CASOS 2002
Day 2, June 22, 2002

Models of Decisionmaking: Their Uses and Limitations

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Abstract

This paper critically surveys explicit models of actual decisionmaking. How are the models derived? How are the models used and evaluated? What conceivable value can the models have? Are there better practices for creating and using models of decisionmaking?

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In his autobiography, Models of My Life (1991, p. 370), Simon describes how he acquired a research problem in 1935 at the age of 19 that sustained him intellectually for life. The empirical question posed to him was: How are funds divided between playground maintenance -- planting trees, cutting grass, etc. -- and playground activity leadership -- planning and running programs -- in Milwaukee?

Pondering this somewhat mundane question about allocation behavior, Simon concluded that the ready hypothesis from his then-limited study of economics, "Divide the funds so that the next dollar spent for maintenance will produce the same return as the next dollar spent for leaders' salaries", was obviously deficient in two respects. First, no one seemed to be thinking about the decision in this way; the hypothesis failed descriptively. Second, he could not see how to weigh the value of one against the value of the other; the hypothesis failed prescriptively.

For Simon, the specific problem about behavior on allocations to playgrounds in Milwaukee became a much more general problem: "How do human beings reason when the conditions for rationality postulated by neoclassical economics are not met?" In much of his subsequent research, Simon labeled the behavior of interest as decisionmaking, choice, or problem-solving interchangeably as synonyms for "reasoning." From the discovery of this problem in 1935 until his death in 2001, most of what Simon published can be understood as contributing more or less directly to answering this question.

"Decision" is a useful, albeit labile, frame for thinking about many instances of human behavior. It is used to organize our thinking about volitional circumstances from simple gambles to the use of nuclear weapons. In the modal application of the decision frame, an individual or group has knowledge and control of the available courses of action, estimates of the consequences of choosing any particular action, ordered preferences (values on estimated future consequences), and a necessity to act or not. Even where these concepts are not very descriptive of what precedes an action, they may be descriptive of the post hoc explanations for actions – rationalizations of actions.

Jose Ortega Y Gasset once observed that "Living is a constant process of deciding what we are going to do." Behavior that can potentially be framed as a "decision" is everywhere and always. You, for example, can be understood to have chosen to read the previous sentence and this one. In doing so, you allocated some time to this reading behavior and not to an infinite set of possible alternatives, some of which may have produced greater value than the reading. You can also be said to have chosen a time and place for reading this document. You can also be said to have made a series of larger decisions about the course of your life that make any reading about any aspect of decisionmaking an option at this moment. Now, about the next thirty minutes of your life and the need to be rational………

What we choose to hack out of the complex thicket of behavior in real time and call a "decision" is somewhat arbitrary. The decision frame is most persuasive and probably most useful for consequential, discrete choices that entail prior, conscious deliberations about the alternative futures as a consequence of particular actions. The decision frame is less persuasive and probably less useful for thinking about behaviors that are inconsequential, habitual, highly emotional, or socially deviant.

Decisionmaking is an important function for leaders in public affairs, business and the professions. Leaders in all types of organizations have central roles in deciding what the "business" is (strategic decisions), how the business is conducted (operating and resource allocation decisions), who participates in conducting the business (personnel decisions), what those participating do in the conduct of the business (organization and tasking decisions), and how the value produced by the business is distributed to groups and individuals (distributive decisions). Leaders as human beings also have the usual array of personal decisions from the mundane, e.g., what to have for lunch today, to the significant, e.g., college or spousal choice, with everything in between.

The "decision sciences" are the accumulated and accumulating knowledge across several fields with respect to three main questions:

1. How do human beings, individually and collectively, make decisions?

2. How should human beings, individually and collectively, make decisions?

3. How can human beings, individually and collectively, make better decisions?

The literature associated with each of these questions is very large and diverse. The most relevant materials for the first question are found in psychology, organization theory, political science, economics, history, and ethics. The most relevant materials for the second question are the products of economists, statisticians, mathematicians, and philosophers. The most relevant materials for the third question are found in operations research, statistics, psychology, and organization theory.

The extent to which much of the knowledge on decisionmaking is "scientific" is debatable. The epistemological evolution and issues are complicated. Much of the empirical work on the first question, how decisions are made, is not very rigorous. The bulk of the work, at least by volume, consists of interpretations of various historical "decisions" based on limited observation, self reports, and fragmentary records of non-experimental behaviors. The behaviors examined range from the monumental to the mundane. While the details vary widely, our reasoning about human reasoning has a certain constancy across many diverse fields. Often there is an individual identified with more control than others. There is a tendency to treat observed effects as intended and behavior as goal-seeking. There is a fascination with obvious mistakes, Napoleon at Waterloo; Lee at Gettysburg; MacArthur at the Yalu River; Kennedy and the Bay of Pigs; Nixon and Watergate; Reagan and Iran-Contra, balancing the budget and regulating the savings & loan industry; Clinton and Monica-gate; Ford and the Edsel; Coca Cola and the New Coca Cola, because the effects are not easily understood as intended and because these natural experiments gone awry suggest that we might learn something to improve future behaviors.

The most scientific of the evidence on human decisionmaking, i.e., evidence with the highest internal validity, is from experimental and process tracing studies by psychologists of individual behavior in laboratory settings. This work is centered on behavior in structured decision tasks; it, has been extended to simple groups especially with regards to competition and cooperation. A very substantial strand of the experimental work on decisionmaking has tested rational models of behavior and posited "heuristics and biases" that explain subject departures from the predictions of the rational models. Much of the descriptive work on decisionmaking behavior that attempts to model explicitly decision agent behavior is due to Simon and his colleagues and students.

Group and organizational decisionmaking poses significant methodological problems; most of the ostensibly scientific evidence is from surveys or observational studies with an intervention here and there.

Most of the statistical and econometric work on data from natural experiments – individuals and organizations choosing -- is confirmatory; it does not seriously test any theory of or rival hypotheses about human behavior; it does not predict choice or decision behaviors successfully. Regardless of the technical sophistication of the analyses and the persuasiveness of the supporting arguments, explanations of why consumers bought what they did or voters voted as they did are of the same intellectual genre as the reasons that the "talking heads" on the financial networks give for why the Dow Jones Average went up or down yesterday. Such commentaries may be entertaining and profitable for the providers, but we don't learn much in the end of value to future decisions.

The voluminous literatures on the second question, how should decisions be made, are primarily the product of mathematicians, statisticians, philosophers, and economists, although some ethicists, historians and novelists have chipped in. Most of the mathematical work on decisionmaking is normatively appealing, empirically false as a positive theory of human behavior where testable, and not pragmatically useful for actual decisions by real decisionmakers.

The rational model in many guises is the most frequently utilized theory in the social sciences, especially in economics and the public choice brand of political science for how decisions are made. Individuals are said to be maximizing expected utility, whatever that is. Firms are maximizing profit, whatever that is. Politicians, government officials and voters are optimizing this or that. While some variant of rationality is a convenient postulate for aggregate analyses, rationality as a positive, predictive theory of behavior does not stand up well upon closer inspection. There is a large body of empirical work, the best of it by experimental psychologists, showing departures from rational behavior on a variety of decision tasks.

Maximizing Subjective Expected Utility (SEU) in some form is probably the correct way, normatively speaking, to make a decision, any decision. If you know all of the actions available, can predict, perhaps with some error, the consequences of taking any combination of these actions, can predict, perhaps with some error, how you will value all possible consequences, SEU is logically an attractive way to proceed; alternative processes are hard to defend a priori or post hoc. The transaction costs associated with executing the SEU approach to decisionmaking – the costs of all that knowing, predicting and valuing – may, however, exceed the expected value from using SEU rather than some simpler heuristic approach. Every champion of SEU should at least once seriously and self-consciously attempt to follow their own decisionmaking advice on a decision important to them personally – perhaps choice of spouse as a contribution to both population control and natural selection – to avoid the age-old trap of anything being possible for someone who does not actually have to do it. It is a truly sobering experience to try to follow the rational process to the letter on even seemingly simple choices.

The third question, how can better decisions be made, is related to the second question in that it is normative in thrust but with an important difference. The second question is in principle normative while the third question is in practice normative. Work on the second question might advise, “maximize utility subject to constraints.” Work on the third question might couple this advice with feasible techniques for estimating the necessary probabilities, eliciting the necessary preferences, specifying the necessary constraints, and doing the necessary predictions and computations. In principle is one thing. In practice is quite another thing.

Many of the tools for decisionmaking are found in Operations Research (Management Science/Industrial Engineering/Applied Statistics). The tools are quite powerful for making decisions where the criterion is clear, the context is stable, and measures exist. Such decisions are, of course, a small proportion of real decisions. Even where the tools are fully appropriate for decisions and competently applied, the effects of resulting information on the eventual decision in supra-individual settings may be slight; the leaders responsible for the decisions are usually not the analysts and frequently have a hard time understanding analytic arguments.

Three inescapable conclusions from a survey of what we know about decisionmaking behavior are: (1) our understanding of how humans individually and collectively make decisions is very incomplete, if not wrong; (2) the technologies for decisionmaking developed thus far are either very general and difficult to apply or very specific and inapplicable to most real decisions; and (3) there are precious few explicit models of decisionmaking that attempt to simulate actual behavior.

Most of the decisionmaking technologies that have been developed apply to structured choices with specified mutually exclusive and exhaustive alternative sets and estimable consequences and values. Most real decision problems have interdependent and incomplete alternative sets and unimagined consequences and values. There are no well developed technologies – techniques that could be taught as recipes with good effect -- for finding and structuring decision problems. Asking the right questions is usually much more difficult than answering the right questions once posed.

This paper critically surveys explicit models of actual decisionmaking. How are the models derived? How are the models used and evaluated? What conceivable value can the models have? Are there better practices for creating and using models of decisionmaking?

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Humans, Computational Advisors, & Decision Inferences: *The Generation of Actionable, yet Legitimate, Information with Computational Models*

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Abstract

Many are the promises of technologies associated with the computer revolution. These promises are varied in nature and outcome, and include improvements in social outcomes such as productivity and well-being. A natural question that arises from positing these promises is how does one better understand the implications of social choices on our ability to achieve improved productivity, social well-being, or other preferred social outcomes. These choices are a challenge in that they occur upon, or within, institutional contexts characterized by emergent properties typically associated with the operations of socio-physical systems. These properties include aspects such as complexity, social dilemmas, and deep uncertainty. Such aspects tend to reduce the ability of decision makers to understand the dynamics of a socio-physical system and appreciate the consequences of choices made with respect to the system. Moreover, these aspects may reduce the likelihood of making "necessary" decisions. It is possible, however, that a transdisciplinary method instantiated as a computational model that credibly represents social dynamics may provide greater insights into society's operations and reduce the likelihood of a decision maker abdicating their choice making authority. At issue, however, is the credible creation, as well as appropriate use, of computational modeling outputs in the support of decision-making. This paper considers the relative role of decision makers and computational models – or rather advisors – in the formulation and implementation of desired social outcomes.

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Key Words: Organizational Legitimacy, Decision Theory, Computational Advisory Models

Support: This paper is part of the *Computational Social Science Modeling* project directed by Desmond Saunders-Newton and Joseph Eash, the Center for Technology & National Security Policy. This work was supported in part by the Office of the Director, Defense Research & Engineering and the Office of the Deputy Under Secretary of Defense for Advanced Systems & Concepts.

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Algorithmic Advisors (*in-Silica)*

Some would argue that the seemingly recent appreciation of the complex nature of organizations and their operational environments necessitates a new means of assessing the implications of past actions, as well as anticipating the likely consequences of choices yet considered. The process of enumerating and evaluating large numbers of plausible, much less possible, consequences is at best a daunting task. Such a task is aided greatly by automated approaches to decision-making. It is important to note, however, that the appropriate role of automated decision aides, typically in the form of a decision support system (DSS), would benefit from greater consideration. Moreover, the rise of a DSS to the status of advisor, especially in light of its "silica-based" nature, will be aided – or deterred – by an appreciation of the factors that give rise to a trustworthy advisor.

In an effort to set the stage for considering the appropriate role of computational models in the decision making process, the author first describes the role of advisors in choice making of executives. Consistent with the past work of Herbert Goldhamer, I also view advisors in terms of services provided to individuals at the executive and administrative levels. These services include friendship, admonition, information, special mission, and analyses and advice. Of particular interest in this exposition is the provision of analyses and advice to decision makers. Goldhamer goes on to describe advisory products typically generated by human advisors, and enunciates the pre-conditions that give rise to necessary advisory capabilities. These pre-conditions included demographics & territory, polity structure, international regime, intellectual, non-existence of pre-destination, and technology progress.

Goldhamer's work describes the role of human advisors over a nearly four millennium period, but the attributes that made for effect human advisors are also useful to consider in the context of the credible use of advanced *computer-based decision support models* (CBDSM). In previous work concerned with appropriate use of computational models in support of public sector decisions, the adviser is defined as an individual who establishes his or herself as a necessary, though not sufficient condition, to informed, rational – and in theory – improved decision making. The legitimate assumption of this role by the adviser, as well as the use of the advice provided by the adviser, presupposes the information results in better decisions due either to its relevance, sanguine-ness, generalizability, or predictive consistency.[i] Moreover, the adviser's ultimate role is to aid the decision maker in becoming politically legitimate through both the adviser's ability to produce rational, objective analysis of an issues, and his or her intuition. (Saunders-Newton & Scott, 2001)

At issue is how artifacts of human intelligence -- a CBDSM(s) -- become viewed as credible, i.e. trustworthy, advisors in the decision making process. And, can such systems become so trustworthy as to result in the abdication of decision-making authority or responsibility by decision makers? This point is important to note since it is assumed that the role of the adviser is to bring into greater focus the options, and their associated consequences, available to a decision maker. The author recognizes, however, that the content of the advice given, as well as the level of influence associated with a given adviser substantially impact the choices selected by a decision maker. It is possible that certain advisers make strategic choices on behalf of a nation or organization due to either the inability or unwillingness of the decision maker, or possibly the duplicity of the adviser. It is easy to argue, given the nature of current problems faced by nation-states and multinational corporations, e.g. Complex Humanitarian Emergencies and global enterprise logistic strategies, CBDSM are likely to become increasingly involved in choicemaking collaborations. As considered earlier, what is the appropriate role to be played by computational advisory models? This question is further considered by exploring these models in the context of organizational legitimacy.

Organizational Legitimacy and Computational Advisory Model Credibility

The modeling of complex phenomenon provides a means for better understanding important relationships and the formulation of strategies that improve organizational operations or macro-level outcomes. Of course, the relative efficacy of these models is always to be questioned, but historical assessments suggest policy analytics based largely on the use of theoretically-derived models, resulted in a form of organizational legitimacy. Put another way, bureaucracies were viewed more favorably due to the use of such models. However, the negative implications of the increased reliance on past modeling approaches is illustrated by the necessity to cleave *facts from values*, and separating context from social problems. Such choices were largely a result of methodological limitations, although there are clearly a number of ontological and epistemological issues associated with the use of traditional modeling approaches from the transdisciplines of multivariate statistics and applied mathematics. Such an approach, however, could not wholly eliminate the existence, as well as importance, of values and context in analysis that supports decision-making. (Saunders-Newton & Scott, 2001)

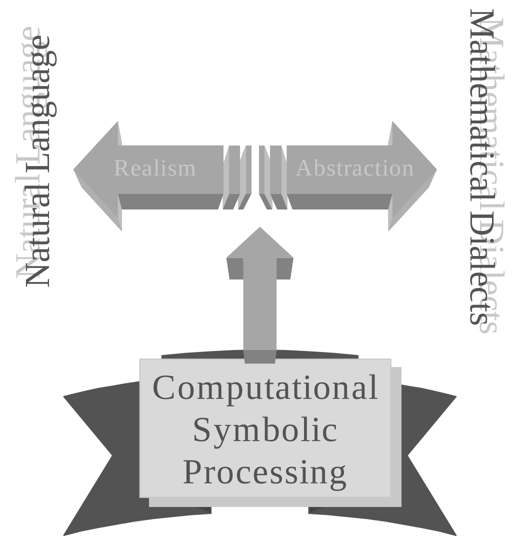

Figure 1: Modeling language continuum.

The increased use of computational advisory models suggests an ability to decrease the challenges associated with the parsimonious nature of traditional modeling approaches used in public sector decision-making and the management sciences. Generally speaking, computational models provide a means of both bridging data and theory, and expressing theory. As a means of expressing theory, computational models can be viewed as one of three model-rendering languages. (Taber and Timpone, 1996) The languages presented by Taber and Timpone suggest that models of theory could be represented in terms of natural language, mathematical dialects, or computational symbolic processes. The relationship of these modeling languages one with another can be viewed as a continuum. (Figure 1) Computational symbolic processing, or computational models, allows for increasing the level of realism one may incorporate in a formal model rendered in a mathematical dialect. As important, computational models do not sacrifice analytic focus, a flaw often associated with models rendered in natural language. This capability reduces the necessity of separating context from social problems, and – given particular model-use strategies such as exploratory modeling (Bankes, 1993) – cleaving fact from values.

Ironically, the fact that rational and logical analysis (in the form statistical and mathematical models) has increasingly served as the primary criterion for the human advisor’s status and authority, and has consequently made the role of the computer advisor more credible. Credible in the sense that machines can engage in a higher level of logical and rational thinking than their human counterparts, which serves as the primary justification for their expanded use in decision making. This is, nevertheless, an extremely circumscribed and narrow view of what it means to provide the decision maker with advice. The question still arises of the extent to which computational advisory models should be used in complex decisions associated with socio-physical systems[ii] that are tightly coupled with their operating environment.

Computational Advisory Models, Decision Makers and Credibility: A Typology of Uses

In order to consider the legitimate use of computational advisory models in support of complex organizational operations, it is necessary to identify appropriate uses of these models. To that end, I focus on identifying credible uses of three computer-based decision support modeling types. These types, or rather general methods for addressing specific classes of decision support “settings,” are as follows:

- Information Management Models

- Advisory Models
- Decision Making Models

Based on the current and potential uses of these types or forms of models, the authors will provide a categorization of credible uses. Prior to presenting this typology, the types of CBDSM being discussed in this exposition are defined, as well as the classes of decision support problems or activities these "methodological types" generally address.

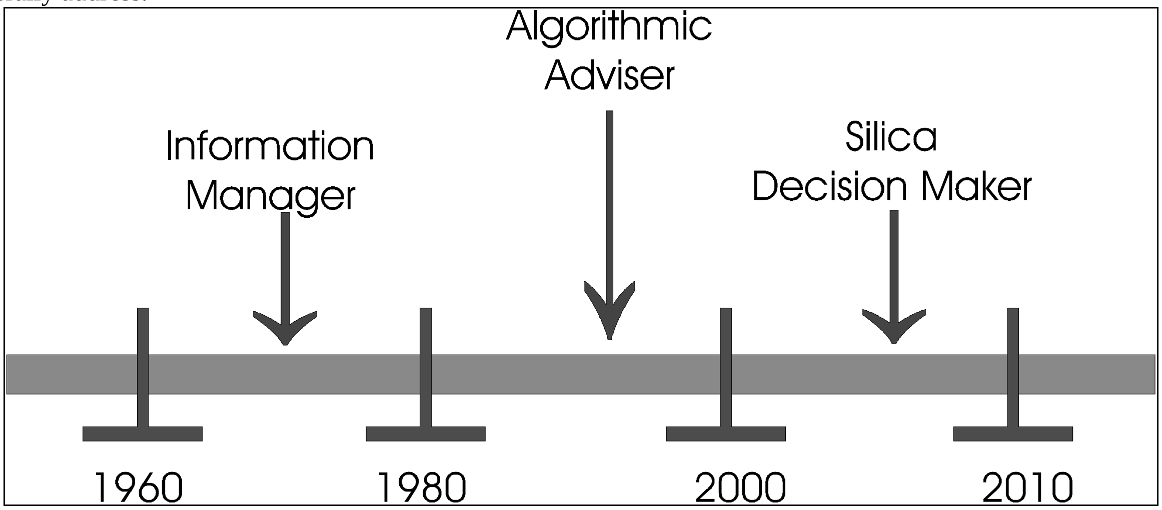

Figure 2: Computer-Based Decision Support Modeling Themes

The three CBDSMs of interest in this paper reflect a progression of methodological or technological themes for supporting the decision making efforts of public sector executives and managers. (Figure 2) These decision support themes constitute perspectives of how the computer has been or will be used to support a decision maker. We suggest that these thematic techniques are becoming more *pervasive*, or rather increasingly *present*, in the decision making process. Without doubt, some of this increase can be attributed to advances in technology, but another reason is the greater willingness of decision makers to trust, and thus use, CBDSMs.

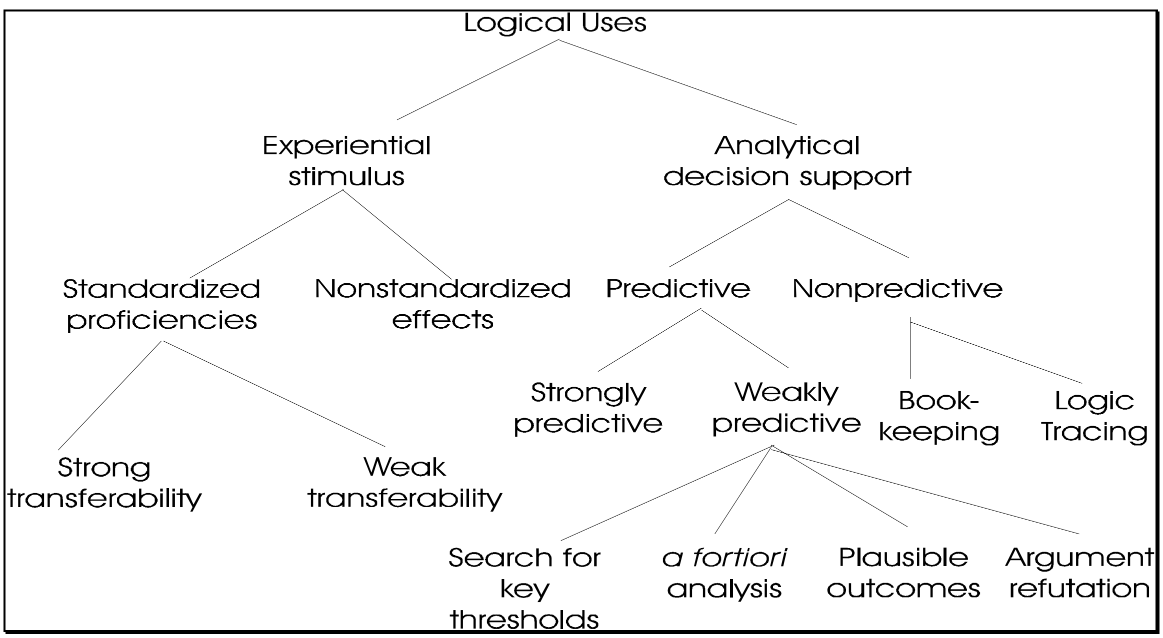

Figure 3: Typology of CBDSMs Logical Uses

I further explore the criteria for legitimate use of these CBDSMs, or computational advisory models. The criteria for use in this case are not optimality or validatability – given that few complex computational models can be realistically validated, but *credibility*. In this case credibility refers to a concept for comparing a model or simulation to the real world with an *intended use in mind* (Dewar, et al. 1996). This criterion allows for considering the usefulness of CBDSMs, which often focus on events that are difficult to model, without becoming bogged down in the *realism*[iii] question.

The credible or logical uses of CBDSMs are illustrated in Figure 3. The primary distinction in this typology is that between experiential stimulus and analytical support. The basis for this distinction is to identify CBDSM outcomes that result in changes in the decision makers processing, i.e. modeling or gaming that results in improving an individual's decision making ability, or that results in autonomous decisions that are either implemented or compared to those being considered by a human decision maker. While the issue of experiential stimulus is of some import in training decision makers, of greater interest in this paper is the role of CBDSMs in the activity of analytical decision support.

Finally, I consider the relative role of the decision maker to computational advisory models. Such a comparison seems timely given the increased pervasiveness of advanced computational metaphors and models. Of particular concern is the balance between organizational legitimacy, credible use – which is by it nature a question about ontology and epistemology -- and technological potentialities. I go on to suggest strategies for simultaneously addressing all three concerns.

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[i] For the authors, the "worthiness" of a decision is reflected by whether the information provided was helpful for a given situation, aided in comforting the decision maker in the midst of a challenging decision context, allowed for dealing numerous future "analogous" decision situations, or has been consistently the correct lens through which to view a situation regardless of how "intuitive" it is viewed by the decision maker or others.

