of this work resulted in, or advanced, structural, contingency theory and neo-institutional theory. This work is independent of the formal 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; e.g., is it the number of personnel or the density of the social network. 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. The Lyapunov exponent is a measure of sensitivity to initial conditions. Further much of the empirical work on complex systems, particularly that on processes, focuses on perceived complexity, which may or may not be systematically related to actual complexity as measured in complexity theory.

An example of this approach is seen in the work of Meyer and Scott (1983). They present a neo-institutional approach in which organizations are complex systems due to their size (e.g., number of employees, number of divisions, number of processes) and are embedded in, define and respond to environments that are themselves complex (e.g., number of stake holders, legislations, institutions, and other organizations). The arguments are supported by a large number of studies many of which are based on large-scale surveys of organizations. As organizational complexity increases on one dimension, such as size, it increases on other dimensions, such as formalization of processes defining linkages. In contrast to the rational actor approaches of economics, they suggest that formal organizational structures are symbolic phenomena designed in response to the environment to demonstrate rationality rather than to achieve efficiency. Thus, complex structures and behaviors emerge from response to external events and processes for achieving legitimation.

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 goal of 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). This body of work is less statistical than the complex systems work. Nevertheless, the research building on the complexity theory as metaphor work moves beyond discussions of 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. coupling, self-organization, bifurcation, and chaos. One of the best examples of such work is Perrow's (1984) study of accidents where in-depth ethnographic and historical analysis lays the basis for arguments about complexity. In contrast to Perrow, many of the studies in this vein simply use the language of complexity and reference organizational examples.

Perrow treats complexity in terms of size (the number of individual decision-makers, knowledge and tasks) and networks (the linkages between individuals, knowledge and tasks). Reasoning from in-depth case studies and archival records he presents the argument that the processes and technologies used in high-risk situations, such as nuclear power plants, have often resulted in tightly coupled systems (many linkages). He argues that errors and accidents are perfectly normal, and indeed inevitable. Moreover, the coupling in these organizations enables the effect of errors to cascade through the organization resulting in catastrophic consequences. Small deviations can have, in a tightly coupled system, large-scale consequences.

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.

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).

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 therefore 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.

One of the earliest works in the area of computational organizational theory is Cohen, March and Olsen's Garbage Can Model of organizational choice (1972). They present a simple information processing model of choice in which agents, solutions and tasks flow through the organization. Effort, saliency, and access link agents to tasks and solutions (resources) and so determine. Results suggest that most decisions are made by oversight. Describing the implications for various types of organizations, such as educational institutions provides the model with face validity. This model, like others of its generation, demonstrates the potential for simple models to generate surprising results.

Key aspects of this model that are retained in current models are the information processing approach, networks linking agents to resources and tasks, and organizational decisions resulting from individual decisions. Current models tend to be more detailed, more algorithmically complex, and to be more grounded on actual empirical data. Modern models vary in their reliance on database, artificial intelligence, and cognitive science techniques. Three models that all derived from the Garbage Can Model, and that have combined a contingency theory, information processing theory, and institutional theory perspective are VDT, ORGAHEAD and the Organizational Consultant.

The virtual design team (VDT) can be used within firms to evaluate the design of teams doing routine work (Jin and Levitt, 1996). VDT characterizes the organization in terms of agents, expertise (knowledge), tasks and the relations among these. Complex inter-connected tasks can be represented. Agents cannot learn. At a technical level project management techniques are combined with information processing models of agents, the organization's authority relations, and the available communication technology. Actual or hypothetical project management plans and organizational charts can be entered. Changes in policies, re-designs, and re-engineered tasks can be examined by looking at the impact of such changes on various outcomes including workflow, re-work, and the speed of processing. Researchers and managers can use VDT to see how small changes in their team's structure can have dramatic effects on the outcomes for routine tasks.

ORGAHEAD (Carley, K.M. and D.M. Svoboda, 1996) is a multi-agent model that can be used to examine the way in which organizations adapt to change. ORGAHEAD characterizes the organization in terms of agents, knowledge (knowledge/resources), tasks and the relations among these. Only simple choice tasks can be represented. There is a learning ecology such that agents and the organization learn, at both the knowledge and structural level. Changes in strategic redesign, HR, and re-engineering policies and personnel characteristics can be examined by looking at the impact of such changes on various outcomes including workload, performance, adaptivity, robustness, and historical trajectories. Technically ORGAHEAD combines machine learning and optimization techniques to create a model of organizational learning and adaptation in which the strategic and tactical levels co-evolve. Actual or hypothetical authority and communication relations as well as access to resources or assignment to tasks for small to medium sized organizations can be entered. Researchers and managers can use ORGAHEAD to see how initial conditions and institutional or cognitive constraints influence adaptation.

The Organizational Consultant (Burton and Obel, 1998) is an expert system model embodying all the findings of contingency theory. The Organizational Consultant characterizes the organization in terms of features of its design (such as size) and processes (such as degree of coupling). Unlike VDT and ORGAHEAD, specific decision makers are not modeled. Rather the organizations performance and suggestions for change, are predicted from a set of rules governing the complex ways in which the various aspects of organizational design and environment interact to effect performance. Changes in processes, structure or environment can be examined by looking at the impact of such changes on various outcomes including potential for errors and locus of problems. Technically the Organizational Consultant combines expert system technology with case study protocols with rules derived from the literature. Actual or hypothetical descriptions of the organization's structure and processes can be entered. Researchers and managers can use the Organizational Consultant to see whether their reasoning is correct about what will happen and why given a particular organizational and environmental configuration.