[ii] These complex systems, defined as structures composed of physical assets, social institutions, and the connections that relate them one to another, vary across adversaries.

[iii] Modern definitions validation are generally akin to the following: *The process of determining the degree to which a model is an accurate representation of the real-world from the perspective of the intended uses of the model*.

Mathematical Models for Studying the Value of Cooperational Leadership in Team Replacement

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Abstract

A collection of mathematical models is presented for studying the value of leadership in a team where the members interact with each other. These models include the role of a leader in achieving cooperation among the team members and hence improving overall team performance. Three different approaches based on Kauffman's NK model are proposed in the full paper. Each model includes controllable parameters whose values reflect the amount of interaction among the workers as well as the skill and variance of the leader in achieving cooperation. Computer simulations are used to show how the skill of the leader can overcome, or at least attenuate, the "interaction catastrophe"—in which team performance deteriorates as the amount of interaction among the team members increases. The effects of the variance of the leader are also explored.

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Key Words: Leadership, Team Replacement, NK Model, Complex Systems

Mathematical Models for Studying the Value of Cooperational Leadership in Team Replacement

Daniel Solow and Chartchai Leenawong

This paper provides managerial insights into the value of leadership on the process of assembling an effective team of workers for accomplishing a task in an organization. Based on the NK model developed by [Kauffman and Levin, 1987] for studying genome evolution, [Solow, Vairaktarakis, Piderit & Tsai 2001] applied the model to the process of replacing members of a team. These models, however, contain no concept of leadership. The contribution of this work is a collection of models that includes leadership.

It is challenging to build models that include simultaneously all the various roles played by a leader. The models proposed here incorporate one important role of the leader, namely, *seeking cooperation* among the team members. Comparisons are made between the performance of teams both with and without this form of leadership. These models include controllable parameters whose values reflect the amount of interaction among the workers as well as the skill of the leader. Through the use of computer simulations, the following intuitively obvious results obtained serve to establish credibility in these models:

1. Having a leader with no cooperational skill is the same as having no leader at all.

2. The expected team performance increases as the skill level of the leader increases, regardless of the amount of interaction among the workers. Also, the greater the skill of the leader, the more interaction among the workers the leader can manage.

New insights obtained from these models include the following:

1. Having a skillful leader can be more important for team performance than controlling the amount of interaction among the workers.

2. A leader skilled in achieving cooperation can overcome, or at least attenuate, the "interaction catastrophe," in which team performance deteriorates as the amount of interaction among the workers increases.

The Team-Replacement Problem with Leadership

A team in an organization is modeled here as a collection of N job positions, each of which can be filled with one of two qualified workers. Thus, $x_i = 0$ means that one of the workers is chosen for position i and $x_i = 1$ means that the other worker is chosen for that position. The objective of the team-replacement problem is for the leader z to choose, for each of the N positions, one of the two qualified workers in such a way that the resulting team is the *best*, according to a specific measure of performance. Here, team performance, $p(\mathbf{x}, z)$, is modeled as a number between 0 and 1. The closer $p(\mathbf{x}, z)$ is to 1, the better the team performance.

This team-replacement problem seems easy to solve at first glance—just assign the best qualified worker to each position. However, due to the interactions among the individuals in the team, assigning the best worker to each position does not guarantee that the team achieves the best performance. Furthermore, there is the issue of how the leader influences team performance because a leader has numerous roles, some of which are amenable to mathematical modeling. Here, the leader's role of achieving cooperation among the team members is selected as the form of contribution. In the full paper, three models for studying the team-replacement problem with *cooperational leadership* are developed. Managerial insights into the value of cooperational leadership are obtained from computer simulations with these models.

A Model Based on the Leader's Role of Achieving a Good Relationship Among the Workers

The one model described here incorporates the leader's ability to achieve a good relationship among the workers. This relationship may include giving advice or attempting to resolve interpersonal conflicts among the team members so that they work better together and thus perform closer to their individual maximum abilities.

In the proposed *NKLC(μ,σ) model*, it is assumed that the worker x_i in position i has a minimum possible contribution to team performance of $a_i(x_i)$ and a maximum possible contribution of $b_i(x_i)$, where $0 \leq a_i(x_i) \leq b_i(x_i) \leq 1$. In the computer simulations, these values are generated from a uniform $0-1$ distribution, as follows:

$$a_i(x_i) = \min\{u_1, u_2\}, \quad b_i(x_i) = \max\{u_1, u_2\}, \quad u_1, u_2 \sim U[0,1].$$

Where within the range $[a_i(x_i), b_i(x_i)]$ worker x_i actually contributes depends on the interaction of worker x_i with K $(0 \leq K \leq N-1)$ other co-workers on the team. Here, K is a controllable parameter in which $K=0$ indicates that the contribution of worker x_i depends only on worker x_i and $K=N-1$ indicates that the contribution of worker x_i depends on all other $N-1$ workers in the team. In the computer simulations, it is assumed that the K workers that affect the contribution of worker x_i are the $K/2$ workers on either side of worker i, wrapping around if necessary.

The role of the leader z is to achieve a relationship between worker x_i and the K workers that interact with worker x_i. This relationship, $r_i(x_i^K, z)$, is modeled as a number between 0 (a bad relationship) and 1 (a good relationship) that is then used to determine where within the range $[a_i(x_i), b_i(x_i)]$ worker x_i actually contributes. Specifically, the contribution, $p_i(\mathbf{x}_i^K, z)$, of worker x_i is:

$$p_i(\mathbf{x}_i^K, z) = (1 - r_i(x_i^K, z))a_i(x_i) + r_i(x_i^K, z)b_i(x_i). \tag{1}$$

Observe from (1) that when the relationship $r_i(x_i^K, z)$ is close to 1, the leader achieves a high level of cooperation between worker x_i and the K other workers and hence worker x_i performs closer to his/her individual maximum potential $b_i(x_i)$. Likewise, when the relationship $r_i(x_i, z)$ is close to 0, the leader causes worker x_i to perform closer to his/her individual minimum potential $a_i(x_i)$.

It remains to describe how the relationship values are obtained. To do so, associated with the leader z are the following two new parameters:

- μ = a nonnegative number that represents the skill level of the leader in achieving cooperation among the workers. If μ is 0, the leader has no skill. As μ increases, so does the skill of the leader.
- σ = a nonnegative number that represents the variation of the skill of the leader, that is, the variance in the leader's ability to achieve cooperation among different subordinates. The closer the variability is to 0, the more consistent the leader is in extracting each team member's actual performance. As this parameter increases, however, the leader's influence on performance varies more from one team member to the next.

The skill and variance of the leader are used to generate the relationship, $r_i(x_i^K, z)$, from what is called here a *shifted normal distribution*, in the following way:

1. Generate a random number y from a normal distribution $N(\mu, \sigma)$.
2. Compute $r_i(x_i^K, z)$ as the area under the standard normal distribution $N(0,1)$ to the left of y. Notationally,
$$r_i(x_i^K, z) = \Phi(y),$$
where $y \sim N(\mu, \sigma)$ and $\Phi(y)$ denotes the cumulative distribution function of the standard normal, that is, the area under the standard normal curve to the left of y.

The team performance, $p(\mathbf{x}, z)$, is then taken to be the average of all the worker contributions:

$$p(\mathbf{x}, z) = \sum_{i=1}^{N} p_i(\mathbf{x}_i^K, z)/N.$$

In trying to find a team with good performance, the leader can choose to replace workers. Specifically, starting with an initial team, $\mathbf{x}$, a new team, $\mathbf{x}'$, is created by replacing the worker in position i with the other available worker for that position, resulting in what is called here a **one-replacement neighbor of x**. The new team is retained only if $\mathbf{x}'$ has better performance than $\mathbf{x}$. This *replacement process* results in a sequence of teams, each with better performance than its predecessor team, until obtaining a **local**

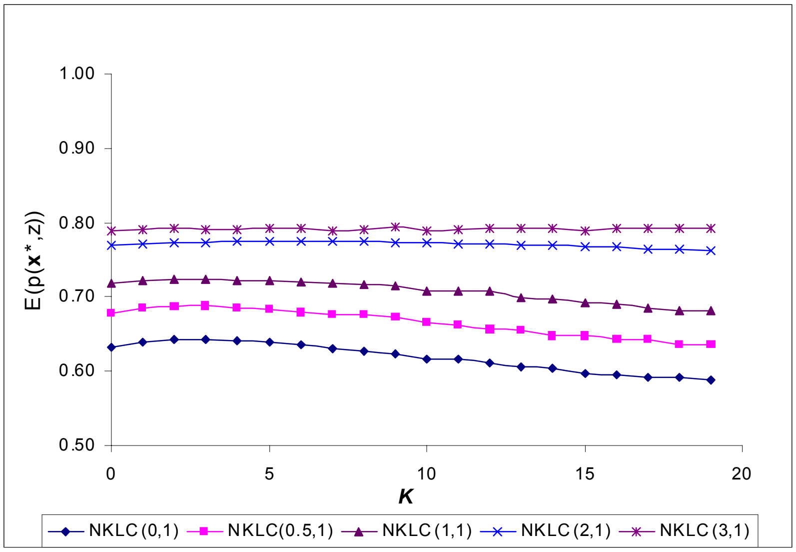

Figure 1: The Expected Performance of a Local Maximum Team in the $NKLC(\mu, \sigma)$ Models as a Function of K when $N = 20$.

maximum—that is, a team whose performance is greater than or equal to that of all its one-replacement neighbors.

Computer simulations were conducted to determine the average performance of a local maximum team obtained from the $NKLC(\mu, \sigma)$ model for a team of size $N = 20$ and for different values of K and μ, with σ fixed at 1. The one-replacement process was used on the workers to obtain a local maximum on 500 randomly-generated problems. The new team $\mathbf{x}'$ was chosen randomly from all the one-replacement neighbors of the current team $\mathbf{x}$ that yielded better performance than $\mathbf{x}$. The results presented in Figure 1 compare the expected performance of a local maximum team in the $NKLC(\mu, \sigma)$ model for different skill levels of the leader when $\sigma = 1$. The following observations and conclusions can be drawn from Figure 1:

- The skill level of the leader improves the team performance no matter how much interaction there is among the workers, as evidenced by the fact that the entire performance curve shifts up from a lower value of μ to a higher one.
- The skill of the leader can be more important than the amount of interaction. For example, in a team with a more skillful leader and lots of interaction, such as when $\mu = 0.5$ and $K = 19$, the average performance of a local maximum team is still higher than the best performance when the leader has no skill and the interaction is small.
- When the skill of a leader is low, the $NKLC(\mu, \sigma)$ model exhibits the interaction catastrophe but this is attenuated as the skill of the leader increases. This means that a more skillful leader is able to manage larger amounts of interaction among the workers than a less skillful leader.

The simulation results reported in Figure 2 illustrate how the variation of the skill of the leader affects the expected team performance when $K = N/2 = 10$. The results show that for a fixed skill level of the leader, the expected performance of a local maximum team appears to approach 0.65 as the variance approaches infinity. Observe that the expected performance increases with σ when the leader is not skillful ($\mu = 0$) but decreases with σ when the leader is skillful ($\mu \geq 1$). Computer simulations were also conducted for other values of the amount of interaction K and yielded similar results.

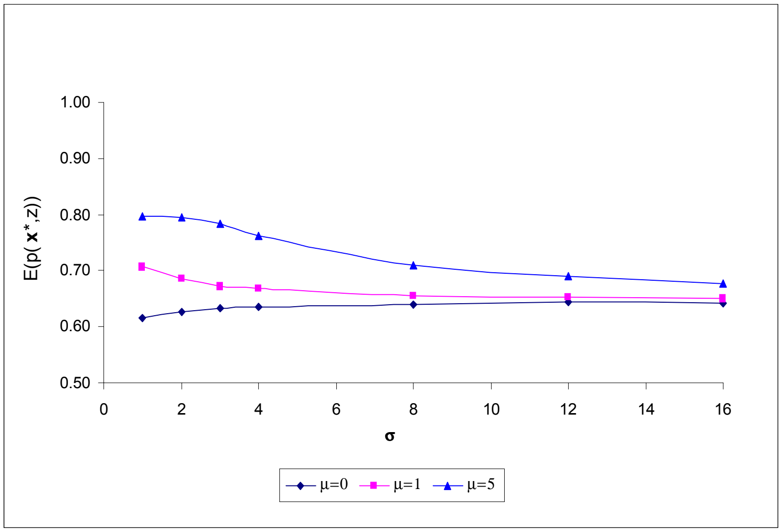

Figure 2: The Expected Performance of a Local Maximum Team in the $NKLC(\mu, \sigma)$ Model as a Function of σ for Different Values of μ when $N = 20$ and $K = 10$.

Here, a model has been proposed for studying the effects of cooperational leadership on the process of assembling a good team. Specifically, controllable parameters representing the leader's skill and variance in achieving cooperation between each worker and the K other workers that affect the contribution of worker i are introduced. New insights obtained from these models include the following:

1. Having a skillful leader can be more important for team performance than controlling the amount of interaction among the workers.

2. A leader skilled in achieving cooperation can overcome, or at least attenuate, the "interaction catastrophe," in which team performance deteriorates as the amount of interaction among the workers increases.

Additional results from two other models that include cooperational leadership in a way that is different from the $NKLC(\mu, \sigma)$ model presented here are described in the full paper.

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Internal Fit between Team Structure, Communication Methods, and Leader's Expertise

----A simulation study of global fixed income team

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Abstract

Although there are some criticisms about the clarity and effectiveness of contingency theory (Schoonhoven, 1981), its underlying assumption suggests that combinations of different levels of different factors can result in fit or misfit (Meyer et al., 1978; Galbraith, 1973). In general, many researchers in this area emphasize the internal fit among organization factors and task complexity. They assume that an organization / team is facing various kinds of tasks all the time. For each kind of task, it needs different structures or methods in order to achieve higher performance. However, we found that besides traditional organizations, there are many global functional teams (members in which locate in different countries). Unlike big organizations, these teams are much smaller and more flexible. The function of these teams is to complete the same kind of tasks instead of various jobs. In this paper we conduct a simulation using Vité to explain how to improve the internal fit, therefore improve the performance of the team when the nature of the task is given. We examine a specific team – the global fixed income team, and we believe that the contingent relationship between team structure, communication methods, and leader's expertise should able to dramatically influence the performance. We list nine efficient combinations. Then we do a virtual experiment to test the robustness of these hypotheses.

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Key Words: contingency theory, fit, performance, team structure, communication methods, expertise, simulation

Internal Fit between Team Structure, Communication Methods, and Leader's Expertise

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Contingency theories

Contingency theories were first introduced in 1960's by sociologists (Thompson, 1967; Lawrence & Lorsh, 1967; Katz & Kahn, 1966), extending "closed system" to "open systems" and "organizations in environment" (Padgett, 1990). At that time it is commonly believed that organizations must achieve both external fit and internal fit, furthermore, these two ends should be compatible also. The assumption underlying contingency theories is task-environment-structure fit. Drazin & Van de Ven (1985) categorized this structural contingent view into three sub approaches: selection, interaction, and systems approaches. Although there are differences among these three perspectives, all of them represent structural view, and, none of them mentions the relationship between fit and organization performance. Researchers in 1970's and 1980's focus more on "fit" itself, instead of its influence on effectiveness and performance. Miller (1992) demonstrates that environmental fit and internal fit do not necessary to be compatible, but his study did not mention organization performance either.

In late 1980's and 1990's, more and more researchers began to explain performance and efficiency by examining fit and misfit (Manor, 1994; Mak, 1989; Gresov, 1989; Pennings, 1987). Another remarkable change is that technology has been broadly added to contingency theories. The task-environment-structure approach gradually switches to task-technology-structure approach. For example, Manor (1994) studied the technology-information processing fit, Lee (1996) studied fit in two different technology contexts, and Yasai-Ardekani & Nystrom (1996) combined environments and technology – they studied the impact of environmental scanning system.

Recently, leadership and entrepreneurship start to join the context of contingency theories. Previous studies were over bureaucratic (Weber, 1942), paying insufficient attention to people inside organizations. As the blooming of small business in late 1990's, the role of the leader and the fit/misfit with other factors inside or outside the organizations attract many researchers' interests. Some of them emphasize the leader's compensation package (Fidler, 2000; Finkelstein, 1998); others study the influence of CEO's attitude (Lewin, 1994).

Although contingency theories have been developed for 40 years, an interesting phenomenon is that all of these researches stay mainly at organization level. Some researchers expand contingency theories to national/political level (Cancel, 1999; Geiger, 1999). However, there are few studies examining contingency theories at lower level – team level. A consequence of this lack is that people always study the task related contingency theories because organizations and nations have to deal with all kinds of uncertain tasks. However, it is still necessary to study fit/misfit in those functional teams which facing same kind of task repeatedly.

Thus, our goal of this paper is to discover when the nature of task is given, what kind of fit between three internal variables – team design, communication methods, and leader's skill – will maximize team performance /effectiveness.

Team Structure

Unlike traditional hierarchical organizations, teams, especially global virtual teams prefer flat design. Time and location differences make it difficult to adjust strategies quickly to adapt the changes of situation. If the subordinates could only contact their direct supervisors, the speed of information processing would be even slower. Therefore, flat structure has more advantage than the hierarchical structure. On the other hand, in this world we have too much information. Many of them are useless and even harmful. In the hierarchical team, lower level employees using their expertise to decide which information is good and which is not, then report to upper level managers. This process filters out most noise. However, in a flat structure team, everyone can communicate with someone else, and in many cases they lack the ability to distinguish useful and useless information. In this sense, flat structure has its own disadvantages. Which one is better, flat, hierarchical, or half-hierarchical (managers contact with each other, while employees can not) depends on whether it is fit to all the other factors.

Communication Methods

Meanwhile, communication costs among members of global virtual team are usually higher than costs of local teams. Costs here include monetary cost, time cost, misunderstanding cost, opportunity cost, etc. In general there are two kinds of communication methods: CMC and FTF. CMC is computer mediated communication, including bulletin boards, email, chat room, telephone conference, etc. FTF is the abbreviation of "face to face". Traditional meeting is a major form of FTF. Although the monetary cost and time cost of CMC are much lower than those of

FTF, according to media richness theory, in certain circumstances CMC is not capable to transfer subtle information. Therefore CMC is easier to result in misunderstandings. Sometimes misunderstanding costs are hugely higher than all the other costs. Thus, like team structure, which method is better relies mainly on fit/misfit. Here we define communication methods into three levels: CMC, FTF, half CMC + half FTF.

Leader's expertise

Leader's characteristics have been deeply studied in leadership for a long time. At first beginning researchers like to examine the demographic characters of leaders, e.g., gender, culture, etc. Recently the focus shifts to charisma, attitude, managerial skills, and so on. We agree that all of these factors are crucial, but in our cases, when the nature of task is given, leader's expertise probably dominates all the other traits. More specifically, if the leader's expertise fit with other variables, we can expect the process to be smooth. If the leader does not have pertinent expertise, or his knowledge conflicts with team structure or communication methods, misfit happens and then the efficiency is reduced. In our case we divide the expertise into three levels: high, medium, and low. High expertise means the team leader was selected from skilled members. He was promoted mostly because he has the best expertise among the whole team. Low expertise means team leader was promoted not because he was the best expert but because he has the best managerial skills and leader charisma. Medium expertise leader is between high and low – he has both expertise and leadership skills but neither is the best among the team.

Hypotheses

As stated above, we have three variables, and each variable has three levels. Mathematically, there are $C_3^1 * C_3^1 * C_3^1 = 27$ kinds of combinations (Table 1):

Table 1: Possible combinations of the three variables

	Team Structure	Communication Methods	Leader's Expertise
1	Flat	CMC	High
2	Flat	CMC	Medium
3	Flat	CMC	Low
4	Flat	CMC + FTF	High
5	Flat	CMC + FTF	Medium
6	Flat	CMC + FTF	Low
7	Flat	FTF	High
8	Flat	FTF	Medium
9	Flat	FTF	Low
10	Half Hierarchy	CMC	High
11	Half Hierarchy	CMC	Medium
12	Half Hierarchy	CMC	Low
13	Half Hierarchy	CMC + FTF	High
14	Half Hierarchy	CMC + FTF	Medium
15	Half Hierarchy	CMC + FTF	Low
16	Half Hierarchy	FTF	High
17	Half Hierarchy	FTF	Medium
18	Half Hierarchy	FTF	Low
19	Hierarchy	CMC	High
20	Hierarchy	CMC	Medium
21	Hierarchy	CMC	Low
22	Hierarchy	CMC + FTF	High
23	Hierarchy	CMC + FTF	Medium
24	Hierarchy	CMC + FTF	Low
25	Hierarchy	FTF	High
26	Hierarchy	FTF	Medium
27	Hierarchy	FTF	Low

Based on our analysis, we hypothesize that 9 out of 27 combinations (yellow shadowed columns in Table 1) are efficient. We address them one by one.

The first hypothesis is: flat structure team in which members communicate with each other by CMC with high expertise leader is efficient. The reason is that flat team using CMC means there are many useful and useless information inside the team. Thus, a leader with high expertise is able to filter useless information so as to make the team efficient.

H1: Flat structure teams using CMC with high leader expertise are more efficient than flat structure teams using CMC with medium/low leader expertise.

For flat teams using both CMC and FTF, like the first situation, there are still many information. Even worse, members have to meet face to face once in a while, that means, the leader of the team must have both expertise and managerial skills. Otherwise the whole situation may be out of control. Thus,

H2: Flat structure teams using both CMC and FTF with medium leader expertise are more efficient than flat structure teams using both CMC and FTF with high/low leader expertise.

For flat teams using only FTF, it is a little difficult for management to acquire the information they want. Low expertise leader (with high managerial skills) can successfully facilitate his employees, therefore this combination will be better than those with high/medium expertise leader.

H3: Flat structure teams using FTF with low leader expertise are more efficient than flat structure teams using FTF with high/ medium leader expertise.

For those "half hierarchy" team (middle level managers contact with each other, but lower level employees can not), if they are using only CMC, it is not very easy to control and filter the information. Consequently, we expect when team leader has both managerial skills and expertise, team efficiency is the best.

H4: Half hierarchy structure teams using CMC with medium leader expertise are more efficient than half hierarchy structure teams using CMC with high/low leader expertise.

For those half hierarchy teams using both CMC and FTF, we believe that the information flow should be under control because management can choose whichever suitable method to fulfill the needs. Thus, the leader does not have to have high/medium managerial skills – those with low managerial skills/high expertise can work well.

H5: Half hierarchy structure teams using both CMC and FTF with high leader expertise are more efficient than half hierarchy structure teams using both CMC and FTF with medium/low leader expertise.

For those half hierarchy teams using only FTF, information flow is under control but may be not freely enough. Therefore, leaders with both expertise and managerial skills are most suitable for them.

H6: Half hierarchy structure teams using FTF with medium leader expertise are more efficient than half hierarchy structure teams using FTF with high/low leader expertise.

For strict hierarchical teams, if they using only CMC methods, information flow is quick and middle level managers can filter and control it. Thus, top leader does not need high managerial skills – he can be a leader with low managerial skills/high expertise.

H7: Hierarchy structure teams using CMC with high leader expertise are more efficient than hierarchy structure teams using CMC with medium/low leader expertise.

Similarly, in hierarchical teams using both CMC and FTF, middle managers can decide which method to be used under which situation. Thus, top leader can have high expertise/low managerial skills.

H8: Hierarchy structure teams using both CMC and FTF with high leader expertise are more efficient than hierarchy structure teams using both CMC and FTF with medium/low leader expertise.

For hierarchical teams using only FTF, things are a little different. Both information volume and information flow are completely in the hand of middle managers, however, top leader is the only one who is responsible for the whole team. In order to acquire useful information, top leader should have high managerial skills/low expertise.

H9: Hierarchy structure teams using FTF with low leader expertise are more efficient than hierarchy structure teams using CMC with high/ medium leader expertise.

Simulation

We use Vité as the simulation tool to do the virtual experiment. Our study object is the global fixed income team. The assignment of global fixed income teams is to contact with organizations which want to issue corporate bonds (issuers), make bond product and price it as issuers' expectation, road show to customers/investors, get feedback, revise the products, then issue to final customers/investors. This process usually lasts half to one year. Although the bonds can be various, the process (nature of task) is always the same. Therefore, this kind of team is quite suitable to our study. On the other side, all global fixed income teams in investment banks are using one structure/communication method/leader's expertise combination: "hierarchy + FTF + medium". Moreover, it is not easy to do experiments in real world – nobody can be responsible for the failure of millions of dollars bond issues. Thus, simulation has absolute advantage over field study in this case.

In Vité, we use the commonly used design (hierarchy + FTF + medium) as our baseline model. Then, we compare this baseline model with the 9 hypotheses one by one to see which kind of arrangement can significantly reduce work volume, rework volume, working time, noise, or any other efficient measures. The ideal situation is that all the nine hypotheses are better than the baseline model. Furthermore, we expect the simulation to show us that there exists one combination which has the best internal fit therefore can maximize the efficiency.

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Defining Micro-Behaviors for Use in Organizational Simulations

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Abstract

This paper identifies the process by which new micro-behaviors are identified, refined and validated for inclusion in computational simulations. A review of the organizational literature provides the basis for an initial prediction of a micro-behavior associated with the use of Communal Knowledge Mechanisms. Conventional wisdom and virtual experimentation validate the potential utility of defining this behavior for simulation. Initial predictions are refined via the application of a survey to contemporary knowledge workers. The refinements then serve as the basis for experimental design and empirical observation as part of the validation process. The data from the survey and the initial experimentation is provided. This documentation provides the potential for the micro-behavior to be integrated into a variety of simulations. As an example, this micro-behavior can now be modeled computationally and used to extend the performance of the existing VDT simulation tool that will enable the user to measure the impact of the CKM on overall project performance.

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Key Words: computational modeling, simulation, organizational theory

Acknowledgement:

This material is based upon work supported by the National Science Foundation under Grant No. 9980109. Any opinions, findings, conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation.

TRACKING SHIFTING PEAKS:
ORGANIZATION DESIGN IN DYNAMIC ENVIRONMENTS

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March 3, 2002

Extended Abstract

Submitted to CASOS 2002, Pittsburgh

Research Question

A central issue in the organizations literature is the question of firm-level adaptation in response to changing external environments (Tushman and Romanelli, 1985). In particular, a considerable body of work addresses the challenges posed for established firms in the face of competence-destroying technological change (Abernathy and Clark, 1985; Tushman and Anderson, 1986). But decisions regarding technology over time are subject to fundamental Knightian uncertainty in that it is impossible to know precisely what future technologies may be developed (Rosenberg, 1982). Even if the new bundle of core competences can be exactly identified, organizations still face the formidable challenge to redesign themselves.

The general issue of firm adaptation can therefore be recast into a more specific question: how do firms design their organizational structure such that they can detect the development of new peaks? Borrowing from the landscape metaphor, a firm faces a fundamental challenge of tracking the emergence of such peaks. The key of successful adaptation lies in an ability to evolve new higher order capabilities to explore new opportunities effectively, as well as to exploit these opportunities of flexibility and adaptivity (Volberda 1998). While many theorists have written about new organizational forms (c.f. Lewin and Volberda, 1999), this specific question of organization design to track new peaks remains poorly understood.

This research attempts to address explicitly how this issue of firm adaptation can be effectively tackled by tuning the extent of interactivity within the organization. By designing the relationships between individual actions and payoffs (Levinthal and Waglien, 1999), firms may be able to consistently track the movement of peaks that emerge in the new landscapes. In particular, we seek conditions under which some specific organization design can lead to improvement rather than to chaotic fluctuations in performance. Discovering such conditions will lead us to identify possible selective processes that explain firms' successful adaptation over time.

Relevant theoretical considerations

In the classic work of Simon and Thompson, the organization design problem is to choose the organizational structure so as to maximize the intensity of interactions within a unit of the organization and to minimize the interactions across elements of the system. Recent thinkers such as Nonaka, however, argue that organizations should embrace uncertainty and interdependency by adjusting their structure to suit the demands of an increasingly complex environment (Nonaka and Takeuchi, 1995). For instance, this newer design perspective calls for the extensive use of cross-functional teams that increases the internal interdependencies to generate a variety of alternatives.

Despite these conceptual arguments, little guidance has been offered as to what ratio between functional specialization and cross-integration might offer selective competitive advantage. On the one hand, minimizing inter-unit interaction generates a single peaked performance that enhances coordination. On the other hand, this may also create too much stability and further enhance organizational inertia. In the context of dynamic environments, we argue that an optimal and positive amount of cross-integration is a desirable feature of organizational design because of the exploration friendly nature of interactivity. This can be attributed to the fact that actions taken by one part of the organization now have a direct impact on another part. As such, interactivity triggers reactions and adjustments and creates a pull and tug among conflicting goals. In this way, the organization as a whole carries out more exploration and therefore increases the chance of tracking the emergence of new peaks.

Research Methods

These conceptual arguments are investigated in an agent-based simulation. The NK model affords tunable rugged landscapes whose richness of interactivity can also be tuned. Hence we have begun building NK systems to explore the issue of firm adaptation in dynamic environments, with particular attention to the way that the construction of internal interactivity affects the effectiveness of organization itself. By tuning the amount of interactivity within the firm, we seek conditions under which a more or less interactive organization design may work to improve system-wide adaptivity.

Illustrative Results:

Due to the preliminary nature of this research, we outline here only results that are expected to surface. In a nutshell, we expect that a system that tunes an optimal amount of interactivity will not only achieve higher fitness in a fixed landscape but also be able to track the emergence of higher peaks in changing landscapes. Furthermore, we expect to find a systematic relationship among model parameters: N (number of elements in the system); K (system-wide interactivity); C (percentage of interactive elements that fall within the same unit) and S (number of equal-sized units).

Potential Contributions

The idea of interdependency has long been at the heart of organization design. Despite the richness of theoretical ideas, there has been relatively little formal investigation as to the extent to which interdependency within an organization can influence organization adaptation over time. This research therefore represents a first step towards understanding how organization design can be used strategically to help track the shifting peaks dynamically.

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Strategic Alliance Formations: Internal Dynamics and Firm Performance

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Abstract

Strategic alliances, as a form for cooperative relationships between firms, have gained increased attention in the management literature. Yet, much less effort has been extended in exploring the dynamics of such member firm relationships and their effect on parent firm performance. This study tackles this issue by examining strategic alliance formations longitudinally using a computer simulation model. In the model, firms can interact with each other for resource accumulations based on either a resource match mechanism, which allows alliance formation to be based purely on resource complementarities, or a learning mechanism, which allows alliance formation to be based on not only resource complementarities but also past interactions. The results show that firms following the learning mechanism outperform those following only the resource match mechanism. In addition, a firm's performance can also be affected by its number of alliances and its centrality within the industry. Contingency variables including the uncertainty level of the resource environment and the size of the industry are also examined.

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Key Words:
Strategic alliances; Firm performance; Computational modeling.

Strategic Alliance Formations: Internal Dynamics and Firm Performance

Zhiang Lin and Dan Li

Theoretical Background

Since the seminal work by Powell [Powell, 1990], differentiating the network form of organization from both the dichotomous view and the continuum view of market and hierarchy, numerous studies have been conducted on strategic alliances. While scholars have started to look into the causes of strategic alliances and their effects on their member firms, they have mainly been concerned with some overall characteristics of such networks or the dyadic relationships that are often treated as dichotomous and stable. As a result, research on strategic alliances has exhibited an obvious lack of understanding of the underlying dynamics of strategic alliances, in particular member firms' evolving relationships, and the effect of such dynamics on firm's performance [Nohria & Garcia-Pont, 1991]. We believe, to advance the field of strategic alliance research, it is critical for us to tackle this issue.

Main perspectives

Consistent with the literature, this study defines a strategic alliance as any voluntarily initiated cooperative agreement between firms that involves exchanging, sharing or co-developing resources or firm-specific assets [Gulati, 1998].

The previous literature has provided us with various explanations on how firms select their strategic alliance partners. From the economic perspective, represented by the transaction cost economics, strategic alliances are considered as an intermediate structural form between market operations and formal hierarchical ones to minimize costs stemming from coordination difficulties and uncertainties [Williamson, 1991]. Business complementarity has been treated as one important reason for alliance formation [Das & Teng, 2000]. In sum, from the economic perspective, alliance formation and subsequent evolution are fundamentally based on partner firms' rational calculations of cost and benefits for obtaining complementary capabilities or resources.

In recent years, there has been a growing interest in understanding alliance formation and evolution from a behavioral perspective, even though the recent economic perspective represented by the likes of transaction cost theory has started to consider the consequences of bounded rationality such as opportunism. The behavioral perspective regards organizations as players who may not always be rational but search adaptively for satisfycing objectives under ambiguity and uncertainty [March, 1989]. From this behavioral perspective, strategic alliance evolution also becomes an adaptive learning process by parent firms [Baum, Li & Usher, 2000]. Such learning behavior is also considered one main contributor for the trust between the firms.

Some recent studies have started to explore strategic alliances based on some combination of the two perspectives [Chiles and McMackin, 1996]. Others have also noticed, from the contingency perspective, the contextual environments under which the effect of strategic alliances on firm performance may vary [Gulati, Nohria, & Zaheer, 2000]. For this study, we intend to compare and integrate the economic and the behavioral perspectives by considering three main factors in strategic alliance formations: (1) resource matching, reflecting the resource complementarity from the economic perspective; (2) organizational learning, reflecting satisfycing search process from the behavioral perspective; and (3) industry environment, reflecting the context of the firms from the contingency perspective.

A Computational Model

We rely on the agent-based computational modeling approach to explore our research questions. We model firms as dynamic agents, who can have some essential organizational characteristics and can form relationships with other agents based on theoretically driven factors.

<u>Resource match</u>. To model this factor, we allow firms to have different resource capabilities and different resource needs. How likely a pair of firms may form strategic alliance will then depend on the degree of resource match between the output of one firm and the input of the other firm.

<u>Organizational learning</u>. To model this factor, we allow each firm to keep track of past interactions with another firm reflected through the strength of ties between them. Therefore, how likely a pair of firms may form strategic alliances will depend on how frequent and successful past exchanges between partners have been, even though resource match is also considered.

<u>Industry environment</u>. To model this factor, we create industry environments with different resource uncertainty levels and different sizes.

The computation model is written in Unix C.

Virtual Experiments

With the above computational model, we conduct a series of virtual experiments in which we vary the firm's strategic alliance formation mechanism (two types: resource match mechanism or learning mechanism), the uncertainty level of the industry environment (three levels: low resource demand, moderate resource demand, or high resource demand), and the size of the industry (3 levels: 20, 60, or 180 total firms).

In each of the experiments, we examine thirty continuous time periods through which alliance formations are observed and the overall patterns in the industry are recorded which will also provide information on the number of alliances a firm has formed during that time period and the centrality of a firm in the industry. We measure a firm's performance in terms of the efficiency for resource accumulation.

Preliminary Results

The results from the virtual experiments show that firms following the learning mechanism can outperform those following only the resource match mechanism. The uncertainty level of the environment has a negative impact on a firm's performance. The number of alliances a firm generally has a positive relationship with a firm's performance, except when the firm is in a highly uncertain industry environment. Central positions in the industry tend to only help firms following the resource match mechanism.

Discussion and Conclusion

Our study intends to provide a more systematic approach to the understanding of the dynamics of strategic alliance formation and the effect on firm performance. We believe our computational models can allow us to explore various theoretical arguments and generate some interesting findings, which can be further tested empirically in our future research.

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An Emergence Model of Organizational Change

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Abstract

The contrast between incremental and episodic change is so fundamental to the conceptualization of organizational change that it provided the basis for a recent review of this literature (Weick & Quinlan, 1999). The incremental viewpoint suggests that change arises from the accumulation of ongoing adaptations, and that although organizational transformations may be inferred by comparing activities over time, no transforming activities are identifiable (e.g. Brown & Eisenhardt, 1997). The episodic viewpoint on the other hand, argues that ongoing tension between forces for stability and change in an organization create long periods of small changes or convergence punctuated by short periods of revolutionary changes or reorientation (e.g. Tushman & Anderson, 1986). We propose that the two viewpoints are neither mutually exclusive nor irreconcilable. Incremental and episodic changes are both emergent features of the same dynamic processes. We present a model of organizational change as an emergent systemic phenomenon to illustrate our argument. The findings from this model are compared with other simulation models of organizational change (Sastry, 1997; Lant & Mezias, 1991) as well as with data from the only empirical study of punctuated equilibrium in organizations (Romanelli & Tushman, 1994). The implications of using an emergence perspective for studying organizational change are discussed.

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Key words: Organizational change, punctuated equilibrium, adaptation, complex systems, self-organized criticality

An Emergence Model of Organizational Change

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The dynamics of change in organizations is an ongoing preoccupation of organizational researchers. Researchers have used different theoretical and methodological approaches to investigate this phenomenon (see reviews by Van de Van & Poole, 1995; Weick & Quinlan, 1999). A fundamental dichotomy in these studies is whether change is viewed as incremental and continuous or as episodic and discontinuous. These viewpoints represent vastly different assumptions about the change processes in organizations and lead to very different expectations about the types of change we are likely to observe in organizations.

We propose that the concept of emergence in complex systems may help reconcile these seemingly contradictory positions. We begin by briefly reviewing the debate between the incremental and continuous viewpoints of change. We then explain the idea of emergence using the concept of self-organized criticality. Following this, we present a model of organizational change and demonstrate that it exhibits both incremental and episodic characteristics. Findings from the model are used to discuss data from an empirical study of organizational change.

Episodic and Incremental Change in Organizations

Organizational change is typically described as being discontinuous and intermittent (Gersick, 1991; Tushman & Anderson, 1986) or continuous and incremental (Miller & Chen, 1994; Orlikowski, 1996; Brown & Eisenhardt, 1997). Discontinuous change arises from conditions created by the growing mismatch between the inertial deep structure of the organization and the perceived environmental demands (Gersick, 1991). Change is triggered by external events such as technological change or internal events such as change in top management or the perceived decline in organizational performance (Romanelli & Tushman, 1994). According to the the punctuated equilibrium model of change, which is an exemplar of this viewpoint, the life of an organization consists of long periods of incremental change or convergence punctuated by short bursts of revolutionary changes or "strategic reorientation." This pattern is assumed to be a result of tension between forces for stability and change and not the cumulative result of incremental changes. In contrast, continuous change is characterized as resulting from continuous modifications to the work processes (Orlikowski, 1996: Brown & Eisenhardt, 1997). Inertia and trigger events play a limited role. Changes are achieved by a series of ongoing adaptations and alterations. Although fundamental organizational transformations may be inferred by comparing organizational activities over time, no specific transforming events are identifiable.

Interestingly, both approaches see interdependencies among organizations, organizational units, and organizational actors as an important pre-condition for change. For instance, Tushman and Romanelli (1985) characterize organizations as sets of tight interdependencies that converge and tighten during a period of relative equilibrium. The result of interdependence is resistance to change. Theories of continuous change, on the other hand, see interdependencies as being necessary for enabling small continuous adjustments across organizational units to cumulate and result in organizational change. The result of interdependence in this case is cascading adaptation over organizational units.

We argue that the two viewpoints are not necessarily irreconcilable, although the punctuated equilibrium viewpoint was developed as an alternative to the incremental view of change. Using the concept of self-organized criticality, we propose that in a complex system made up of interdependent parts such as an organization, incremental change can and indeed does give rise to changes of different magnitudes including those that may be considered episodic. More importantly, the size distribution of changes will exhibit regularities that provide clues to the processes driving change in these systems.

Emergence in Complex Systems – Self-Organized Criticality

An important feature of many complex systems is that they exhibit emergent properties. By "emergence" we refer to the appearance of a non-random regularity or statistical distribution at the system level that cannot be inferred or observed at the local level. A common example in biology is the emergence of proteins from individual cells. We suggest that organizational change represents an emergent property of organizations functioning as adaptive systems and that emergence manifests itself as regularities in the size distribution of change. Specifically, we use the concept of self-organized criticality (SOC) to suggest that the size distribution of change in organizations will follow a 1/f distribution, a feature that cannot be explained by looking at change at the level of organizational sub-units.

SOC is a dynamic concept that seems to be so ubiquitous in complex systems that Bak (1996) tends to identify SOC with complexity or to treat SOC as a basic feature of complex systems. The concept of SOC is best understood by turning to two widely studies examples in the CST literature—sand pile cellular automata (Christensen et al, 1991) and punctuated equilibria (Bak & Sneppen, 1993). The sand pile cellular automata attempts to model the behavior of a sand pile (it is not a realistic model of a sand pile though). Grains of sand fall one by one on the ground, building a cone. The cone becomes steeper and steeper up until the slope reaches a critical value. Adding more grains of sand at this point leads to avalanches. Computer simulations show that the frequency of the avalanches in this model is inversely proportional to their size (this is referred to as the 1/f law). The system is then "Self Organized Critical."

Studies of punctuated equilibria model the progress of biological evolution (Gould & Elridge, 1977). In this case the models capture a well-known feature of biological evolution—it does not proceed smoothly. There are periods of fast evolution between long moments of stagnation. In this example, the evidence of SOC is the fact that the frequency of the periods of large evolutionary activity is inversely proportional to the size of the evolutionary activity. Once again, this distribution follows the 1/f law.

The evidence of SOC or its most conspicuous signature is the so-called 1/f law (which in fact means 1/fa, a<2). 1/f distributions are a ubiquitous phenomenon which is found in physics (press, 1978), size distribution of business firms (Ijiri & Simon, 1977), earthquakes (Gutenberg & Richter, 1956), biological evolution, linguistics (Zipf, 1949), etc. SOC is an emergent property that may, in some cases, correspond to a dynamic optimization. For example the heart is healthiest, i.e. it has the highest level of adaptability, when the heart rate has a 1/f power spectrum (Kobayashi & Misha, 1982).

The apparent universality of the 1/f law may reflect the ubiquity of SOC, although the reason for it is still mysterious. The examples of the sand pile CA and punctuated equilibria seem to cover different types of dynamic situations. The SOC displayed in sand piles cellular automata corresponds to a dynamic equilibrium resulting from the combined effect of a linear instability (the slope of the cone getting steeper than the critical value), and a non-linear feedback or dissipation (avalanches). The SOC displayed in punctuated equilibria on the other hand, does not reflect a dynamic equilibrium but is part of the dynamics of change. To be able to differentiate between different types of dynamic situations, conceptual refinements to SOC are of the essence.

Stochastic explanations have been offered as an alternative to the dynamic explanations of the occurrence of 1/f law. Consider the robust finding that the size distribution of firms in an economy follows the 1/f distribution. Simon (1955) demonstrated that 1/f distributions correspond to the stationary state of stochastic processes where the probability that an event occurs is proportional to the number of times it has occurred in the past. This interpretation implies that the rate of growth of a firm should be proportional to its size. But, this is not what is observed. In fact, the relative rate of growth of firms seems to decrease with their size (Sutton, 1997). 1/f distributions may have a still completely different origin. They may reflect the tail of a stable non-Gaussian distribution which is known to have an asymptotic power law behavior (Mandelbrot, 1963). This explanation too is problematic. It requires the unlikely condition that the distribution of sizes of business firms is the sum over a large number of independently identically distributed random events, with large variance (Gnedenko & Kolmogorov, 1954). Our point is that although stochastic explanations for 1/f distributions may hold in non-dynamic cases such as the number of words in a text, they fall short in dynamic situations.

If the size distribution of firms is due to SOC, it raises an important question: what are the underlying dynamics responsible for this distribution? It may be related to the dynamics of growth of business organizations in a competitive economy. Or it may reflect a dynamic equilibrium of some sort or even a dynamic optimum of some sort.

Emergence Model of Organizational Change

We ran a simulation of a model of evolution abstracted from Bak and Sneppen (1993). This is an extremely simple model that still has dynamical content rich enough to include features such as punctuated equilibria, dynamical self-organization, 1/f power spectrum etc. Basically, we model organizations by a tree diagram where the vertices represent organizational units. The edges represent functional relationships between units. We identify the unit that has the lowest performance level and draw a new random value for the performance of that unit, as well as for all the units directly connected to it. This procedure is iterated until the performance of the lowest-performing unit ("gap") ceases to increase i.e. a "steady state" is reached. The dynamics of the growth of the gap (corresponding to an improvement in organizational performance) exhibits punctuated equilibria. What is more, the size of the avalanches (succession of steps leaving the gap unchanged) is roughly inversely proportional to their frequency i.e. it follows a 1/f distribution. This is a signature of SOC, but not a proof. The punctuated equilibria and their distribution are emergent properties resulting from the interactions of many adaptive agents (Cohen, 1984). The fundamental results of this model are robust even if we change the underlying assumptions. This model suggests that incremental change can, at least analytically, lead to the emergence of punctuated equilibria.

Emergent Properties in Romanelli & Tushman (1995) Data

We applied this insight to data from the only empirical investigation of punctuated equilibria in organizational change—Romanelli & Tushman's (1994) study of minicomputer firms. We realized that the authors may have unwittingly provided an early evidence for self-organized criticality in organizational change. This study examined changes in strategy, structure, and power distribution of 25 minicomputer producers founded between 1967 and 1969. The authors reported frequencies for four levels of changes and concluded that the observed patterns supported a discontinuous model of change. Our reading was different. Their model suggests that small-scale changes and large-scale changes are completely different in nature and purpose. If this were true, one would expect the distribution of changes to be bimodal i.e. it should have a peak for small changes and a peak for large changes. However their empirical results show that the distribution of changes in monotonous without a peak suggesting that the line dividing "revolutionary" changes from "small" changes is not well defined. More important, the frequency of changes that they report has some underlying structure, specifically a 1/f distribution. Again, we take this as an indication and not as a proof of SOC. Of course this is based on a single study and we need to analyze more data sets before we can make a conclusive statement. All the same, it is intriguing that the data collected across several organizations over time should display the 1/f characteristic. We discuss how the dynamic processes described in our model generate punctuated equilibria with fewer assumptions and without the post fact adjustments contained in two other published models (Sastry, 1999; Lant & Mezias, 1996).

Agent-Based Modeling Reveals The Rules And Results Of Multi-Team Cooperation

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Abstract

The effort to understand cooperation in the workplace in the face of free riding has long been a topic of dynamic analysis. In a single round interaction, cooperation does not pay (e.g., Dawes). Yet, in a dynamic interaction over time, finding others who will reciprocate cooperation does pay (Axelrod, 1984). Yet, reciprocity may not be the only motivation for cooperation. This paper proposes that social comparison across teams, and the competitive desire to come out ahead in that comparison, generate increased cooperation within teams. Through a lab experiment, the increase in cooperation generated by individuals who can make positive social comparisons is demonstrated. Subsequently, agent-based modeling is used in two unique ways to extend this conclusion. First, an agent-based simulation, closely modeled on the laboratory conditions, verifies that a modified reinforcement rule may describe the decision processes of the lab subjects. Second, an agent-based model using freely acting agents explores the impact of all team members actively using the reinforcement rule. The simulation generates an aggregation pattern with a striking threshold effect. The threshold occurs as agents' aspiration levels increase. Only over this threshold, do social comparisons increase the collective level of cooperation among the members of all teams. Thus, the agent-based model demonstrates a non-linear aggregation pattern. It reveals that while individuals cooperate more frequently in the face of positive social comparisons, a population of individuals arrayed in multiple teams only increases its cooperation levels when the individuals are highly competitive with members of other teams.

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Key Words: cooperation, work teams, prisoner's dilemma, social dilemma, agent-based modeling, emergence, threshold

Acknowledgement: I would like to acknowledge my committee members—Michael Cohen, Jerry Davis, Bob Quinn, Carl Simon, and Rick Riolo—without whose help I could not have finished this dissertation work.

Agent-Based Modeling Reveals the Rules And Results Of Multi-Team Cooperation

Corinne Coen

The effort to understand cooperation in the workplace in the face of free riding has long been a topic of dynamic analysis. In a single round interaction, cooperation does not pay (e.g., Dawes). Yet, in a dynamic interaction over time, finding others who will reciprocate cooperation does pay (Axelrod, 1984). Yet, reciprocity may not be the only motivation for cooperation. This paper proposes that social comparison across teams, and the competitive desire to come out ahead in that comparison, generate increased cooperation within teams. Through a lab experiment, the increase in cooperation generated by individuals who can make positive social comparisons is demonstrated. Subsequently, agent-based modeling is used in two unique ways to extend this conclusion. First, an agent-based simulation, closely modeled on the laboratory conditions, verifies that a modified reinforcement rule may describe the decision processes of the lab subjects. Second, an agent-based model using freely acting agents explores the impact of all team members actively using the reinforcement rule. The simulation generates an aggregation pattern with a striking threshold effect. The threshold occurs as agents' aspiration levels increase. Only over this threshold, do social comparisons increase the collective level of cooperation among the members of all teams. Thus, the agent-based model demonstrates a non-linear aggregation pattern. It reveals that while individuals cooperate more frequently in the face of positive social comparisons, a population of individuals arrayed in multiple teams only increases its cooperation levels when the individuals are highly competitive with members of other teams.