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. Garbage Can Model (Cohen, March and Olsen, 1972) is simple and abstract. VDT (Jin and Levitt, 1996)

and the Organizational Consultant (Burton and Obel, 1998) are more detailed and less abstract. ORGAHEAD is in between. The simpler more abstract models are typically referred to as intellectual models. For these models, the 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. In general, both the intellectual and the emulative models can be used for theory building. One reason for this is that the act of building a model requires theory specification.

From the body of work in computational organization theory, which goes well beyond the examples described above, a neo-information processing paradigm has emerged. 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 replaced 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.

Contemporary issues and debates

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, is the glue that needs to be examined in order for computational theorizing to move beyond simple statements about individuals or dyads. The network approach is resulting in common representation schemes thus enabling data to be transferred between computational models and enabling experimental and field data to be used as input to or for validation of 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 and organizational 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. 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 among computational researchers 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. If IT is an enhancer then 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 proponents of this view 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; Allstynne 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. 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. 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. 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.

Comparison of Models

The art of analyzing complex systems involves finding the means to extract from the computational theory no more information than we need and to map processes and results from one model onto another. This means that the researcher is called upon to 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). 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. Thus computational theorists have developed a variety of techniques for generating hypotheses, determining the veridicality of the results, and determining the generalizability of the results. These techniques include 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 used to understand the match between two models with different core processes.

Computational models of organizations need to be built at varying levels; e.g., micro and macro, or human as actor, group as actor, organization as actor etc. 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. 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.

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 intellectual 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 is that the observed performance of the simulated organizations varied with structure and the level of detail in the agent model. In other words, we 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 who takes what actions when, 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 intellectual 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 is 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 materials 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, mutable boundaries, the study of emotions, and the development of data archives and intelligent analysis tools. In all cases, the advances are being made possible by linking computational modeling of complex systems to other areas. Linking work on mental models and cognitive agents to work on social networks and task management facilitates the extension of the network approach. 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.

Direction 1: Extending the Network Approach

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. The growing need to understand how agents and knowledge link within and among organizations is leading to new network based studies of learning, adaptation, impact of technology, and so forth. 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. Carley and Hill (forthcoming) proposed a similar approach in the area of knowledge management. 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. 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. 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.

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

Direction 2: IT Focus

The rapid development of new forms of information technology (IT) creates 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.

Direction 3: Mutable Boundaries

One interesting notion that has emerged in the neo-information processing area is 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 retains the same configuration and remains essentially the same. However, from a neo-information processing perspective, the characteristics of these configurations depends on the information available and their information processing capabilities, including their ability to learn. 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. Boundaries are, in this sense, mutable. Since the information available to the agents in a configuration depends on the exact position of the entity in the meta-network, moving it about changes its' characteristics and affects learning at the individual, group, structural and organizational level. Thus, not only are the boundaries around agents, task, etc. mutable, particularly for synthetic agents such as workgroups and organizations; but these configurations exist within an ecology of learning mechanisms which enables 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. Advances in emergent agents and intelligent systems are enabling organizational theorists to rethink the basic nature of organizing, the mutability of boundaries, the impact of learning ecologies, and the conditions under which self-organization occurs and synthetic agents emerge. Research on the processes underlying meta-learning and institutionalization of behaviors needs to progress. Such progress is likely to blur the line between intra- and inter-organizational behavior.

Direction 4: Emotions

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, such as trust, and the role they play in distributed work settings within or between groups and 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. Research needs to be directed at developing a model of the emotional-organizational agent, determining the value of emotions as a coordination mechanism, and the factors that may make the play of emotions important or irrelevant in an organizational context.

Direction 5: On-Line Data Archives

The network approach also 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) multiple computational models can employ it. Web-accessible data archives, where there is a common meta-network representation, will enable more grounded theories, and make it possible for the models to serve as virtual laboratories where practitioners and scientists can conduct what-if analysis on the potential impact of policy changes, new procedures, new institutional arrangements and new IT. Such archives need to be created and research needs to proceed on how to automatically collect and maintain such data at the requisite level of detail.

Direction 6: Intelligent Analysis Tools

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 is possible to run a comprehensive analysis of the impact of all parameters built into the model. The space of outcomes can 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. Thus, a key area 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.

Synopsis

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.

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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 The edited volume by Kiel and Elliot (1996) provides base models and measures as does 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. There are also a number of very useful websites in this area:

<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://necsi.org>

<http://www.santafe.edu/>

<http://www.soc.surrey.ac.uk/research/simsoc/simsoc.html>

ⁱⁱⁱ An example here is the A2C2 project funded by ONR, where a network representation scheme of the organization's architecture is used to represent all relations among personnel, tasks, and resources. The same representation scheme is used in the petri-net models at George Mason, the excel models at University of Connecticut, the ORGAHEAD simulations at Carnegie Mellon University, and the experiment data collection efforts at the Naval Post Graduate School. This facilitated direct comparison of the output of the three models and the experimental data.