The Lab Experiment and Results

Subjects—MBA students in one group and undergraduates in another—were led into a room with multiple computer terminals. They were assigned to teams and then spread out to different terminals far away from their teammates. The subjects were asked to imagine they were members of a consulting company who had both individual work assignments and team assignments. In each round of the game, they had to decide whether to put their efforts into the teamwork or their individual work. They were shown a payoff structure and informed that they would be paid in cash based on their earnings at the end of the experiment. After each decision, they were shown the choices of other members of the interaction (see below for conditions), and their rankings based on their cumulative earnings.

The payoff structure was in the form of a 6-person social dilemma. Half of the subjects were shown only the performance of members of their own team and thus their ranking within their own team. The other half of the subjects was shown the performance by teammates along with the performance of members of another team in the room. They saw their relative ranking across the two teams. Of the subjects who could observe the performance and ranking of members of another team, half were able to make favorable comparisons of their performance in contrast to these others (they were ranked high); half could make only unfavorable comparisons (they were ranked low).

Unbeknownst to the subjects, they were not actually interacting with any of their teammates in the room. The behavior of their purported teammates and members of the other team were based on scripts built into the web-based computer program.

Table 1 - Twelve round average level of cooperation

N = 99

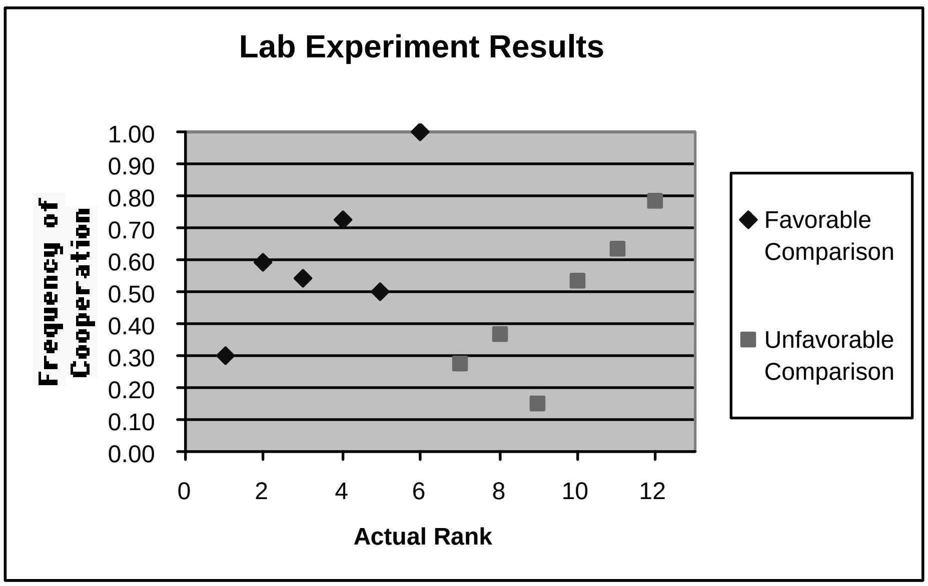
	Favorable Comparisons	**Unfavorable Comparisons**
Ranking across two teams	50%	35%
Ranking across own team	38%	39%

The subjects were told that the game involved an indefinite number of rounds. In practice, the experimenter ended the game after twelve rounds. Table 1 shows the mean level of cooperation in interactions over those twelve rounds. Being able to make favorable comparisons with members of another team due to relatively high ranking, led to positive and significant effects on the decision to cooperate with one's teammates. The level of cooperation in the two-team, favorable comparison condition is significantly higher than the level of cooperation in the two-team, unfavorable comparison condition ($p < .05$, $df = 54$). So, there is support for the hypothesis that favorable comparisons generate cooperation more frequently than do unfavorable comparisons. In addition, cooperation levels were higher in the two-team, favorable comparison condition than in the single team, favorable comparison condition ($p < .08$, $df = 43$). Thus there is support for the hypothesis that comparison rather than pay generates the increase in cooperation.

Finding the Decision Rule

While it was useful to aggregate the subjects' choice behaviors to draw conclusions about the effect of social comparison, more information can be drawn from the lab experiment data. Cooperation frequencies depending on prior round ranking are show in Graph 1.

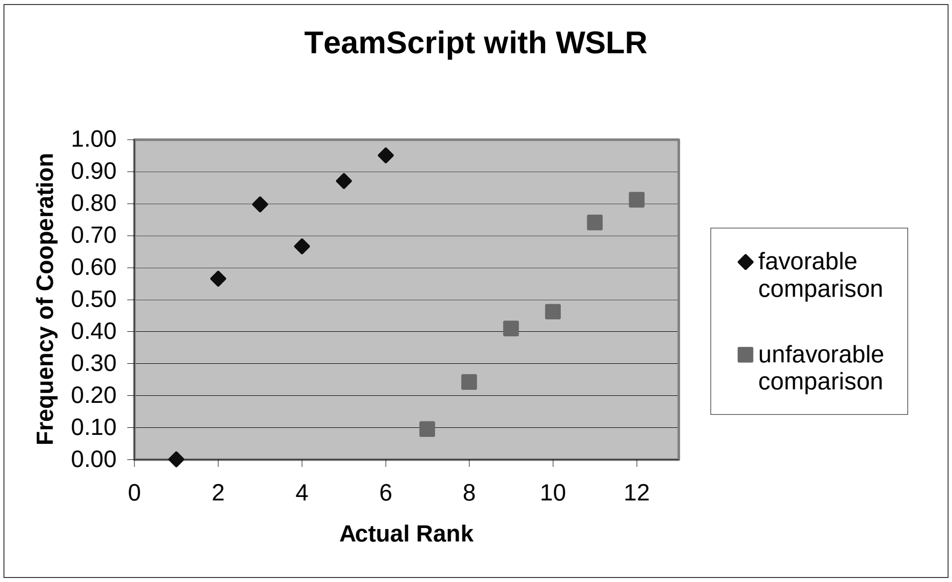
Graph 1



I built an agent-based simulation in the Swarm environment (Minar, Burkhart, Langton & Askenazi, 1996) using an object-oriented approach to computer programming. Unlike equation-based models, agent-based models do not require the use of averaged behavior. Nor do they require aggregation techniques like adding up individual actions from minimal group data. ABMs are unique among simulations in that they allow each agent to make individual decisions while interacting with each other and their environment. In this case, their environment was the behavior of other members of their team and in half the instances, members of another team. In order to reproduce the lab experiment conditions, I imported the scripts used by fictional teammates in the lab, and applied them to all but one agent in the model. I tested an array of decision rules, by having a single active agent use one rule, and doing so over many initializations of the simulation. (Each simulation varied by the active agent's initial propensity to cooperate.) In each test, on the first step, the agent cooperated or defected depending on its "Propensity to Cooperate," and in subsequent steps followed its test rule.

I graphed the results of each test rule, contrasting frequency of cooperation based on actual rank in the prior round, just as I had for the lab experiment. I modified the rules in a systematic way until I found one that was consistent with the lab subjects' descriptions of their behaviors and most closely matched the outcomes observed in the lab experiment. That rule, "Win-Stay, Lose-Revert" (WSLR) generated the results in Graph 2. Using WSLR, an agent would reproduce its prior behavior (cooperate or defect) if it decided that its rank was high enough. If its rank were not sufficiently high, it would "revert" to its initial "Propensity to Cooperate."

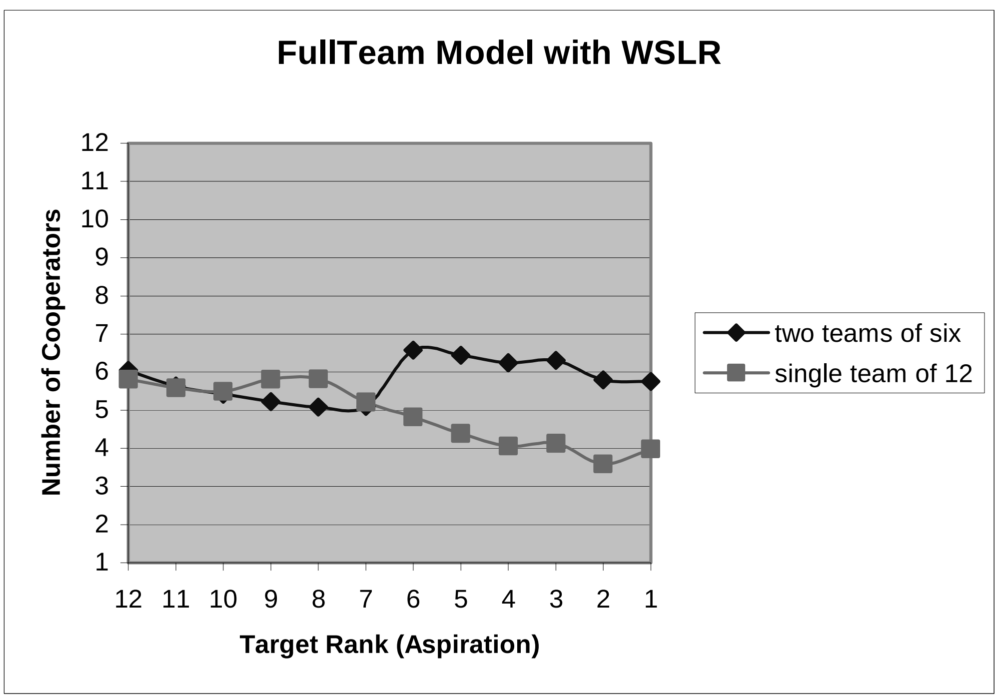
Graph 2



Aggregating Social Comparisons

Computer simulation can be used in other ways. An agent-based model can be used to study mutually dependent interactions. In this part of the study, unlike in the laboratory component or the prior simulation, I built an agent-based model that allows all members of the teams to react to one another. Scripted team members or scripted agents are eliminated. Every member of both teams acts according to its personality type and the WSLR decision rule. Consequently, the simulation can reveal how individual behaviors aggregate when the underlying dynamics of interaction are non-linear. The aggregation describes the outcomes at the level of the team and the multi-team level. The frequency of cooperation given the competitiveness of the agents (i.e., the rank at which they consider themselves "winning") is shown in Graph 3.

Graph 3



A threshold arises in the two-team model. Agents in a single team are less and less likely to cooperate as their aspiration levels rise. This makes sense as the defectors outperform cooperators in the single team social dilemma. Yet, the dynamics and thus the payoff to cooperation are quite different in the two-team model. It is no longer sufficient to be the defector in order to outperform other agents. Defecting can give an agent the highest payoff and thus the highest rank on its own team. But if the other team has many cooperators, its payoff will be lower than some or all of the members of the other team. In the two-team model, the ability to reach each aspiration level depends on dissimilar dynamics. Below the threshold, agents find it relatively easy to reach their aspiration levels; defecting can often be sufficient to reach 7-12th place in the rankings, just as in the single team model. But at or above the threshold, agents cannot sustain the higher rankings relative to members of the other team unless they cooperate with their teammates. Thus, in the two-team world, cooperation pays in a social dilemma when ranking comparisons with members of can be kept positive.

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The Evolution of Metanorms: Reproduction, Extensions, and Insights

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Abstract

A computational study was conducted that replicated and extended the Metanorm game described originally in Axelrod (1986). Specifically, more runs (samples) were conducted to increase the power of the study and more generations were allowed to evolve per run. The results revealed that the inclusion of Metanorms did indeed effectively influence the emergence of a norm-against-defection. Increasing the number of <u>replications</u> significantly reduced the *variance* in boldness and vengefulness scores. Increasing the number of <u>generations</u> significantly increased the initial *form* of score differences in low replication conditions.

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Key Words: meta-norm, evolution of norms, genetic algorithm

The Evolution of Metanorms: Reproduction, Extensions, and Insights

Dan Conway, Mike Prietula

Robert Axelrod's (1986) classic paper illustrated how an evolutionary approach (via a genetic algorithm) can simulate the emergence of norms in a small group. In particular, Axelrod explored the "metanorm game" where a tiered approach defined the influence of norms monitoring defectors (and punishing them) from an n-person prisoner's dilemma game, and included the influence of meta-norms that influenced how failure to enforce norms would be punished. Norms enforce norms, where norms are defined as "coordinated behavior that serves to regulate conflict" (Axelrod 1986, p. 1096).[1]

In Axelrod's metanorms game (hereafter referred to as AMG), agents are faced with a three-tiered decision situation (see Figure 1):

1. An *n-person prisoner's dilemma* decision is the core, where each agent, upon its turn, chooses whether to defect or not.
2. A basic *norms game* decision, where each agent chooses whether or not to punish a defector, if that defector is observed.
3. A *metanorms game* decision, where each agent chooses whether or not to punish an agent who did not punish an observed defector.

Agents in AMG behave in each of these decision situations according to their particular decision strategy. Strategies, in AMG, are defined in a 2-dimensional space where one axis is <u>boldness</u> − likelihood to defect in the n-person prisoner's dilemma decision. The other axis is <u>vengefulness</u> − the level of punishment imposed for defection or non-punishment. Thus, in AMG, there are two mechanisms for enforcing norms: punishment of defecting agents and punishment of the agent who do not punish the defectors.

Note that the enforcement and punishment costs for metanorms (Figure1) are equivalent to those of norms. This is a plausible policy assumption for it makes no distinction between enforcing norms or metanorms; that is, the likelihood to enforce *any* norm is opportunistically dominated by a singular strategy.

That norms exist and that they often play important roles are given. What is less obvious is the articulation of the mechanisms under which norms emerge, and how much control could be employed to influence such development.

Reproducing the Results

The first step was to attempt to reproduce the findings of AMG. This involved running the Norms game and the Metanorms game with the parameters used in the original paper. To facilitate the interpretation, a space of possible strategies was defined in terms of a 2 x 2 categorical grid by using a value of 3.5 (midpoint between 0 and 7 boldness and strategy values) as defining a breakpoint between two levels of a strategy (low and high). This would then define the following four basic types of strategies based on the possible low-high combinations in a grid-space.[2]

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[1]Axelrod's argument, in part, is that norms may be sustained by a variety mechanisms, such as reputation, law, internalization, and metanorms (the topic of this paper), but do not depend on a principal-agent relationship.

[2]All of these categories could be considered evolved norms – norms TO defect and norms NOT to be vengeful against defectors; however, as the focus is the norm-against-defection, we will explicitly entitle that as a norm. "Weakness" refers to the norms anchored at the low end of the vengefulness/boldness continua. Adapting Simon's terminology, these types of norms could be described as *docility*, where docility is defined as receptivity to social influence (Simon 1990, 1991). Weakness can also be thought of as "low cost" as their low value implies that their application is less likely and, therefore, less of an enforcement cost to the group (i.e., individuals in the group are less likely to enforce the norm and, therefore, less likely to incur a cost).

1. *Docility* – Low vengefulness and low boldness.
2. *Norms Against Defection* – High vengefulness and low boldness.
3. *Defection* – Low vengefulness and high defection.
4. *Norm Turbulence* – High vengefulness and high boldness.

The results are slightly different but sufficiently similar to AMG for both games.

Extending the Model

The next step was to augment two strategic components of the simulation to determine the sensitivity of the initial results and to explore the behaviors in detail for additional insight into the processes involved in the evolution of strategic behaviors in both types of games. Two strategic modifications were made in the Norm and MetaNorm game runs: increasing the number of *replications* per game, and increasing the number of *generations* allowed for the evolution of strategies. These were considered less as modifications to the games and more to the experimental situation surrounding the game.[3]

Replications. The basic Norm and Metanorm games were run again, but the number of replications was increased from the original five to 10, 100 and 1000 replications. The results revealed that there were two dominant areas of strategic concentration in the evolutionary grid for the Norm game (defection and docility) a well-defined aggregation around norms-against-defection for the Metanorm game. This is seen as results that complement those found by AMG.

Generations. In the original AMG, evolution was given 100 generations to evolve the final strategies for the game. Ideally, these were assumed to be evolutionary stable.). The results suggest that extending generations appears to have increased the dominance, and distinction, of the norm-for-defection and defection in the Norm and Metanorm games respectively.

Replications x Generations. By analyzing the two effects together, it was revealed that increasing the number of replications significantly reduced the *variance* in boldness and vengefulness scores across games, while increasing the number of generations significantly increased the initial *form* of score differences in low replication conditions across games.

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[3] In an empirical sense, these two modifications could be viewed as both extending the experimental sampling period and incorporating more experimental observations, while retaining the experimental manipulations intact.

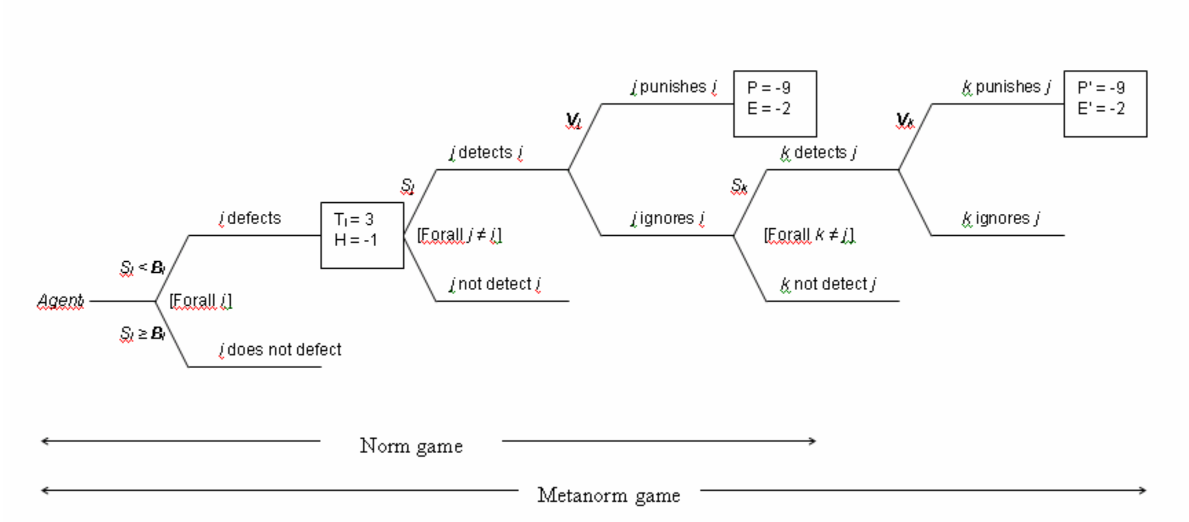

Figure 1. Structure of Metanorm game with payoffs

Flock Theory: Cooperative Evolution and Self-Organization of Social Systems

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Abstract

Everyday conversations, music performance, task groups, improvisational theatre, chat rooms are all contexts that pose a situation to the people interacting where they can evolve as a unit--situations where cognitions and actions can meet to support and collaborate in an evolutionary process. Where cooperation and improvisation can result in egalitarian manifestation, social systems can be simultaneously fragile and stable, autonomous and interdependent, top-down and bottom-up, and all the time allowing for individuality and identity. Such collaborative evolution can be called jamming or improvisation or emergent evolution or the emergence of creativity, but it is argued that they all reflect a situation where equality and support reign over control and power. In this paper, an attempt to model the cooperative evolution of human interaction called Flock Theory is developed.

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Flock Theory: Cooperative Evolution and Self-Organization of Social Systems.

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"...and the thousands of fishes moved as a huge beast, piercing the water. They appeared united, inexorably bound to a common fate. How comes this unity?"
--Anonymous, 17th century

Everyday conversations, music performance, task groups, improvisational theatre, chat rooms are all contexts that pose a situation to the people interacting where they can evolve as a unit--situations where cognitions and actions can meet to support and collaborate in an evolutionary process. Where cooperation and improvisation can result in egalitarian manifestation, social systems can be simultaneously fragile and stable, autonomous and interdependent, top-down and bottom-up, and all the time allowing for individuality and identity. Such collaborative evolution can be called jamming or improvisation or emergent evolution or the emergence of creativity, but it is argued that they all reflect a situation where equality and support reign over control and power.

Flock Theory (Rosen, 2001) is an attempt to model the cooperative evolution of human interaction. A combination of self-organizing systems theory, network theory, and emergent evolution, flock theory bridges across traditional disciplinary boundaries by proposing rule-based axioms regarding the complexity of cooperation.

Conceived to model jazz improvisation, and catalyzed by a computer graphics simulation of bird flocks, this theory pulls from several unique sources. Since there is no existing literature on "flocking" in social contexts, the literature covered is largely to set the stage as a call for research as well as to display an effort by researchers to capture what in essence is flock theory. First, the work Craig Reynolds has done on the successful simulation of flocks is presented as an initial model of flock behavior. Then, work done in organizational communication by Eric Eisenberg on jamming and organizing is discussed, followed by R. Keith Sawyers work on the emergence of creativity. As an example of the breakdown of cooperative evolution, groupthink implications are elaborated upon. Communication convergence and the self-organizing systems concept of autopoiesis provide theoretical referents toward axiomatic development. Finally, the formal axioms and tenets of flock theory are presented. Although this paper focuses mainly on the theoretical aspects of Flock Theory, the two main methodological inquiries and applications conclude this extended abstract.

Boids

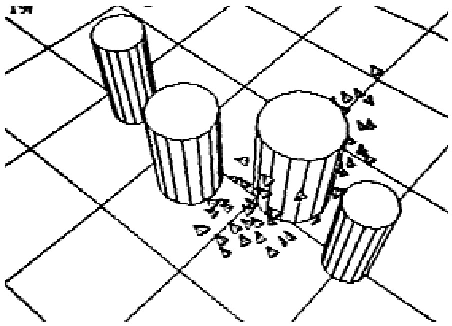
In 1987, computer scientist Craig Reynolds undertook the task of creating a computer rendering of a bird flock. This seminal work provides a new way to explore cooperative evolutionary process. Reynolds comments:

"A flock exhibits many contrasts. It is made up of discrete birds yet overall motion seems fluid; it is simple in concept yet is so visually complex, it seems randomly arrayed and yet is magnificently synchronized. Perhaps most puzzling is the strong impression of intentional, centralized control. Yet all evidence indicates that flock motion must be merely the aggregate result of the actions of individual animals, each acting solely on the basis of its own local perception of the world" (Reynolds, 1987, p.2).

As Reynolds was tackling with the representation of such group movement, he derived three simple rules that can incorporate the vast complexity of a flock.

Rule 1. *Collision Avoidance*: Avoid collisions with nearby flockmates
Rule 2. *Velocity Matching*: Attempt to match velocity with nearby flockmates.
Rule 3. *Flock Centering*: Attempt to stay close to nearby flockmates.

Using these rules Reynolds is able to successfully represent flocks as "boids" in computer simulation. These boids can avoid environmental objects as well as split of from and rejoin the flock. A still-photo example of this phenomenon s provided below:



For an example of this phenomenon as a graphical process, reference http://www.red3d.com/cwr/boids/

Reynolds' ability to capture coordinated evolution in a flock setting is groundbreaking, yet to apply this phenomenon to human interaction is quite a different task. Humans interact using symbol sets as the means of understanding, thus any coordination therein needs to use assume that the agents will use the symbols to maintain organization. However, one of the main aspects of a flock is that the flock as a whole is moving somewhere, but the direction is unknown to the flock before each moment in time.

The transition from simulated physical flocking of birds to human interaction includes theoretical models based on efforts of other researchers attempting to investigate similar phenomena. Two main areas of work that have attempted to visit cooperative evolution are Eric Eisenberg's writings on Jamming and R. Keith Sawyer's research on the Evolution of Creativity. In describing this research, it should be noted that neither offers an explicit model to capture such phenomena (while both duly noted the need) and, thus, the *raison d'etre* of this extended abstract.

Jamming: Transcendence Through Organizing

Eisenberg (1990) describes characteristics of "jamming" experiences, or fluid behavioral coordination that occurs without detailed knowledge of personality. These experiences are seen as sparking a balance between autonomy and interdependence (and can even be transcendent).

Effective balance of autonomy and interdependence can be seen as communicators in all social organizations, from friendships to societies, walk a "narrow ridge" between self and other to attempt to achieve and maintain a balance between the two (Arnett, 1986). Yet in any case either too much or too little consensus can be dysfunctional. Groups that foster too much independence can stifle creativity and can lead to a decayed ability to adapt. Whereas groups that promote excessive autonomy may become inundated with conflict, or simply dissolve. Thus, every action either brings us closer together or farther apart, the challenge is to maintain a balance between degree of closeness and amount of difference, "close-but-not-too-close" (Pacanowski & O'Donnell-Trujillo, 1983). As Wentworth (1980) presents: "The opposite of anomie is not necessarily consensus … the key to grasping the difference between order and consensus lies in the parallel difference between *shared* and *common* reality. To share an apple, for example, cannot mean taking the same bites." (p. 97).

Similar to mutual equivalence structures (Weick, 1979), jamming situations may be highly rule governed, structured activities where little to no personal information is exchanged. Yet, goals are accomplished and a strong bond is formed amongst actors. "Jamming encourages both cooperation and individuation. Jamming experiences provide an opportunity to transcend the autonomy-interdependence dialectic, simultaneously allowing for the possibility of both. These experiences are refreshing, as they satisfy cravings for both closeness and independence" (Eisenberg 1990, p. 146). Jamming provides some sense of reintegration into a communal life (Philipsen, 1987).

Jamming, however, may not be a condition easily attained or maintained. This cultivation requires a clear set of rules and structures. Actors need to surrender to the experience, engaging respectfully in the interaction, dominant leader qualities such as using the exchange to unload on or control others dissolves the possibility for such an interaction.

Structurally, jamming illustrates a case where structure can be seen as liberating instead of constraining. There are low expectations for future interaction as a result of the lack of emphasis on individual personality traits, allowing the actors to cooperate unself-consciously. Likewise, this highly structured setting places relatively few requirements on dealing with and accounting for individual personalities, “jamming experiences permit a *sense* of community that is difficult to achieve through more disclosive interaction” (p. 154).

Improvisation then becomes an important aspect of jamming, where a minimalist view of organizing is crucial – making due with minimal commonalities and magnifying simple structures in complex ways. This notion of structure includes formal and informal rules. In jazz these can be seen as rules of musical keys or progressions (formal) and how long you can play (informal). And as local conventions vary, there is a set of core rules that an actor must know and follow in order for the interaction to take on a jamming situation. However, too much attention to the rules increases the possibility of ego and opens the individual to self-consciousness. Thus, jamming is only possible when this rule and role structure is assumed and taken for granted.

Eisenberg sees modern communication theory as focusing too much on the cultivation of shared interpretations and not enough on how action occurs under conditions of limited shared understanding. He goes on to pose that the ultimate measure of communication success is the degree to which actors achieve and sustain a balance between autonomy and interdependence leading to a sense of meaning and purpose (Eisenberg & Phillips, 1990). Supporting this process, theories of communication and organizing must “acknowledge the multiple communicative avenues members may traverse in their pursuit of personal and social significance” (p. 160).

The Emergence of Creativity

Working on the emergence of creativity, R. Keith Sawyer has established a formidable body of work visiting notions such as collaborative emergence and emergent evolution as support. Properties of what Sawyer calls the emergence of creativity via emergent evolution capture the essence of cooperative evolution. Discussion of these concepts stems from a seminal paper by Sawyer (1999) entitled *The Emergence of Creativity*.

Central to his constructs is wholeness, or that a result is not necessarily reducible to the sum of its parts. Emergence was first used by Lewes in 1877 when he delineated the difference between resultant effects and emergent effects. Lewes was posing that an emergent effect is not predictable from knowledge of its components, and not decomposable into those components. Much like his classic example of the properties of water as being emergent from the combination of oxygen and hydrogen, social emergence can be seen as the effect of the actors, which are the cause. Sawyer uses his analysis of improvisational theater as analogy to these concepts. Much as actors create a dialogue with no preconceived notions of where they will go, an understanding of this cannot stem from knowledge of each individual actor. Understanding can only arise out of the collaborative creation and the analysis of the group as a whole.

Wholeness in-group behavior is emergent in instances where a structured plan directing the group is not present, or where there is no defined leader directing the group. Thus collaborative emergence occurs in such routine situations as conversations and brainstorming sessions, where improvisation results from the lack of a director or script. This emergence of creativity is not simply the making of new combinations, as Poincare (1913) points out, "It is not merely a question of applying rules, of making the most combinations possible according to certain fixed laws. The combinations so obtained would be exceedingly numerous, useless and cumbersome. The true work of the inventor consists in choosing among these combinations so as to eliminate the useless ones" (p. 28). Thus, emergent novelty is a “bottom-up process in complex systems, appropriateness requires that we also consider top-down effects in systems with multiple levels of emergent process” (Sawyer, 1999, p. 3).

Sawyer notes that although collaborative emergence requires individual agency and creative potential in the individuals, most computational models of emergent systems have far too simple models of each agent with no potential for creative action.

To date, computational models of emergence have yet to incorporate complex communication, though some researchers in emergence have alluded to the importance of this. It is proposed by Darley (1994) that emergence is a result of the number of units as well as the complexity of the rules of interaction. And Baas (1994) suggests that nonlinear interactions are where emergence occurs. Yet neither provides an algorithm nor theory of complexity in interaction. Computational representations of collaborative emergence to date seem to be difficult because there are no adequate computational models of complex social communication systems (Sawyer, 1999). Sawyer calls for a “complex dynamical theory – one that incorporates the unique features of collaborative emergence-may lead us to a unified theory of creativity” (Sawyer, 1999, p. 17).

Likewise, researchers have not explored implications of high-density networks. In situations such as improvisational communication or collaborative evolution the network is maximally connected, since every agent can receive messages from every other agent. Connection density is also likely related to decomposition of the group. For example, improvisational situations (i.e., a completely-connected network) are difficult to hierarchically decompose because of the high interdependence between elements in this unique form of social network structure.

Although Eisenberg and Reynolds' work highlights the emergence of cooperative evolution, groupthink (Janis, 1972) exemplifies the breakdown of this evolution. The two central conditions, cohesion maintenance and leadership avoidance, provide two main antecedent conditions of groupthink--and groupthink provides tangible instances where extreme cooperation can be detrimental to the cooperation and, hence, flocking in social systems.

Communication Convergence and Autopoiesis

Setting the stage for the elements of flock theory, communication convergence is offered one theoretical explanation of the process that humans undergo to organize and converge about a central theme or topic. This is crucial for the process of collaborative evolution in that the actors are constantly undergoing attempts to continue as a cohesive yet fluid system. For this system to move collectively, communication as a process must be implemented in a convergent manner. Likewise, this process is largely self-organizing in so far that the actors within the system need to maintain the structure without energy from the environment. For this element autopoiesis is offered.

Communication convergence is considered as a fundamental principle of human communication and interaction (Kincaid, 1988). Convergence theory implies that there are two or more things that are moving toward a point, which could be toward each other, toward a common interest, or toward uniformity (Kincaid, 1988). This movement highlights that convergence implies both process and time, making the application of flocking within cooperative evolution extremely pertinent, as evolution is at its root a process oriented phenomenon. Likewise, the uniformity and common interest is also central to the maintenance of a flock.

The process that individuals undergo to attempt to increase the level of understanding between each other is a function of autopoiesis, or the recursive self-reproduction of components in a system. Yet one of the main functions of an autopoietic system is to maintain it's autonomy, and thus can be further defined as a network of processes that produce all the components necessary to embody the very process that produces it (Krippendorff, 1991). In this sense, autopoietic systems recursively produce all the components necessary to have a historically reproductive network, and likewise self-reproducing. Yet Maturana and Varela (1987) argue that within this reproduction it is important for organization, or the system (and in this case the flock), to maintain its identity while it's structure can change to adapt to the environment. Thus, autopoietic systems, as a form of self-organizing system (Barnett, in press), have the ability to maintain an organization in relation to a structure while remaining operationally closed. As a result, the system is viewed as being both structurally coupled with and organizationally closed to the environment. The convergence of communication is then a coupling of the individual pattern system with other pattern systems, be it another individual or a flock, in which the individual organizes the internal structure to adapt to environmental forces. And, while it is important to maintain internal organization of the flock, both structural coupling and evolution operate on a pattern based recognition and accommodating replication.

Flock Theory

Combining the central concepts of Jamming (Eisenberg, 1990) and the Emergence of Creativity (Sawyer, 1999) and using communication convergence (Kincaid, 1988) and autopoiesis (Maturana & Varela, 1980) as explanatory processes, flock theory (Rosen, 2001) models the self-organizing principles of cooperative evolution in human interaction. The below axioms follow the template Reynolds (1987) used to simulate a bird flock, but reframe his axioms social contexts.

Axiom 1: Distance optimization
Tenet A: Separation: Avoid crowding group members
Tenet B: Cohesion: Move toward the central tendencies of group members
Axiom 2: Motion Replication
Tenet A: Direction Matching: Match direction of group members
Tenet B: Velocity Matching: Match velocity of group members
Axiom 3: Leadership maintenance: Group leaders (if any) must shift efficiently
Axiom 4: Elimination of Extreme Dissenters: In-group/out-Group deviation correction

Axiom 1: Distance optimization

Axiom 1 captures the concept explained by Eisenberg (1990) as the balance of autonomy and interdependence, the "close but not too close" element. Such that groups that foster excessive autonomy dissolve and groups that foster too much independence stifle creativity. This also allows for the importance of coordinated beliefs to diminish as the focus is on the coordination of action. Organization is created by the shared repertoire of communicative behaviors.

This axiom is also related to cohesion networks, where distance is too little or too much cohesion, decays productivity. The actors need to maintain a level of cohesion that allows for individual input without sacrificing group acceptance.

Distance in this case is also related to communication convergence. Convergence implies that the individuals are moving toward a point, which could be toward each other or toward a common interest (Kincaid, 1988). As the actors attempt to converge they must maintain an optimum distance from each other as to allow for the inclusion of all actors to participate in that convergence, resulting in the mutual convergence of the group. Likewise, as the interaction progresses, the amount of convergence will fluctuate and the structural needs of the flock will require the individuals to monitor cognitive as well as cohesive distance.

Tenet A states the first half of Axiom 1, where the actors avoid situations where the others within the group are too convergent, or too homogeneous. If this tenet is not maintained then group cohesion will increase resulting in groupthink from self-censorship and unanimity. Research has found that high levels of cohesion can lead to groupthink and decay the quality of the group interaction. For example, Turner & Pratkanis (1992) found that groupthink occurred more frequently in situations of extremely high cohesion.

Another interpretation of this tenet is that of accountability. If cooperation is to happen within the group each member must be accountable for their own actions without relying on cohesion to bail them out. Accountability can be related to two antecedent conditions of groupthink. First, accountability inhibits the possible insulation of the group by forcing the members to consider other party's point of view. The second is the lack of impartial (promotional) leadership, and that accountability makes it crucial for all individuals in the group to be able to justify the decision reached by the group, resulting in the decrease in the concentration of power in one domineering leader. Kroon et al (1991) postulate that accountability is expected to reduce the likelihood that group members will give in to conformity pressures.

Tenet B completes Axiom 1 by maintaining the inverse of Tenet A. This tenet operates under similar theoretical justification as Tenet A but balances potential situations where efforts to maintain individuality is surpassed. The actors must attempt to converge with others to maintain a cooperative group, even if this movement is simply for greater uniformity in situations of system breakdown.

<u>Axiom 2: Motion Replication</u>

Tenet A of Axiom 2 states that the group members must converge to the direction that the other group members are moving. This could be a change of topical direction in a conversation or a change of key in improvisational music. Regardless, if the group is to evolve in a collaborative manner than the members' organization about this change maintains the structural properties of the system.

Tenet B of Axiom 2 states that the group members must accommodate the rate that the other members are delivering messages, making successive moves, and allowing for space between these moves. In a face-to-face context this is theoretically justified through speech accommodation theory and the norm of reciprocity, whereas this metacommunicative function defines further moves of the group. This happens in conjunction with Tenet A of Axiom 2 (Direction): if velocity is matched, but not converged to a similar direction, then the system breaks down.

<u>Axiom 3: Leadership maintenance</u>.

Axiom 3 states that if a leadership role (if present) must shift in a manner that no one actor maintains leadership for too long. Eisenberg (1990) and Sawyer (1999) both stress the importance of the lack of leadership within a collaborative evolution. This Axiom also secures that Janis' (1972) groupthink doesn't ensue, as strong leadership is one of the main causes of groupthink. Flowers (1977) studied directive or participative leaders. Leaders, appointed to four person groups, were trained to be either directive or participative. Flowers found that groups with directive leaders proposed fewer solutions, covered less case information, and used fewer case facts both before and after reaching a decision. Leana (1985) employing a similar design as Flowers, found that groups with directive leaders discussed fewer solutions than the groups with participatory leaders.

<u>Axiom 4: Elimination of Extreme Dissenters</u>

Axiom 4 states that if the group is faced with the presence of an actor with a level of extreme dissention, as to break down the group, the other actors must converge to correct deviation or eliminate the divergent actor. This Axiom operates on the theoretical basis of cybernetic systems theory (Wiener, 1948), where a goal parameter is to be maintained and any deviations from this parameter require correction (i.e., negative feedback in cybernetic terminology). In-group and out-group effects are another element of this axiom, as supported by aforementioned findings of Turner and Pratkanis (1992).

Applications

Two main streams of research are underway to test and elaborate elements of flock theory. The first is an application to online communication via Internet newsgroups and chat discussion groups. Newsgroup flocks are being examined with Dr. Dean Krikorian, director of the Communication Network Analysis Laboratory at Cornell University, and his Internetwork measures of asynchronous group communication (see Krikorian, in press). Collaborative research efforts with the Cornell Theory Center on the use of 3-D Graphical Chat Rooms for Informal Science Education, focus on the use of semantic network analysis tools incorporating word co-occurrences in chat conversation using Catpac (Woelfel & Woelfel, 1998). Further extension of this work is underway with Dr. Joseph Woelfel (SUNY-Buffalo), the creator of Catpac (see Rosen & Woelfel, 2002). The focus of this path is two fold, first to test whether online environments already exemplify an increased likelihood of cooperative evolution; second, as a potential means for experimental testing of cooperative task and social groups.

The second research stream involving flock theory is in cooperation with Dr. Michael Macy in the Department of Sociology at Cornell University and Dr. Andreas Flache in the Department of Sociology at the University of Groningen in the Netherlands. This collaboration is an effort to replicate flocking behavior using cellular automata to simulate multi-agent interaction using the conditions of flock theory. Proposed applications include task groups and simulated musical improvisation. Likewise, different forms of cellular automata are being considered such as Dr. Flache's *Tmesh* software for cellular automata with irregular grids.

Both of these research directions are fairly young and are still in the initial stages of investigation, yet both provide promising outlets for the application of flock theory and can be used as examples to highlight the applications and development of flock theory in applied contexts.

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An Agent Implementation of Transaction-Based Internal Control Systems

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Abstract

This research reports on an on-going effort to model agent societies in continuous auditing environments. Continuous auditing is an extension of traditional periodical auditing. In traditional auditing systems, the operation of the system is audited *ex post* and an opinion is rendered on the financial statements (external audits) or recommendations are made for control system changes (internal audits). *Ex post* auditing is founded on the concept of a period of time. Continuous auditing can be conceptualized as making this period of time arbitrarily small. The research focuses on risk management, systems of internal controls, and transaction processing environments. In this setting, investments in systems of internal controls are justified by their risk reducing properties. By extending the framework reported in [Nehmer, 2002] into a web-based eCommerce application setting, the domain structure is defined in a way to allow the implementation of systems of internal controls as systems of agents which perform risk monitoring activities. There have been few formal attempts to define systems of internal controls in the accounting literature. The system defined here is based solely on the risk reducing activities of a community of software agents. The community is implemented as a three-tier hierarchy. The lower tier monitors risk at the elementary transaction level, which is defined as validity of the transaction components. The next tier in the hierarchy monitors the risks over the class of transaction components. The upper tier monitors risks across transactions. The research provides a concrete definition of a system of internal controls in a transaction setting as well as a means of implementing those controls as software agents.

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Key Words: continuous auditing, agent frameworks, transaction agents

An Agent Implementation of Transaction-Based Internal Control Systems

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This research reports on an on-going effort to model agent societies in continuous auditing environments. Continuous auditing is an extension of traditional periodical auditing. In traditional auditing systems, the operation of the system is audited *ex post* and an opinion is rendered on the financial statements (external audits) or recommendations are made for control system changes (internal audits). *Ex post* auditing is founded on the concept of a period of time. Continuous auditing can be conceptualized as making this period of time arbitrarily small. The research focuses on risk management, systems of internal controls, and transaction processing environments. In this setting, investments in systems of internal controls are justified by their risk reducing properties. By extending the framework reported in [Nehmer, 2002] into a web-based eCommerce application setting, the domain structure is defined in a way to allow the implementation of systems of internal controls as systems of agents which perform risk monitoring activities. There have been few formal attempts to define systems of internal controls in the accounting literature. The system defined here is based solely on the risk reducing activities of a community of software agents. The community is implemented as a three-tier hierarchy. The lower tier monitors risk at the elementary transaction level, which is defined as validity of the transaction components. The next tier in the hierarchy monitors the risks over the class of transaction components. The upper tier monitors risks across transactions. The research provides a concrete definition of a system of internal controls in a transaction setting as well as a means of implementing those controls as software agents.

Risk Management in Systems of Internal Control

Taking the control components identified in [COSO, 1994] and [COBIT, 2000] as a framework, internal control consists of five activities: the control environment, risk assessment, control activities, monitoring, and information and communication. Points of control are defined as simple control activities whereas bands of control are sets of control activities. When we are considering internal controls and agents, the match of agent communities to systems of internal control is especially relevant. This is particularly true in the case of risk assessment. While we might think about a point of risk from the perspective of internal control, the idea does not translate well from the perspective of a software agent's activity. This is because the agent's activities, reading a memory location for instance, are not in one-to-one correspondence with the system of internal control. That is, the design problem is not trivial. In the case of risk assessment, agent activities include data collection, trending the data over time, and communication of the trends. It is the collection of activities that defines the risk assessment process. The example of risk assessment is thus integrated into the structure of the system of internal controls.

Consider control activities that are part of risk assessment. Keeping track of technology, legal, or economic changes in the businesses environment are essential activities that are well suited to implementation by software agents. Bands of control can be applications, such as sales or inventory, or model components such as a database. This work considers bands of control to be at an application level. Agent activities at the application level include validation and evidencing authorization. At the component level, some possible activities include searching event logs for unusual items and testing connectivity with business partners.

Transaction agents are naturally suited to serve as monitors of other software applications. In addition to simple monitoring activities, agents can be designed to monitor other agents. There has been a lot of theoretical work done on building stable agent communities. [Holland, 1995] is a very assessable first pass at some of this work. [Fingar, 1998] and [Farhoodi, 1997] discuss agent systems from an executive, decision making perspective. Monitoring, measuring, and communication through information exchange between agents are very important in transaction contexts. Building stable agent communities in transaction contextx will therefore be very important in using agent communities as systems of internal control.

The use of agents in the communication of control in internal control settings can be viewed as a set of communication strategies. These strategies consist of communication protocols among agents of the same type and between agents of different types. Other strategies include communication protocols among agent communities, protocols for communication with management, and communication with the agent's environment. These protocols will lend themselves to method sharing and inheritance in object-oriented design environments. Tying these communication strategies both to the internal control framework as well as to the agent community is essential induce community stability.

The final control objective includes planning and organizing systems, controls, and systems of control. Again, by its nature this is a systemic objective. Bands of control will be evidenced by any agent community that can exhibit self-organization. Self-organization is the capacity for complex systems to evolve into new structures with new processes (activities) as conditions change. This is the very nature of planning. This type of structure is used to define systemic validity in the next section.

A Multi-Agent System of Internal Control

The multi-agent system designed for the present work consists of agents that operate in a three level hierarchy. This was done because it is one design where the structure of a system of internal controls can be closely paralleled by the structure of an agent community. The first or lowest level of the hierarchy maps the transaction elements to the activities of agents that check the validity of individual elements. We call this "elemental validity," making it correspond to tests of field-level validity of transactions. Agent activities consist of checking a field's value against a certain minimum or maximum of again a list of valid values. The control risk associated with this level is the risk that the transaction contains elementally valid values but is still invalid. This type of risk can be controlled for in part at the next level of the agent structure, the transaction level. We define transactions as a collection of elements (or attributes). Further, risk is defined on the interactions among the elements of a particular type of transaction. Agent activities at the second level of the hierarchy consist of performing tests across the elements of the transaction, such as matching the state from where the transaction originated with the appropriate sales tax. We call this level of agent activities "transaction validity." Business transactions are usually embedded in systems known as application systems or application cycles. The flow of processing activities within an application system comprises more than one transaction. An example is a sales order placed on a web-based eCommerce system which might include a transaction to determine customer validity, a transaction to check on inventory status of ordered items, a check of customer credit or payment, and an update to the marketing database upon order submission. The risk at this level is associated with whether all of the dependent transactions associated with a particular triggering event (e.g., potential sales order) are executed validly and in a valid order. This type of validity is called "systemic validity." The agent activities that comprise systemic validity include determining individual transaction validity, dealing with combining partially "tainted" transactions, and ensuring that all of the necessary dependant transactions are executed. Within this hierarchical system of controls, we build regimes of internal controls with known costs. The regimes are then run again known transaction populations to simulate the risk reducing effects of the regimes. This provides an estimate of the cost of the regimes and a measure of their potential effectiveness.

The Processing Environment

The system is implemented in a mixed UNIX/Windows environment. A simulation of a web-based sales order system was constructed to operate on an Apache webserver. The website is contacted by programs running on Windows2000 client machines. The web client program is written to simulate submission of sales orders to the webserver. The clients can be tuned to submit sales order data with known validity properties. Using simple CGI processing technologies and scripting, the sales order data is forked to the agent internal control regime for processing. The system collects statistics on the types of validity problems found by the agent regimes. These statistics will be compared across regimes by the validity properties seeded into the input streams. The results of the statistical analysis will give a first approximation of how well different internal control regimes detect and control validity problems in streams of input data.

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Waiting for Godot:
The limits of scheduling meetings

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Abstract

The results of a simple computer simulation show that the expected length of wait for a meeting increases exponentially with three factors: the size of the meeting (number of participants); the length of the meeting (time); and the proportion of time previously filled in each participant's schedule. The exponential increase places severe practical limits on the size and length of meetings. Some implications of these limits are discussed, as are the possible limits of two putative solutions: asynchronous meetings and priorities.

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Key Words: scheduling, schedules, meetings, simulation

Waiting for Godot: The limits of scheduling meetings

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Organizations breed meetings. People in organizations meet for a variety of reasons, sometimes only to exchange information, sometimes to coordinate effort, sometimes to seek a solution to a problem, or to choose a solution or implement it. Perhaps because of this variety, or because of the growing size and complexity of organizations, meetings have become ubiquitous, inspiring all manner of attempts to increase their efficiency. General Henry Robert's [1876/1915] Rules of Order offered an early attempt to increase meeting efficiency by organizing discussion and debate. More recently, programmes such as Microsoft's *NetMeeting* or CoVision's *Council* have attempted to provide a virtual forum for people geographically distant, saving the time and money needed to bring them together to meet in a common location. Variations of this software offer the possibility of asynchronous meetings as well as synchronous ones, providing greater scheduling flexibility for members of groups given tasks with leisurely deadlines.

As the use of means to increase meeting efficiency has multiplied, the time freed for other activities has often been invested in more meetings. One consequence has been an increase in problems of scheduling. Most graduate students seeking a meeting of their PhD committee, for example, have become distraught by the rounds of rescheduling needed to get four or more busy professors together at the same time and place. A recent meeting among four university professors and four government administrators at our university was postponed three times over six months before all could find 60 consecutive minutes in common to spare. Our sense of an increase in such incidents, and a glance at some queuing literature [e.g., Newell, 1982; Schwartz, 1975], led us to wonder about the relationship between (1) how busy people are, (2) how many of these people must attend a given meeting, (3) the length of the meeting, and (4) the average wait needed before all people have the same free time available for the meeting. A simple computer simulation was conducted to examine these relations.

The Scheduling Simulation

We created the simulation by first defining a hypothetical calendar for each of several hypothetical participants in a meeting. Each calendar was represented as a vector, each element of the vector representing a 30-minute "slot" (30 minutes were arbitrary, inspired by the smallest default time slot on the calendar of a Palm Pilot). At the beginning of each simulation run, our programme asked for the proportion time each simulated participant had free, then filled the participant's calendar slots at random with 1s and 0s (0 meaning *slot open*, a 1 meaning *slot filled*) according to the proportions we declared. Once the calendars were thus filled, our programme asked for the length of a meeting, in number of slots, we wanted to schedule (1 = a 30-minute meeting, 2 = a 60-minute meeting, etc.) and the number of people we wanted to meet, then went across their calendars in search of the first available set of consecutive slots all people had free. In this way, our programme was a crude version of many commercial scheduling programmes. Ours, however, recorded of the number of slots searched until the first one when all people desired for a meeting were free. In addition, our programme repeatedly and randomly shuffled the 1s and 0s in each calendar, then again searched for the first available slot for the required meeting. Each shuffling resulted in a different first-available slot according to the luck of the draw. The programme kept track of the first-available slots for each of 500 shuffles in a run. Then it calculated the average number of slots.

One of 500 iterations of a typical simulation run is portrayed in the matrix of Table 1, each row representing a calendar vector of one hypothetical committee member (A, B, C or D). In this example, the first time all four committee members can all meet for 30 minutes comes at slot 7; the first time they can all meet for an hour comes at slot 17.

Table 1. Hypothetical Calendars of Four Committee Members

	Eighteen consecutive, 30-minute time slots																	
Member	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
A	1	1	0	1	0	0	0	1	0	1	1	0	1	0	0	1	0	0
B	0	1	1	0	0	1	0	1	1	1	1	0	1	0	1	1	0	0
C	1	0	0	1	1	1	0	0	1	0	1	0	1	1	0	0	0	0
D	0	1	1	0	1	1	0	0	0	0	1	1	0	0	1	1	0	0

N.B. 1 = time slot filled; 0 = time slot free

The proportion of 1s in a calendar defined the amount of busy-ness; a calendar with, say, 80% of its slots filled might represent someone who is very busy, while a calendar with 10% of is slots filled would not. Though normal 8-hour working days contain eight 30-minute slots in the morning and eight in the afternoon, the slots on our calendars were contiguous from day to day, morning to afternoon. As a result, long meetings just before lunch or the end of a work day, which might otherwise be postponed, would in our calendar be undertaken if all relevant participants were free. This meant that more opportunities for meetings would appear in our simulation than would appear in the referent world. As it happens, this did not matter a great deal (see Results below).

Results

We ran the simulation with several combinations of busy-ness, meeting length and number of people required for the meeting. A regular exponential pattern emerged, which allowed us to induce the mathematical rule generating the expected number of slots one must wait for a meeting of any length and size, given the busy-ness of its members. The rule is as follows:

$$\mathbf{ew = (1/pf)^{np*lm}}$$

Where:

ew = the expected wait (in # of slots)
pf = the proportion of free slots (0.00 to 1.00)
np = the number of people needed for the meeting
lm = length of the meeting (# of consecutive slots)

To illustrate, if we wanted three people to meet for an hour (2 consecutive slots) when 40% of their slots were already filled (60% were free), then our expected wait for this meeting would be

$$ew = (1/0.60)^{3*2} = (1.67)^{6} = 21 \text{ slots} = \text{about } 2.6 \text{ work days.}$$

If we wanted five people to meet for an hour when 40% of their slots were filled, the we should expect to wait

$$ew = (1/0.60)^{5*2} = (1.67)^{10} = 169 \text{ slots} = \text{about } 10.6 \text{ work days.}$$

If we wanted 8 people to meet for two hours and each had 60% of their slots filled, we should expect to wait

$$ew = (1/0.40)^{8*4} = (2.5)^{32} = 5.42e12 = \text{about } 928{,}250{,}000 \text{ work years.}$$

Discussion

Our simulation assumes that each participant had an equal proportion of time slots available. It also assumes that the slots were filled at random, making a run of n+1 consecutive slots filled a constant proportion (1-pf) of number of n consecutive slots filled. These assumptions allow for elegant programming, but neither are especially realistic. Our current research attempts to provide more realistic assumptions by estimating the relative frequencies of meetings of varying lengths, and individual differences in busy-ness, from an examination of colleagues' calendars. But we do not expect the results of this research to be radically different than those reported above. The current results suffice to suggest why it is so difficult to find a common time for a large number of busy people to meet: the expected wait rises exponentially with the length of a meeting and the number of people required to attend.

The exponential rise in waiting time for meetings places a practical limit, ultimately set by years until retirement or death, on the number of people or the length of time required for a meeting. Organizations requiring many people to attend long meetings on a moment's notice must ensure that during the interim they are not busy. This is what happens in fire halls, where fire fighters spend most of their time at leisure, waiting to respond quickly as a group to often lengthy crisis calls. Organizations pushing their members to avoid slack time must ensure that their short-notice meetings are either short or small. Otherwise, they must be prepared to wait.

Each of these alternatives breeds its own problems. A short meeting might be insufficient to accomplish the tasks for which it was called. A small meeting might exclude crucial people and similarly lower the chances of accomplishing its tasks. Yet the increase in waiting time expected by increasing the length or the size of a meeting might allow problems to exacerbate or multiply.

Asynchronous alternatives to synchronous meetings, afforded by group e-mail or similar software, promise to reduce the wait to begin a meeting by allowing it to commence as soon as the first participant is free. Yet, depending on procedural rules, most of these meetings do not end until the last participant is free, which often is no sooner than the time of scheduling a synchronous alternative. Because asynchronous meetings can so easily fill empty slots, they tend to proliferate, especially in organizations requiring the opinions or coordination of many people. As the slots fill, the advantages of asynchronous meetings decline. We are currently developing simulations to determine the conditions and procedural rules favour synchronous or asynchronous meetings.

In most organizations, conflicts of meeting schedules are often resolved by setting priorities. Some meetings bump others, usually in order of importance or the imminence of opportunity or catastrophe. The result is often an escalating organizational competition for *now*, forcing losers towards the back of the line [Thorngate, 1988]. While waiting for solutions, many small problems have an opportunity to grow. Those growing to crises are bumped to the front of the line, filling an increasing proportion of slots with increasingly long meetings seeking solutions. The length of such meetings limits the number of participants who attend to those who have the time, and prevents these people from attending other meetings, including meetings to coordinate solutions to other problems generated in parallel meetings within the organization. Problems generated by uncoordinated solutions then multiply, setting the stage for dis-organization. In future simulations we hope to explicate the conditions under which such organizational collapse can occur.

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Agent Interaction and the Formalization Process

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Abstract

The present paper uses the framework of social agent modeling and simulation (SAMS) to illustrate basic issues addressed through the microdynamics of formality construction, including: 1) the abstraction of situations, 2) the spanning of temporality, and 3) the reconciliation of competing formalisms. In each case, a dynamic model of agent interaction, framed in situation-theoretic terms, is employed to explore the emergence and application of formality.

Agent models of the formalization process have the potential to address social complexity by demonstrating the natural linkages between moment-to-moment social interaction and the larger social structures to which they give rise. Chains of constrained interaction situations provide a conceptual framework to span multiple levels of aggregation. Progress in this type of modeling has the potential to contribute to a theory of organization dynamics, as well as social theory generally.

Key Words: abstraction, formalism, temporality, situation theory, agent model

Agent Interaction and the Formalization Process

David L. Sallach

A defining insight of microsociology is that moment-to-moment social interaction creates, sustains (and ultimately dissolves) all larger social phenomena [Maynard & Wilson, 1980; Scheff, 1990; Collins 1981; 1988; 2000]. As examples, society, social structure and norm are generalizations and reifications of underlying microsocial processes, recognizing that they are frequently reifications of the participant as well as the theorist. The basic insight provides a multilayer framework for describing micro/macro dynamics [Shegloff ,1987; Collins 1987; Hilbert, 1990].

In organization theory, the power of informal organization is well-established, manifesting as a process through which formal objectives are realized as well as sometimes circumvented and frustrated. The tendency, however, has been to view formal and informal processes as counterposed, with the latter processes realizing similar or conflicting goals in spite of, or contrary to, the former. A multiscale theory of organization will need to demonstrate how and why informal social processes create, sustain and utilize formality. An important contribution in this area has been recently been made by Stinchcombe [2001], who considers how systems of formal abstractions are generated and applied in diverse domains, as well as how they must evolve to remain effective.

The present paper uses the framework of social agent modeling and simulation (SAMS) to illustrate basic issues addressed through the microdynamics of formality construction, including the abstraction of situations, the spanning of temporality, and the reconciliation of competing formalisms. In each case, a dynamic model of agent interaction, framed in situation-theoretic terms, is employed to explore the emergence and application of formalities.

The Abstraction of Situations

In recent decades, the 'situation' has emerged as a focus in the scientific modeling of social complexity. Philosophically, Popper [1995] describes situations as having objective propensities that tend to be realized. In linguistics [Barwise & Perry 1983], mathematics [Devlin 1991] and logic [Barwise 1989], situation theory has emerged as a powerful and flexible formalism for modeling context. In sociology, Collins [1994] has proposed 'situational reductionism' as a way to potentially bridge micro and macro dynamics. In artificial intelligence, situated agents of varying degrees of complexity have been an important innovation [Hendriks-Jansen 1996; Clancey 1997; Ferber 1999], addressing issues on which earlier approaches to AI foundered [Brooks 1999].

The relationship between organizational formality and informality is here expressed in situation theory [Barwise 1989; Devlin 1991]. The 'situation' is regarded as a conceptual primitive. Whether identified by a theorist or a participant, a situation is a temporally proximate context in which pertinent social interaction occurs.[1] In any situation, formalities may be defined, invoked, utilized, mediated, challenged, accepted, modified or rejected, but each of these processes occurs through direct social interaction. Stated differently, unmediated social interaction provides the enveloping context in, by and for which social formality is created, focused and employed.

Stinchcombe [2001:54] identifies three broad qualities that together define the efficacy of formalization:

> Formalities of the most various kinds can be described by the degree to which they are cognitively adequate to the situations they govern, are communicable to the people who must act in those situations, and are improvable, and in fact improving.

These qualities describe important ways that the formalization process is embedded within informal social interaction. It is also possible, in various domains and settings, for multiple formalisms to be applicable. The process of applying and reconciling competing abstractions is another way that formalisms are embedded in social informality [Stinchcombe, 2001:27-29].

Formalisms define the situations to which they apply and, at the same time, their application, reconciliation and co-evolution involve socially situated cognition and action. Specific situations that are differentiated depend upon the domain of application. Stinchcombe discusses construction blueprints, civil law and procedures, the commodification and liquidification of residential mortgage pools, the presumptive classification of aliens at border crossings, and the stratification of scientific knowledge. Formalisms applicable in each domain give rise to distinct abstractions, and the application of those formalisms requires officials, agencies and other participants to distinguish and reason about pertinent situations.

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[1] In this definition, proximity and pertinence are necessarily defined indexically. Fortunately, indexical defintion is one of the requirements that situation theory was articulated to support [Barwise & Perry, 1983].

The specification of theoretical, domain-specific and empirical situations will benefit from a common formalism that is flexible and expressive.[2] Accordingly, the present analysis draws upon situation theory as a focus of the present discussion.

Temporality and Persistence

While moment-to-moment interactions are the site where living social processes manifest, agents within such settings have an inescapable problem of temporality. They frequently wish to use their immediate actions to affect later events. As one example, agents at strategic locations within an organizational hierarchy may wish to shape or control future actions of their subordinates. As another, one generation may wish to bequeath (impose) a set of operational principles to (upon) a subsequent generation.

The formalization process creates social artifacts (e.g., oral histories, rituals, written documents) that are conveyed through a network of situations in order to be available and invokable in future settings [cf., Ihde, 1990]. Of course, whether such artifacts are invoked, how they are interpreted, and what ultimate effect they have is a product of social interaction in the relevant situations. It remains the case that the presence or absence of formality persistence is a product of microdynamics in both the source and target situations (as well as the accuracy maintained, or distortions introduced, in the chain of intervening settings).

In models of the formalization process, part of the complexity of social dynamics results from the ability of human agents to define the same events relative to a variety of temporal scales. A battle is part of a campaign, a war and a period of national renewal or decline; similar scale effects are found in a variety of diverse domains. Further, since each participant may focus upon events at differing scales, definitions of situations abound and require reconciliation. Common definitions of relevant situational scale may contribute to social coherence, while divergent scales may make coordination difficult. Scale reconciliation processes thus constitute a vital aspect of agent cooperation, and resulting micro and macro dynamics.

The Reconciliation of Abstractions

In addition to scale reconciliation, informal social processes are also used to reconcile the integration (or boundaries) of potentially conflicting formalisms. As Stinchcombe writes [2001:186]:

> Formality has its greatest effects when it is not formalizing one abstraction, but a system of abstractions, along with a social system for improving that system of abstractions.

Such systems of abstractions are generally domain-specific. Competing claims are resolved in informal settings that may, however, be themselves structured by (the application of) applicable formalisms.

Models exploring formalism reconciliation are likely to be particularly effective in revealing the social tissue connecting micro and macro processes. As a result, this focus holds promise as a strategy for controlling complexity in social science models.

Situation Theory

Situation theory defines a mathematical theory of information content in which meaning is defined by the relationship between two potentially successive situations:

$$S \Rightarrow S'$$

One of the most important relationships between two situations is the constraint relation. Constraints may be of many types, including: 1) determinant, as by natural law, 2) necessary, as by definition, and 3) conventional, as defined by social rules or norms. Regardless of type, constraints are used by social agents to project from a present situation to a future situation, and to adapt their strategies and actions accordingly.

In a given situation, particular facts may be true or not. Facts are indicated by 'infons', represented by:

$$\ll P,\ x_1, \ldots, x_n,\ i \gg$$

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[2] An effort to formalize the formalization process is self-referential and potentially recursive. These properties are noted, not because prospective paradoxes will be resolved in this discussion, nor because the present analysis will explore recursive strategies, but simply for the sake of completeness.

where P is an n-place relation, $x_1, \ldots, x_n$ are objects for the argument roles of P, and i represents the situated polarity (truth value) of the fact. When an infon σ supports the presence of a given situation *s*, it is written:

$$s \models \sigma$$

An infon representing a constraint might take the form:

```
<<constrains, S, S', B, 1>>
```

where B represents the set of background conditions that make the constraint effective. Similarly, an organization infon might take the form:

```
<<org, type, l,  t, i>>
```

where `l` identifies the area in which the organization is located, and `t` the time period under consideration.

The cognitive processes of individual agents gives rise to (potentially idiosyncratic) notions of common situations [Devlin, 1991:145-186]. Such notions form the raw material to which scale and abstraction reconciliation algorithms may be applied. The exploration of such dynamics constitutes a major focus of the paper.

Situated Formalization

Agent models of the formalization process have the potential to address social complexity by demonstrating the natural linkages between moment-to-moment social interaction and the larger social structures to which they give rise. Chains of constrained interaction situations thus provide a conceptual framework for spanning multiple levels of aggregation. Such progress has the potential to contribute to a theory of organization dynamics, as well as social theory generally.

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Innovation versus Imitation in Stochastic Social Networks with Decentralized Reinforcement Learning

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Abstract

We explore the evolution of a social network in a population of individuals who engage in search for local optima in potentially diverse task environments. The search is carried out via stochastic choices between innovation and imitation and, if imitation, whom to learn from. The probabilities with which these choices are made are dynamically adjusted through reinforcement learning via individual experiences. By tracing the evolution of these choice probabilities and constructing the "entropy" measure for the social network using these probabilities, we examine the relative intensity of endogenous innovation over imitation as well as the evolving structure and performance of the stochastic social network.

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Key Words: Endogenous Social Network, Innovation, Imitation, Reinforcement Learning

Acknowledgement: We thank Jon Harford for helpful comments.

Support: This work was supported in part by the National Science Foundation through Grant SES-0078752.

Innovation versus Imitation in Stochastic Social Networks with Decentralized Reinforcement Learning

Myong-Hun Chang and Joseph E. Harrington, Jr.

The acceleration of scientific progress in seventeenth century Western Europe is often attributed to the founding of learned societies and improved communication among the contemporary researchers: "Here was a widely dispersed population of intellectuals, working in different lands, using different vernaculars – and yet a community…… In the seventeenth century, these links were institutionalized …… in the form of learned societies with their corresponding secretaries, frequent meetings, and periodical journals." [Landes (1998), pp.204-205] The emergence of such formal and informal networks of scientists marked the beginning of the institutionalization of scientific investigation which eventually paved the way to the Industrial Revolution.

The latter half of the twentieth century has seen another major explosion in the formation of such networks and informal communities, thanks to the advent of internet and world wide web. In the communities of research scientists, learning what others are working on and what methods they are using to address them used to entail letters requesting working papers, frequent trips to professional meetings and workshops, and laborious search in the dust-covered library stacks. All this has changed dramatically in recent years with the spread of internet. Acquiring information that used to take weeks, if not months, can now be accomplished in a matter of minutes through emails, personal and public websites, and on-going projects that facilitate dissemination of research over the internet via decentralized database of working papers, journal articles, and software components.

The three hundred years of separation notwithstanding, these two episodes share a common element; the prominent role played by the social learning network in achieving and sustaining scientific progress at the macro level from the chance occurrences of minor local innovations scattered across wide geographic areas. Given this relationship between local innovations and the social learning via community networks, what are its implications for the individuals' decisions to engage in independent innovation versus to rely on the social networks for observing and adapting someone else's idea? If the networks themselves are an emergent outcome of interactive choices among individuals as to whom to observe and whom to ignore, what are the parameters in the social system that determine the structure of such networks? Will the improvement in imitation technology (such as learned societies and internet) be sufficient to generate superior performance at the individual and the community level or are there other complementary factors essential for the social networks to realize its potential? Our objective is to explore these issues by building a computational model of an evolving social network with potentially innovative individuals and analyzing its emergent structure as well as its long run performance.

We start with the view that each individual in our social system is endowed with a goal (local optimum) unknown to him *ex ante*. This goal is uniquely defined for each individual, where any diversity among goals reflects diversity among local environments surrounding the individuals. The individuals are assumed to be boundedly rational and engage in myopic search for the unknown goal. They are, however, adaptive and capable of learning from past experiences. In any given period they may choose to engage in innovation or imitation. In the event the individual chooses imitation, he taps into the network (comprised of all individuals in the population) and chooses whom to learn from. The choices of innovation vs. imitation and whom to learn from are made probabilistically. These choice probabilities are then adjusted over time by the individuals on the basis of the feedbacks (reinforcements) from the actual experience. The modeling approach allows us to examine the emergent structure of the social network in the form of how observation probabilities are distributed across individuals as well as to track the evolving choice between innovation and imitation for each individual.

The Model

Consider a population of M individuals. Each individual $i \in \{1, 2, \ldots, M\}$ engages in an N-dimensional task common to all of them. There are two possible methods, 0 or 1, that can be used in each dimension of the task. In any period t, an individual i is fully characterized by his current method vector,

$z_i(t) \equiv (z_{i,1}(t), z_{i,2}(t), \ldots, z_{i,N}(t))$, where $z_{i,k}(t) \in \{0,1\}$ is individual *i*'s chosen method in dimension *k* of the task in period *t*.

Each individual possesses a unique goal vector, $z^*_i(t) \equiv (z^*_{i,1}(t), z^*_{i,2}(t), \ldots, z^*_{i,N}(t))$, where $z^*_{i,k}(t) \in \{0,1\}$ is the optimal method from individual *i*'s perspective for dimension *k* of the task in period *t*. The dependence of the goal vector on time *t* allows for the possibility that the task environment for *i* may change over time, thereby resulting in the shift of local optimum from *i*'s perspective. The individuals are uninformed about $z^*_i(t)$ *ex ante*, but engage in perpetual search to get as close to it as possible. In measuring the distance between two task method vectors, z_i and z_j, we use "hamming distance" which is defined as the number of dimensions for which the chosen methods differ: $d(z_i, z_j) \equiv \Sigma_k \mid z_{i,k} - z_{j,k} \mid$.

An individual's search for local optimum is carried out through two distinct mechanisms, innovation and imitation. Innovation occurs when the individual actively tries a different method for a randomly chosen dimension without observing what anyone else is doing. Imitation is when the individual chooses another member of society, observes her method in some randomly chosen dimension and then tries the method herself. Whether through innovation or through imitation, an experimental method is actually adopted if and only if its adoption gets the agent closer to her goal by lowering the hamming distance between her new methods vector and her goal vector.

Exactly how does an individual choose between innovation and imitation? If he chooses to imitate, how does he decide whom to imitate? We model this as a two-stage stochastic decision process with reinforcement learning. In stage 1 of period *t*, an individual *i* is in possession of the current method vector, $z_i(t)$, and chooses to innovate with probability $q_i(t)$ and imitate with probability $1 - q_i(t)$. Suppose he chooses to innovate. He then has an externally determined probability of μ_i^{in} which is a parameter measuring the innovativeness of the individual. With probability μ_i^{in}, he comes up with an idea which entails a randomly chosen dimension $k \in \{1,\ldots, N\}$ and an alternative method, $z'_{i,k}$ ($\neq z_{i,k}(t)$), for that dimension such that the experimental vector is $z'_i(t) \equiv (z_{i,1}(t), z_{i,2}(t), \ldots, z'_{i,k}, \ldots, z_{i,N}(t))$. This experimental vector is adopted by *i* if and only if its adoption lowers the hamming distance to his goal vector.[1] Otherwise, it is discarded. Alternatively, with probability $1 - \mu_i^{in}$ the individual fails to generate an idea, in which case he simply sits idle and his current methods vector stays fixed: $z_i(t+1) = z_i(t)$.

Suppose now that the individual *i* chooses to imitate in stage 1. Given that he decides to imitate someone else, he now taps into the network to make an observation. Tapping into the network is also a probabilistic event, in which with probability μ_i^{im} the agent is connected to the network, while with $1 - \mu_i^{im}$ the agent fails to connect to the network. μ_i^{im} is then a parameter that controls the externally determined extent to which the agent has access to the network. Once the agent is connected, he then enters stage 2 of the decision process in which he must choose which of his acquaintances he will attempt to emulate. Let $p^j_i(t)$ be the probability with which *i* observes *j* in period *t*. Obviously, $\Sigma_{j\neq i}\, p^j_i(t) = 1$ for all *i*. If the agent *i* observes another agent *l*, the observation involves a randomly chosen dimension *k* and the current method used by agent *l* in that dimension $z_{l,k}(t)$. The ultimate adoption or rejection of the observed method follows the hamming distance comparison discussed above. If the agent fails to connect to the network, which occurs with probability $1 - \mu_i^{im}$, he sits idle and $z_i(t+1) = z_i(t)$

The probabilities, $q_i(t)$ and $\{p^1_i(t), \ldots, p^j_i(t), \ldots, p^M_i(t)\}_{j\neq i}$, are adjusted over time by individual agents according to a reinforcement learning rule. We adopt the *Experience-Weighted Attraction (EWA) learning* rule as described in Camerer and Ho (1999). Using this rule, $q_i(t)$ is adjusted each period on the basis of evolving attraction measures for innovation and imitation. The rule is specified so that a favorable experience through innovation (imitation) will raise the attraction level of innovation (imitation). The resulting increase in the attraction level of innovation (imitation) will raise the probability that the agent will choose to innovate (imitate) again in the future: *a positive outcome realized from a course of action reinforces the likelihood of that same action being chosen again*. The stage-2 probabilities, $\{p^1_i(t), \ldots, p^j_i(t),$

[1] While the goal vector itself is unknown to the agent, the payoff from the adoption of the experimental vector – as a decreasing function of its hamming distance to the goal vector – is assumed to be immediately and fully revealed to him.

…, $p^M{}_i(t)\}_{j\neq i}$, are adjusted by i on the basis of evolving attraction measures for observing each individual $j \neq i$. Again, a successful imitation of another person k will raise i's attraction to k, thereby raising the probability that k will be observed again next period.

There are then two distinct sets of probabilities in our model. One set of probabilities, $q_i(t)$ and $\{p^1{}_i(t)$, …, $p^j{}_i(t)$, …, $p^M{}_i(t)\}_{j\neq i}$, are endogenously derived and evolve over time according to the individuals' reinforcement learning. Another set of probabilities, μ_i^{in} and μ_i^{im}, are exogenously specified and imposed on the model as parameters. They represent respectively the inherent capacities of a given individual to independently innovate – *creativity* – or to imitate someone else in the population – imitativity – and are both beyond the control of the agents within the model. They will, however, allow us to examine directly how the innate creativity and imitativity of individuals affect the dynamic structure and performance of the endogenous social networks thus formed.

Measuring the Network Structure and Performance

A social network emerges when individuals rely on observation and imitation of others with strictly positive probabilities. A main structural characteristic of a social network is how concentrated it is: Does an individual learn from many or from a relatively narrow set of other individuals? In our context, this question can be addressed by observing the distribution of $p^j{}_i(t)$'s. If an individual's observation of another is equally likely across all individuals in the population, there is no order in the social network in a probabilistic sense. One does not perceive any advantage to learning from a specific individual in such a situation. Alternatively, if the probability of observing another agent is concentrated on a single individual, then there is a maximal degree of order in the network in the sense that the uni-directional learning taking place between the two individuals is essentially deterministic.

An appropriate measure of network structure for our purpose is that of Shannon's (1948) "entropy" which was originally defined in the context of information theory as a measure of shortage in the information content in a message. Adaptation of this measure for our social network is done as follows. For each i, we construct an entropy measure, $H_i(t)$, using $\{ p^j{}_i(t)\}_{j\neq i}$:

$$H_i(t) = - \sum_{\forall j\neq i} p^j{}_i(t) \times \log_2 p^j{}_i(t)$$

By taking an average of $H_i(t)$ over all individuals in the population, we obtain the *mean entropy* of the network system in period t: $\bar{H}(t) = (1/M)\sum_i H_i(t)$. We shall refer to a social network with M agents as a *random network* if $\bar{H}(t) = \log_2 (M - 1)$ and a *deterministic network* if $\bar{H}(t) = 0$. In between these extreme values, the network structure becomes more ordered (random) as $\bar{H}(t)$ decreases (increases).

The performance of a social network is measured by how close the individuals are to their respective goals. Given N dimensions in a task and the goal vector $z^*{}_i(t)$, the period-t performance of individual i with its current method vector $z_i(t)$ is then measured by $u_i(t)$, where

$$u_i(t) = N - d(z_i(t), z^*{}_i(t)).$$

The payoff is, hence, a function of hamming distance alone and is linear with coefficient -1 on all deviations. In analyzing the simulation outcome, we trace the evolution of the population-average performance $\bar{u}(t)$, where $\bar{u}(t) = (1/M)\sum^M_{i=1} u_i(t)$.

Results

We consider both the case in which the task environment remains fixed over time and the case in which it may undergo inter-temporal fluctuations. In both cases, we find that the simple existence of social network with imitation capacity is not enough to carry out the search for local optimum. There must be a sufficient degree of diversity in the population in order for the social network to perform as an effective search mechanism. In the absence of pre-existing diversity in individual methods vectors, the effectiveness of a social network as a search mechanism then entirely hinges on μ_i^{in} being positive: The individual capacity to carry on independent innovation, however meager they may be, is crucial to supplying the necessary fuel for the effective operation of the social network.

Some of the results obtained thus far include:[2]

- An increase in μ_i^{in} raises the endogenous probability of innovation ($q_i(t)$) for the agents, while an increase in μ_i^{im} lowers it.
- The social network is more ordered (random) in the long run as the individuals have a greater (smaller) capacity to innovate: A higher (lower) value of μ_i^{in} results in a lower (higher) value of $\bar{H}(t)$.
- The performance of the social network, $\bar{u}(t)$, is found to be increasing in μ_i^{in} but non-monotonic in μ_i^{im}.
- Innovation (imitation) is chosen with higher probability as the individuals in the population start from more homogeneous (heterogeneous) positions: A greater degree of uniformity (diversity) in $z_i(0)$'s leads to a higher value for $q_i(t)$.
- Innovation (imitation) is chosen with higher probability as the individuals have more diverse (uniform) goals: A greater diversity (uniformity) in $z^*_i(t)$'s leads to a higher value for $q_i(t)$.
- A more stable environment leads to a more imitative population that relies mainly on the endogenous social network (a lower $q_i(t)$), while a more turbulent environment gives rise to a more self-reliant innovative population (a higher $q_i(t)$).
- Stable environment with more imitative population generates a more ordered social network (a lower value of $\bar{H}(t)$), while a turbulent environment leads to a more random social network (a higher value of $\bar{H}(t)$).

We also consider the potential emergence of sub-communities in the presence of some inherent heterogeneity among the population members. We discover that the inter-personal differences that are unobservable *ex ante* can easily lead to the formation of local learning communities *ex post*, where the members mainly learn from one another rather than from the population at large. Such emergence of unintended consequences through complex interactions within the social network is strongly reminiscent of Schelling's (1978) original "self-forming neighborhood model" of segregation.

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[2] These results are based on observations along the steady-state paths.

The Contingency Effects of Transactive Memory

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Abstract

Previous studies have shown that transactive memory systems have positive effects on group performance through efficient storage and recall of knowledge as a whole. Does transactive memory help group performance equally under different group settings or environments? If not, what are the moderating factors that come into play between transactive memory and group performance and what are the contingency effects? In this paper, we attempt to address these questions by applying a multi-agent computational model – ORGMEM. Two potential moderators, group size and task changing environment, are examined. Through a series of virtual experiments, we find that although groups with transactive memory take less time to finish their tasks regardless of group size or task environment, the effects of transactive memory are contingent on group size and task environment. In other words, transactive memory plays a more important role in middle-size groups and groups in a volatile task environment.

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Key Words: transactive memory, contingency effect, group size, task environment, simulation, computational modeling

Acknowledgement: we are grateful to Nicole Lazar for her statistical advice.
Support: This work was supported by the National Science Foundation KDI IIS 9980109 and by the Center of Computational Analysis of Social and Organizational Systems (CASOS).

The Contingency Effects of Transactive Memory

Yuqing Ren, Kathleen Carley, and Linda Argote

Transactive memory systems refer to the idea that people in continuing close relationship develop a shared system for encoding, storing and retrieving information from different substantive domains (Wegner, 1987). Previous studies provide both direct and indirect evidence of the positive impact of transactive memory on group performance, such as efficient storage and recall of knowledge through interpersonal relationships, better decisions based on accurately weighing and recognizing expertise distribution within the group, and more efficient group training (e.g. Hollingshead, 1998; Liang, Moreland, & Argote, 1995; Moreland, Argote, & Krishnan, 1996).

Modeling Descriptions

ORGMEM is a multi-agent simulation system that imitates the interpersonal communication, information-processing, and decision-making processes in organizations. In ORGMEM, agents are intelligent, adaptive, and heterogeneous (Ren, 2001). In other words, each agent has access to some knowledge (intelligence), is able to conduct a specific number of tasks, and can learn from each other (adaptation). As socially connected agents, each of them also has a transactive memory about who talks to whom, who knows what, and who does what in the group. During the operation process, each agent is able to conduct a variety of activities, such as communicating knowledge, searching for resources, and making decisions. Over time, organizations receive a series of tasks. Agents work on subtasks assigned by the program, make decisions by combining personal knowledge and information from their subordinates, communicate both technical knowledge and social knowledge, and learn from each other. As a result, group communication structure regarding who talks to whom, skill structure regarding who knows what, and transactive memory change over time.

Model Validation

Moreland, Argote and Krishnan (1998) systematically study the role of transactive memory in group training using lab experiments and find out that group performance can be improved by training its members together rather than apart and better transactive memory is developed in groups whose members are trained together. Using a three-person group setting, we run a virtual experiment and the results are compared to the lab experiment results by Moreland, Argote and Krishnan (1998). The results under two experiment settings correspond with each other in both directions and significance, and thus on one hand, confirming the role of transactive memory in group training and performance and on the other hand, suggesting that ORGMEM is a valid model to study transactive memory.

Model Application – Contingency Effects

According to Galbraith's Contingency Theory, there is no one best way to organize. The best way to organize is contingent upon the uncertainty and diversity of the basic task being performed by the organizational unit (Galbraith, 1973). Accordingly, we suspect that transactive memory is not equally beneficial to all kinds of groups. We study two organizational variables: group size and task environment. In the virtual experiment, six group sizes are examined under three different task environment and 54 groups are generated using random techniques. Groups perform their decision tasks under two conditions – with transactive memory versus without transactive memory. The length of time taken for each condition is averaged and plotted in Figure 1 and Figure 2.

As shown in Figure1, no matter how big group size is, groups with transactive memory tend to take less time to finish their tasks while the magnitude of the effect is not equal across all conditions. There seems to exist a non-linear relationship between the effect of transactive memory and group size. More specifically, transactive memory helps middle-size groups more than small or large groups. On the other hand, three task environments are examined – groups never change tasks, groups switch from one task to a new task once in the middle, and groups oscillate between two tasks. The results in Figure 2 indicate that although groups with transactive memory take less time to perform their tasks, surviving in a volatile task environment without transactive memory is more challenging,

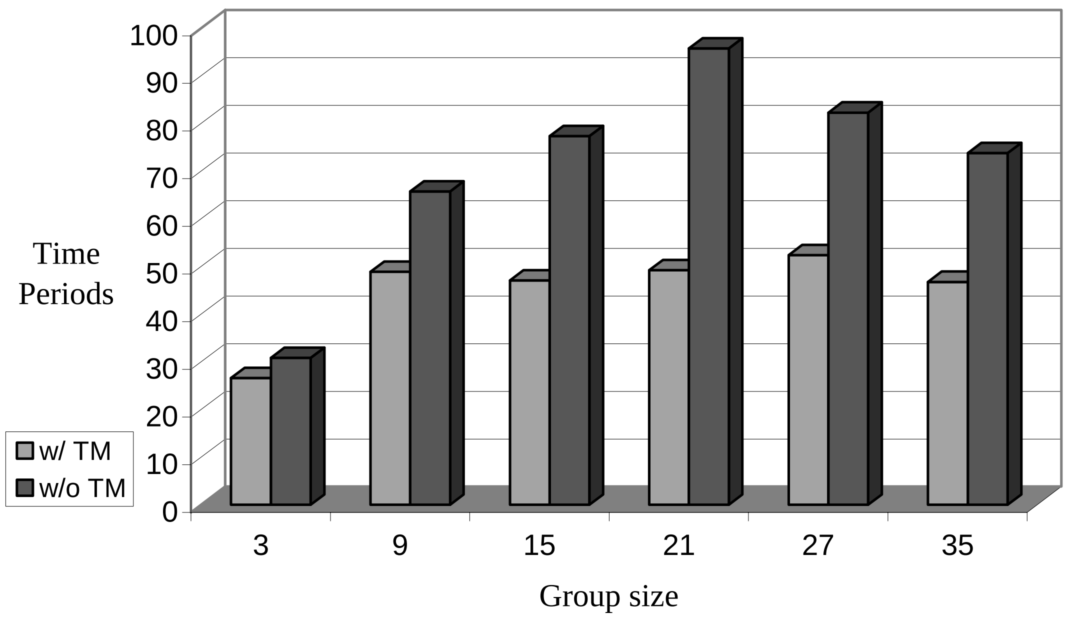

Figure 1: Time Periods Taken to Finish Tasks under Different Group Sizes

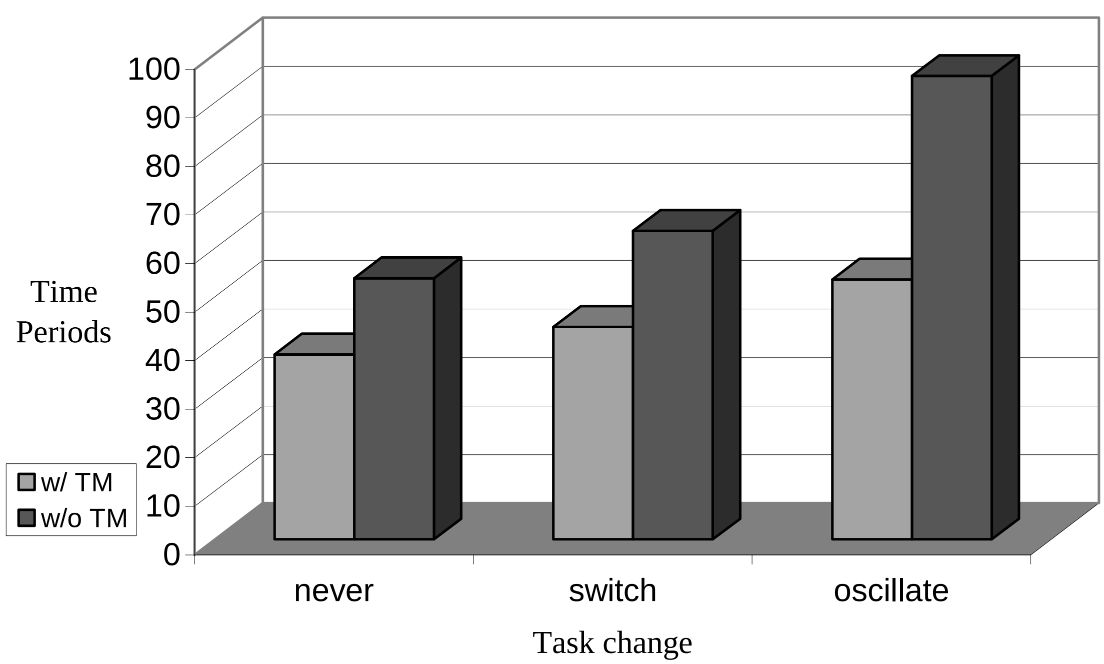

Figure 2: Time Periods Taken to Finish Tasks under Different Task Environments

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Boundary Spanning and Tie Strength: A Computational Model of Knowledge Transfer in Dynamic Technological Environments

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Abstract

The efficient flow of knowledge across organizational boundaries is critical to an organization's ability remain effective in dynamic and complex technological environments (Allen, Tushman & Lee 1979). Boundary spanners support the transfer of knowledge by acting as conduits to knowledge by maintaining informal relationships that facilitate the transfer of external knowledge across organizational boundaries to peers. Work by Tushman, Allen, & Katz (Tushman 1977; Allen, Tushman & Lee 1979; Tushman & Katz 1980; Tushman & Scanlan 1981) found that the most effective boundary spanners engage in frequent informal communication with both internal and external relationships, yet it is not clear whether these relationships are comprised of weak or strong ties. While both weak and strong ties have their relative advantages with respect to knowledge transfer little is know regarding which type of relationship is more effective for accessing valuable knowledge. Weak ties allow for greater access to more diverse knowledge while strong ties allow for greater transfer of more tacit knowledge. Drawing upon recent work in knowledge transfer and network structures (Hansen 1999) this study proposes a computational model to compare the effectiveness of boundary spanners under varying environmental, knowledge, and network conditions. It is expected that this study will enhance our understanding of the contingencies of the transfer of external knowledge across organizational boundaries.

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Key words: knowledge transfer, social networks, boundary spanners, organizational design

Boundary Spanning and Tie Strength: A Computational Model of Knowledge Transfer in Dynamic Technological Environments

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The efficient flow of knowledge across organizational boundaries is critical to an organization's ability remain effective in dynamic and complex technological environments (Allen, Tushman & Lee 1979). Boundary spanners support the transfer of knowledge by acting as conduits to knowledge by maintaining informal relationships that facilitate the transfer of external knowledge across organizational boundaries to peers. Work by Tushman, Allen, & Katz (Tushman 1977; Allen, Tushman & Lee 1979; Tushman & Katz 1980; Tushman & Scanlan 1981) found that the most effective boundary spanners engage in frequent informal communication with both internal and external relationships, yet it is not clear whether these relationships are comprised of weak or strong ties. While both weak and strong ties have their relative advantages with respect to knowledge transfer little is know regarding which type of relationship is more effective for accessing valuable knowledge. Weak ties allow for greater access to more diverse knowledge while strong ties allow for greater transfer of more tacit knowledge. Drawing upon recent work in knowledge transfer and network structures (Hansen 1999) this study proposes a computational model to compare the effectiveness of boundary spanners under varying environmental, knowledge, and network conditions. It is expected that this study will enhance our understanding of the contingencies of the transfer of external knowledge across organizational boundaries.

TECHNOLOGICAL ENVIRONMENT

Dynamic technological environments create a need for organizations to acquire knowledge from external sources and transfer it to organizational units. *Emerging technological environments* are dynamic and evolving, thus the knowledge that is available is developmental is more complex and more tacit than when the technology becomes more established (Nelson & Winter 1982). Thus, knowledge in emerging environments is more critical to organization's ability to maintain fit with its environment, but it also more costly to locate and transfer. As the technology matures knowledge in *established technological environments* becomes more codified and available in forms more easily appropriated by the organization, such as journals, books, and university educations. So, in established environments knowledge is more readily available and more easily transfer, but its value to the organization may not be as great as in emerging environments. Therefore, we argue that knowledge possess greater value to an organization in emerging environments than in established environments, yet it is assumed for this model that there is no relationship between the value of the knowledge and the complexity and tacitness of that knowledge.

Knowledge found in the environment may be assessed along three dimensions: complexity, tacitness, and relevance. *Complexity* is the number of components or concepts that comprise the complete bundle of knowledge and it partially determines the cost to evaluate and transfer knowledge. More complex knowledge contains a greater number of concepts and thus organizations incur a greater cost to evaluate and transfer such knowledge. *Tacitness* is the degree to which the knowledge is difficult to codify into a shared language for transfer (Polanyi 1966). The tacitness of knowledge influences the type of relationship and degree of reciprocity required to transfer the knowledge. Knowledge with higher levels of tacitness require more effort by individuals transferring knowledge to ensure that the knowledge is accurately received and understood and thus greater reciprocity. *Relevance* is the value that the knowledge provides the organization. Knowledge that is more relevant to the needs of the organization the greater value it has to the organization.

BOUNDARY SPANNERS

Boundary spanners support the transfer of knowledge by acting as conduits to knowledge, maintaining informal relationships that facilitate the transfer of external knowledge past organizational boundaries to peers. The effectiveness of boundary spanners is contingent upon the type of organizational task they support. Work by Tushman, Allen, & Katz (Tushman 1977; Allen, Tushman & Lee 1979; Tushman & Katz 1980; Tushman & Scanlan 1981) found that boundary spanners are most effective when the organizational boundaries are well defined, the technological environment is dynamic, and the task is developmental rather than research or service. Since developmental projects tend to be specialized and deep within organizational boundaries (Burns & Stalker 1966; Allen 1977) boundary spanners provide project members with informal communication links to extraorganizational information (Tushman & Katz 1980).

TIE STRENGTH AND KNOWLEDGE TRANSFER

Boundary spanners are characterized by both frequent communication and access to diverse knowledge (Tushman & Katz 1980; Tushman & Scanlan 1981). Frequent communication implies strong relationships, while access to diverse knowledge implies weak relationships (Granovetter 1973). Yet since it is difficult and cost for individuals to maintain a large number of both strong and weak ties it is unclear what type of ties boundary spanners possess. *Strong ties* are characterized by frequent and reciprocal interactions. Because strong ties imply shared sentiments (Homans 1950) individuals are likely to share similar knowledge and are willing to take the time to engage in interactions to transfer knowledge (Kogut & Zander 1992). Thus, strong ties are efficient for the transfer of complex and tacit knowledge (Hansen 1999), but because of their greater levels of reciprocity strong ties are also costly to maintain. Given that individuals have time and resource constraints they are likely to possess a relatively few number of strong ties. Thus, while strong relationships allow for the transfer of nearly all relevant information a boundary spanner encounters, a small number of strong ties reduces the probability of finding relevant information.

Weak ties are characterized by loose, infrequent interactions, which result in lower degrees of reciprocity than strong ties (Homans 1950). Less reciprocity enables individuals to maintain a greater number of ties along which to search for knowledge and, thus, a greater likelihood of locating relevant knowledge (Granovetter 1973). At the same time lower levels of reciprocity make it very difficult and costly to transfer more complex and tacit knowledge (Hansen 1999). In other words, weak ties are efficient for searching a larger number of ties for relevant knowledge but there are less capable of transferring more complex and tacit knowledge. Thus, boundary spanners with weak ties as opposed to strong ties are more likely to locate relevant knowledge but less capable of transferring that knowledge if it is highly complex and tacit.

Boundary spanners use their ties to search the environment for knowledge. When knowledge is located they evaluate the complexity and tacitness of the knowledge relative to tie strength to determine the cost and capability of transferring the knowledge from their external relationship into the organization. The boundary spanner will choose to transfer knowledge only if the value exceeds the costs. Since the value of knowledge is determined by its relevance to the organizational and not by its complexity or tacitness, the key question is *should boundary spanners maintain more weak ties, which increase the probability of finding valuable knowledge, or fewer strong ties, which increase the probability of transferring more complex and tacit knowledge into the organization?*

VIRTUAL EXPERIMENT

This study proposes a virtual experiment to identify the environmental and structural contingencies of boundary spanner effectiveness. By manipulating the knowledge environment and the strength of boundary spanner ties this study will contrast the effectiveness of four boundary spanner designs to maximize the net value of knowledge transferred into an organization under emerging and established environments. While it is expected that the effectiveness of boundary spanners with ties with complementary strengths (i.e. strong-strong or weak-weak) will be greater than boundary spanners with incongruent tie strength (i.e. strong-weak or weak-strong) the magnitude and direction of difference between complementary strengths is as of yet unknown.

The computational model will generate a pool of knowledge for both emerging and established environments. Each bundle of knowledge will be comprised of values of complexity, tacitness, and value drawn from distributions for both emerging and established technological environments. Boundary spanners will randomly access knowledge from this pool through their ties and assess the bundle for its net value; that is, the cost to transfer the knowledge subtracted from its value to the organization. While knowledge may possess great value to the organization, high degrees of complexity and tacitness might result in costs that far exceed the value gained. Thus, tradeoffs must be made between the capability to transfer knowledge and the value that knowledge will provide the organization.

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Evaluation of Collective Actions of Heterogeneous Agents at the Macro and Micro Levels

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Abstract

We consider several types of organizations of heterogeneous agents in which they have motivation to exchange their private knowledge with others. They have diverse preferences, motivation or objectives on knowledge exchanges. Some types of organizations will accelerate knowledge transactions, or other types of organizations discourage members to share their knowledge. Rational agents change to behavior by an organization in which they exist. In this paper, we evaluate collective knowledge transactions at both the macro and micro levels. We show the each agent's attitude hidden by collective behavior.

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Key Words: knowledge trading, collective transaction, satisfaction, equity

Evaluation of Collective Action of Heterogeneous Agents at the Macro and Micro Levels

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The study of knowledge creation has begun to gain a new wave. Nonaka and his colleagues have developed a new theory of organizational knowledge creation [Nonaka & Takeuchi, 1995]. They focus on both explicit knowledge and implicit knowledge. The key to knowledge creation lies in the mobilization and conversion of tacit knowledge. They emphasize knowledge creation in two dimensions, epistemological and ontological knowledge creation. A spiral emerges when the interaction between tacit an explicit knowledge is elevated dynamically from a lower ontological level to higher levels. The core of their theory lies in describing how such spiral emerges.

We consider organizations of heterogeneous agents, and knowledge transaction among agents with private knowledge and common knowledge. Both knowledge can be accumulated through knowledge transaction. Agents benefit by exchanging their private knowledge if their utility will be increased. In this paper, we evaluate collective behavior through knowledge trading with the two criteria, satisfaction and equity. Some agents may consider sharing knowledge with others is important for cooperative and joint works, or others put the high value on hiding their private knowledge from other agents. We investigate how each agent feel through the knowledge trading in an organization. We show completely different characteristics at the macro and micro levels.

Formalism of Knowledge Trading

In this section, we formulate knowledge transaction in an organization. We consider an organization of agents $G=\{A_i:1\le i\le N\}$ with both private knowledge and common knowledge. We also define that each agent $A_i\in G$ has the following two strategies:

S_1 : Trade private knowledge

S_2 : Does not trade (1)

We define the utility function of each agent as the function of both private knowledge and common knowledge. The utility function of agent A_i is defined as the semi-liner function of both private knowledge Ω_i and common knowledge *K*, such as;

$$U_i(\Omega_i,K)=\Omega_i+v_i(K) \quad (2)$$

The value $X-v_i(X)$ represents the relative value of agent A_i when he holds knowledge *X* as private knowledge or the common knowledge. We consider a knowledge transaction in an organization. Agent A_i has his private knowledge *X* and the trading partner has his private knowledge *Y*. The associated payoffs of both agents in Table 1 are given as follows:

Table 1 The payoff matrix of agent A_i

Own's strategy \ The other's strategy	S1	S2
S1 (Trade)	U_i^1	U_i^2
S2 (Not trade)	U_i^3	U_i^4

$$\begin{aligned}U_i(S_1,S_1)&=\Omega_i-X+v_i(X\vee Y)\equiv U_i^1\\U_i(S_1,S_2)&=\Omega_i-X+v_i(X)\equiv U_i^2\\U_i(S_2,S_1)&=\Omega_i+v_i(Y)\equiv U_i^3\\U_i(S_2,S_2)&=\Omega_i\equiv U_i^4\end{aligned} \quad (3)$$

The above associated payoffs can be interpreted as follows: Each agent has each payoff function which describes the outcome of the interaction between them. That means heterogeneous agents exist in an organization. And once they decide to trade their private knowledge, it is disclosed to the other agent, and it becomes as common knowledge. When both agents decide to trade their private knowledge, the payoffs of both agents are defined as their values of common knowledge minus their values of private knowledge. If agent A_i does not trade, and the partner trades, he receives some gain by knowing new knowledge *Y*. If agent A_i trades knowledge *X* and the trading partner does not trade, his private knowledge *X* becomes as common knowledge, and some value is lost because of the cost of trading. If both agents do not trade, they receive nothing.

Knowledge trading has unique features which are not found in the commodity trading. With knowledge trading, agents do not lose all the value of their traded knowledge. They also receive some gain even if they do not trade if the partner trades.

In this case, the optimal strategy is obtained as the function of the strategy of his trading partner as follows: We denote the proportion of agents to trade in an organization at p. Then the expected utility of agent A_i when he chooses S_1 or S_2 is given as follows:

$$\begin{aligned}U_i(S_1)&=pU_i^1+(1-p)U_i^2\\U_i(S_2)&=pU_i^3+(1-p)U_i^4\end{aligned} \quad (4)$$

Agents will transact if the following inequality is satisfied:

$$pU_i^1+(1-p)U_i^2\ge pU_i^3+(1-p)U_i^4 \quad (5)$$

By aggregating the payoffs in Table 1, we define the following parameter termed as threshold.

$$\theta_i = (U_i^4 - U_i^2)/(U_i^1 + U_i^4 - U_i^2 - U_i^3) = \frac{X - v_i(X)}{v_i(X \vee Y) - v_i(X) - v_i(Y)} \quad (6)$$

The denominator of threshold in (6) represents the multiplier effect of sharing knowledge, and the numerator represent the cost of the trading. Equivalently, the payoff matrix in Table 1 can be transformed the payoff matrix in Table 2. This payoff matrix becomes a symmetric coordination game if $0 < \theta_i < 1$.

Table 2 The transformed payoff matrix of agent A_i

Own's strategy \ The other's strategy	S_1	S_2
S_1 (Trade)	$1-\theta_i$	0
S_2 (Not trade)	0	θ_i

The social optimal situation is (S_1, S_1). That is, both agents can share knowledge. If $\theta_i < 0.5$, S_1 becomes to both individual and collective rational strategy. However, if $\theta_i > 0.5$, S_2 becomes to individual rational strategy although S_1 is collective rational strategy.

Collective Action in Knowledge Tradings

There are many situations where interacting agents can benefit from coordinating their actions. Agents also face problems of sharing and distributing limited resources in an efficient way. An interesting question is under what circumstances will a collection of agents realize some particular stable situations, and whether they satisfy conditions of social efficiency?

In order to describe the interaction among agents, we introduce the global matching model [Fudenberg & Levine, 1998]. The approach of global matching is follows: in each time period, every agent is assumed to match (interact) with one agent drawn at random from a population as shown in Figure 1. Each agent chooses an optimal strategy based on information about what the other agents have done in the past [Hofbauer & Sigmund, 1998]. And each agent can calculate his reword or other's rewords and can play the best action in a population. On an important assumption of the global matching, they receive information of the current situation through global matching. The agents gradually learn the strategy in the population.

The proportion of agents to trade at time t is denoted by $p(t)$ $(0 \le p(t) \le 1)$, the expected utility of agent A_i when he chooses the strategy S_1 or S_2, is given as follows:

$$U_i(S_1) = p(t)(1-\theta_i)$$
$$U_i(S_2) = (1-p(t))\theta_i \quad (7)$$

The optimal trading rule is obtained as the function of the payoff parameter θ_i as follows:

If $p(t) \ge \theta_i$ then, trades S_1.

If $p(t) < \theta_i$ then, does not trade S_2. (8)

The crucial point for dealing with heterogeneity in a population is the payoff parameter θ_i in the payoff matrix in Table 2.

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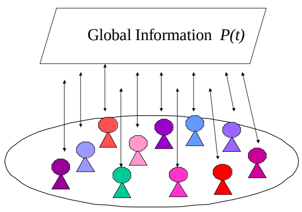


Figure 1 Global matching model

Next, we model the collective actions in knowledge trading. The heterogeneity of the organization G is represented as the distribution function of their payoff parameter θ_i. We denote the number of agents with the same payoff value θ by $n(\theta)$ in G. And the divided $n(\theta)$ by N is the distribution pattern of payoff parameter $f(\theta)$, which is given by $f(\theta) = n(\theta)/N$. This function is defined as the density function of payoff of G. The proportion of agents whose payoff parameter is less than θ is then given by

$$F(\theta) = \int_{\lambda \le \theta} f(\lambda)d\lambda \quad (9)$$

This function is defined as the accumulative distribution function of payoff G.

We denote the proportion of trading by the *t-th* transaction by $p(t)$. Since the optimal transaction rule was given in (8), agents with the payoff parameter satisfying $p(t) \ge \theta_i$ trade at the next time period. Therefore the proportion of agents who trade is given by the following dynamics:

$p(t+1) = F(p(t))$ (10)

The dynamics has an equilibrium at

$p^* = F(p^*)$ (11)

Characterization of Heterogeneous Organizations

Each agent has different payoff, and his behavior depends on his payoff parameter. We characterize with the following three types depending on his payoff parameter in Table 2:

(a) $\theta_i \approx 0$: Hard-core of trading

An agent who has low payoff parameter has high utility of sharing knowledge. He is willing to disclose his private knowledge without regarding the other agent's strategy. Therefore, we define an agent who has low payoff parameter is a hard-core of trading.

(b) $\theta_i \approx 1$: Hard-core of no trading

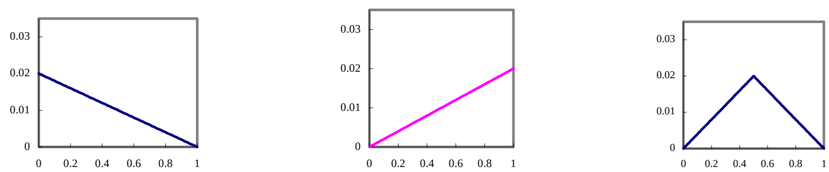
An agent who has high payoff parameter has high utility of hiding his knowledge. In this case, He has the strategy S_2 as a dominant strategy. He does not trade his knowledge without regarding the other agent's strategy. We define an agent who has high payoff parameter is a hard-core of no trading.

(c) $0 < \theta_i < 1$: Opportunist

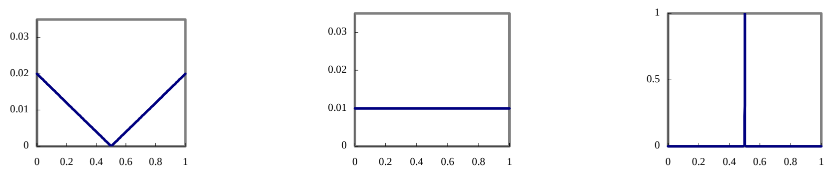
In this case, the optimal strategy depends on his partner's strategy. Therefore we define this type of agent as an opportunist.

Each agent has idiosyncratic payoff matrix reflecting his own value judgments for knowledge trading. Therefore, we aggregate the heterogeneous payoff parameters, one for each member who represents the heterogeneity of an organization.

As examples, we consider several distributions functions of payoff parameter $n(\theta)$ as shown in Figure 2.



(a) An organization :Type 1 (b) An organization :Type 2 (c) An organization :Type 3



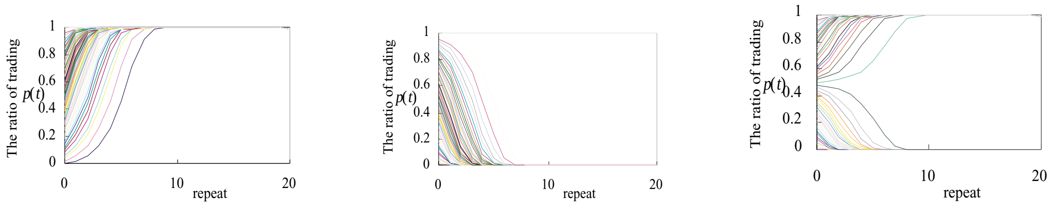
(d) An organization :Type 4 (e) An organization :Type 5 (f) An organization :Type 6

Figure 2: The threshold distribution in an organization

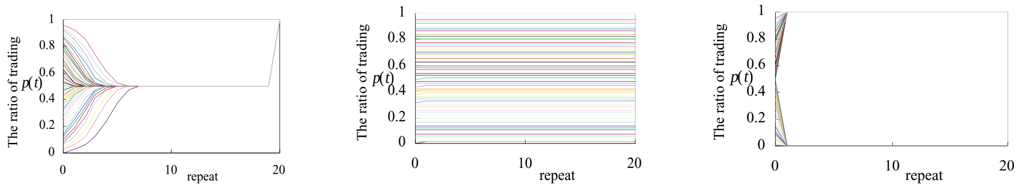
Evaluation of Collective Action at the Macro Level

In this section, we investigate knowledge trading of various types of organizations as shown in Figure 2. We evaluate knowledge trading as their collective behavior at the macro level.

We show the ratio of agents who trade starting from any initial value of knowledge trading in Figure 3 (a)-(f). In these figures, the x-axis represents the repetition time of knowledge trading, and y-axis represents the ratio of agents who trade. Figure 3(a), all agents finally trade because they have high utility of sharing knowledge. Figure 3(b), no agents trade at equilibrium because they put high value of hiding their knowledge. Figure 3(c), the initial ratio of trading becomes to be important. If the initial ratio of trading is less than 0.5, no agents trade their knowledge, however if the initial ratio of trading is greater than 0.5, all agents become to trade. Figure 3(d), half of agents trade their knowledge and other agents do not trade at equilibrium in spite of any initial condition. Figure 3(e), what proportion of agent does trade at equilibrium depends on the initial proportion of trading. Figure 3(f), collective behavior becomes the same that of organization type 3.



(a) An Organization :Type 1 (b) An Organization : Type 2 (c) An Organization : Type 3

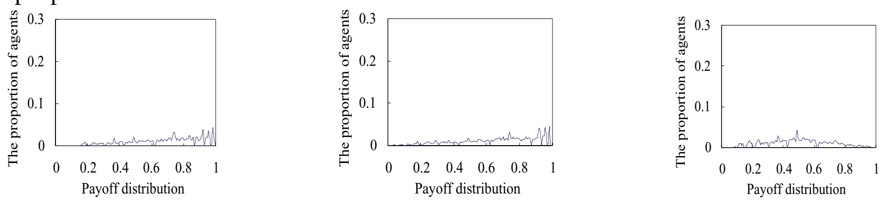


(d) An Organization : Type 4 (e) An Organization : Type 5 (f) An Organization : Type 6

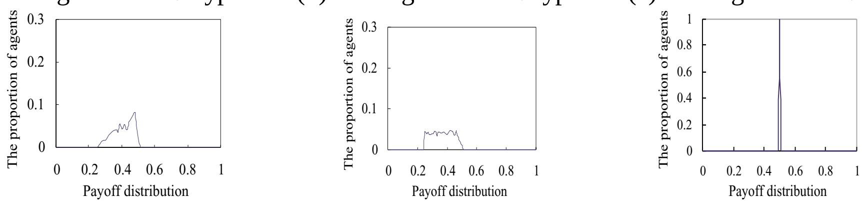
Figure 3: Dynamics of knowledge trading

Evaluation of Collective Action at the Micro Level

A collection of agents realizes some particular stable situations. But how does each agent feel that conditions of social efficiency? To analyze the satisfaction of each agent, we investigate average payoff of each agent exist in previous organizations. The collective behavior should be also evaluated at the micro level, since each agent desires to trade in order to satisfy individual good. We obtain the payoff distribution functions at the collective tradings. In organization type 1 and 2, the average payoffs are almost 0.66, but in organization type 3-6, the average payoffs are almost 0.5. In previous two organizations, they gets higher payoff than other organizations. Because many agents can select individual rational strategies. Besides, we investigate each agent's payoff at equilibrium through knowledge trading. Figure 4(a)-(f) show the agent's payoff distribution at equilibrium when the initial ratio of trading is set 0.5. In organization type 6, that is in homogeneous organization, all agents get same payoff 0.5, but in other types of organizations, we find that there are huge discrepancies among agents. Especially in organization type 1 and 2, their average payoffs are so high, but they show the most inequitable distribution among six types of organizations. In an organization type3, collective behavior depends on the initial ratio of trading at the macro level. But if we evaluate collective behavior at the micro level, payoff distributions are almost the same at any initial condition. And in an organization type 3, it gets average payoff of 0.5 as same as organization type 4 and 5, but agent's payoff distributions are completely different. We find completely different characteristics between the macro behavior (collective knowledge trading) and the micro behavior (payoff distribution). This fact reminds us to need the two criteria for measuring the performance of collective behavior as we proposed here.



(a) An Organization : Type 1 (b) An Organization :Type 2 (c) An Organization : Type 3



(d)An Organization :Type 4 (e) An Organization : Type 5 (f) An Organization :Type 6

Figure 4: The distribution of agent's payoff (When initial proportion of trading is 0.5.)

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Interaction Value Analysis
For Organizations with Reciprocal Cooperation

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Abstract

An organization can be viewed as an information-processing system composed of the individual persons who occupy positions in the organization. Although it leaves out many of the properties that characterize an organization, the information-processing view allows us to evaluate the suitability of different organizational structures for different types of work, different work environments, and other factors that affect the organization. These factors are generally known as *situational contingencies*, and the empirical and theoretical study of how these factors affect the performance of an organization is usually termed Organizational Contingency Theory (OCT). Interaction Value Analysis (IVA) is a way of modeling an organization engaged in information exchange work by considering the value created by dyadic information-exchange interactions between members of the organization. The behavior of a generic value-maximizing agent in this model is consistent with the behavior of human actors as summarized in empirical OCT research. This paper will examine how an IVA model gives rise to this behavior, and how different assumptions about the actors change quantitative results of the model. In particular, I will demonstrate the effects of introducing actors who fulfill requests for information exchange in a way that favors a subset of the other actors. The ability to determine the extent of favoritism or of a requirement for reciprocity when exchanging value-adding information can help in designing organization for carrying out a variety of projects in real-life settings and in different cultural milieus.

Key Words: Interaction Value Analysis; Organizational Contingency Theory; Queuing Theory; Social Networks; Communication; Firm Structure; Game Theory.

Interaction Value Analysis
For Organizations with Reciprocal Cooperation
Walid Nasrallah

Introducing the Interaction Value Analysis model

The IVA methodology is fully described and developed in several past papers [Nasrallah 1998, 2001 and 2002]. The following is a very brief summary of the model.

The main assumption of IVA is that individuals derive value from the organization through successful interactions with other members of the group. This assumption can be viewed as an abstract articulation of the observation that resources, goods, services, and other sources of value are usually owned or guarded by someone who needs to approve their disbursement to or usage by other individuals. These types of utility-generating interactions may be as numerous as the membership of the organization. However, because many of these may be mutually substitutable, we can produce a representative and tractable representation of the interaction space by only considering sources of value whose utility to different users is linearly independent of each other. This number of linearly independent types of interaction can be derived from certain properties of an idealized population, or it can be distilled from a comprehensive description of a population using matrix reduction.

The starting point for IVA model is therefore an N-by-N matrix of N linearly independent interaction types. The rows of the matrix represent the rankings (from 1 to N) of the value of a successful interaction of each type, to someone who can provide one of the N interaction types. For example, if we examine a firm at the level of its functional departments, then we might come up with the following 6-by-6 matrix for the six types of interaction provided by the six departments (Figure 1):

In this fictitious example, members of both “HR” and “Sales” departments derive the most value from interactions with the “Management” department. Engineering and manufacturing derive the most value from interactions between one another. Marketing derives the most value from interactions within the department.

Party doing the Ranking

	HR	Sales	Manuf	Mktg	Eng.	Mgmt
HR	2	3	5	4	6	1
Sales	5	2	6	4	3	1
Manuf	6	4	2	5	1	3
Mktg	3	2	6	1	5	4
Eng.	4	5	1	3	2	6
Mgmt	5	1	6	2	4	3

Ranking of Possible Interaction Partners by Interaction Value

Figure 1: A sample interaction-ranking matrix

Depending on the particular population we are modeling, the ranking matrix will give rise to different matrices of interaction values. Highly differentiated populations will have a greater difference between the value of the top ranked interaction provider and the lower ranked providers of the same interaction. Finding a maximum value for the following expression solves the IVA model:

$$\text{Effectiveness} = \sum_{i} \sum_{j} h_{ij} \times p_{ij} \times s_{ij} \tag{1}$$

Where

h_{ij} is the value that accrues from an interaction requested by party i and granted by party j

p_{ij} is the proportion of party i's interaction requests directed at party j , and

s_{ij} is the probability that an interaction requested by i and granted by j succeeds in providing value to i

Given a matrix H of all the interaction values hij, it is possible to select a matrix P of pij values that maximize the objective function (Effectiveness) while maintaining the common-sense constraint that all the pij must be positive numbers that add up to 1 for every i. The complexity of the optimization depends on how we choose to define sij. In [Huberman and Hogg, 1995], each sij was a function of pij alone. In that model, success of any interaction only depends on how often the seeker of that interaction attempts to attain it. Later IVA models [Nasrallah et al., 2002] introduced the concept of bounded rationality [March and Simon, 1958] in the form of a new function for computing the probability of failure. In this new function, it is possible for an interaction seeker i to fail because other seekers after the same interaction partner j make that partner too busy to respond in a timely manner.

Various parameters of the model govern the different failure functions. Each parameter has an interpretation that depends on the modeling domain. Different combinations of parameter values constitute different circumstances, and the values of pij that maximize effectiveness indicate of the pattern of interactions common in a population facing that circumstance.

Representing Organizational Contingencies in IVA

The organization under study is idealized into a set of parties, which derive value from dyadic interactions. The number of parties defines the **diversity** of the organization. Each party represents either a distinct subset of the organization members, or a linear combination of different members who both possess and utilize different skills or specializations to different degrees. The specializations are defined in such a way so as to be linearly independent, yielding an invertible matrix of interaction values H where hij is the value added to the organization when party i is successful in interacting with party j.

The rows of the H matrix are all idealized into different permutations of the same geometric series, and the ratio of the highest value to the lowest value in that series represents the degree of **specialization** in the organization. Doing so makes the mathematics tractable. More importantly, it imbues the results with generality by making them approximately applicable to organizations that deviate from the idealization in any direction.

Two queuing processes that go on in parallel define the probability of obtaining an interaction that is sought. One of these processes is governed by the organizational parameters of **load** and **urgency**. The closed-form steady-state solution of a queuing model with reneging is used as formulated by Ancker (1962). Load is defined as the rate at which requests are serviced relative to the rate at which they arrive. It represents the scarcity of the resources available to do work. Urgency is defined as the rate at which communication requests become superfluous, relative to the rate at which they are serviced. It represents the competitiveness of the external market or the premium placed on timeliness.

The other queuing process in IVA determines whether an interaction happens at the correct time to be of value. **Interdependence**, the final parameter that defines the IVA model, governs the rate at which interactions with the same specialization relative to the rate of all possible interactions. Higher interdependence means that more specializations have to be consulted in turn before returning to the same specialization. The mathematical representation of interdependence is based on a model by Huberman and Hogg (1995).

For any value of these five parameters, it is possible to allocate attention time among different parties to maximize the expected value of all interactions. The interaction time allocations are represented in a matrix P of the same order as the H matrix. Different ways of maximizing aggregate expected value yield different optimal P matrices. In particular, global optimization by a rational actor who can control the whole organization can be contrasted to a game-theoretic steady state between several competing local optimizers who control (and benefit from) a subset of the organization. These two optimization modes represent different governing structures of the optimal organization.

Reciprocal vs. Unconditional Cooperation

The queuing solutions used to construct the existing IVA model are First-In-First-Out models with Poisson processes for arrival, service, and defection. The new research presented here introduces a priority queue, where requests are serviced according to the value given to the requestor by the respondent. A new parameter will be introduce to indicate the "degree of reciprocity" used in favoring certain interaction requests according to how much the respondent requires reciprocal accommodation by the requestor. Low reciprocity means that everyone responds to requests equitably, in the interest of the organization at large. High reciprocity means that requests that are urgent form the point of view of the requestor, and hence from the perspective of the entire organization, are delayed because they have to wait for the responder to finish dealing with his own favorites. The effect of this attitude on organizational performance will be negative on average, but there may be combinations of factors that either minimize or exacerbate this effect. There may even be situations where reciprocal behavior serves a useful purpose for the organization, such as when interactions need to happen between mutual favorites anyway, and there is no cheaper means of communicating this need than reciprocal behavior.

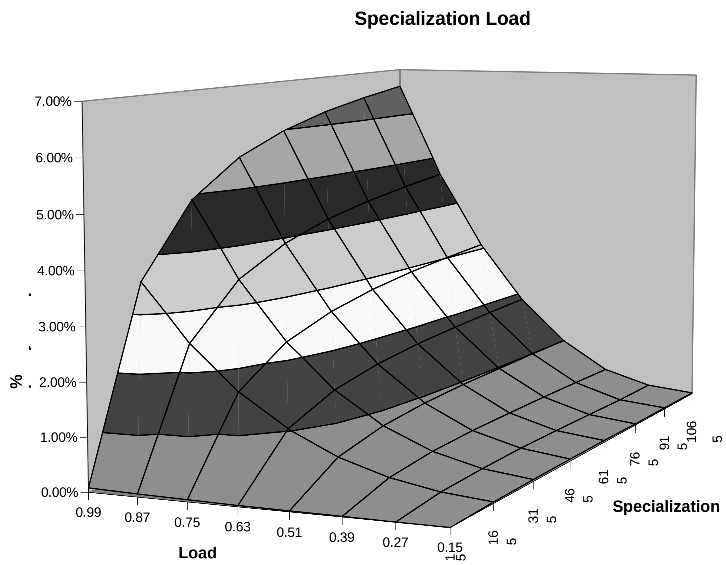

Figure 2 : A sample 3-D plot of the model's output

The paper will present general results derived form an idealized IVA model. Varying parameters within a reasonable range will give different types of optimal behavior. For example, the chart below shows the percent difference between the "global optimum" aggregate value, and the aggregate value obtained from an equilibrium of individual party optimizers. The open question following from this research is to consider how to average observations throughout a real organization to obtain a single representative figure for the parameters of interest.

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TrustMe: A Social Simulation of Trust, Advice and Gossip (with Emotion)

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Abstract

TrustMe is a computer simulation of a group of interacting agents. Underlying this simulation is a simple model of what we call "TAG models" of social interactions. TAG models of social interaction are those that involve information dissemination within the context of task performance (advice), information dissemination regarding agent behavior with respect to advice (gossip), and affiliated submodels of believability of information (and reputation) of those dissemination sources (trust) – Trust, Advice, and Gossip. In addition, this simulation is being expanded by a computational emotion engine that weaves together theoretical components of sociology and psychology to account for non-linearities in behaviors in the TAG models.

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Key Words: simulation, emotion, trust, agent models

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(with Emotion)

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TrustMe is a simulation of agents in a simple social context. In general, social contexts are based on simple interactions; furthermore, the nature of a "social context" is being broadened such that disparate communication links, such as email and chat rooms, are considered "social."[1] The important thing to keep in mind is that the interesting elements of the investigations you can make with TrustMe are based less on the complexity of those engaging in the social interaction, and more on how those interactions evolve over time. TrustMe weaves simplicity and representativeness. *Simplicity* is a relative evaluation based on the number of perceived concepts, constructs and interactions of the model, while *representativeness* is a relative evaluation based on "how much" of the real world (or, "which important elements") is modeled. Although the fundamental TrustMe model is intuitively appealing, TrustMe has substantial theoretical roots that contribute individually and collectively to the core formulation (Carley & Newell 1994, Carley & Prietula 1994, Prietula & Carley 1999). A general argument why computational models, such as TrustMe, are plausible and effective is what we call the "induced simplicity hypothesis."

Induced Simplicity Hypothesis. This hypothesis proposes that, for many social and organizational settings, much of the available set of decisions (say, the problem space for the task) is relatively restricted and defined by a confluence of the task, the situation, and the individual (Prietula & Carley 2002). These three factors act as constraints that often severely restrict the behavioral options of the individual, such that models of individuals behaving in those contexts can be sufficiently representative to account for parameters underlying most of the variance. Furthermore, because of the plasticity of the adaptive nature of individuals, much of their behavior can be explained in terms of task and situational components; conversely, examining the nature of how humans adapt to tasks and situations can yield insight into the specific influences of those factors. Behaviors are barometers to the tasks and situation; tasks and situations are drivers of behavioral adaptations. Tasks and situations define "what kind of behaviors" a human may engage or define; defined behaviors reflect demands of the tasks and situations.

TrustMe Models. TrustMe involves a set of virtual agents exchanging information and performing an abstract problem – searching for objects scattered around their world. A *problem* is comprised of one or more objects to be found by the agents. Each assigned object to be located is called a *task* of the problem. Problems are made up of tasks to complete. The world of TrustMe agents is comprised of a 12 x 12 grid of "locations," where objects and agents are collocated. This world can be viewed as a set of physical locations and objects (e.g., a warehouse, a neighborhood), as a set of virtual locations (e.g., a WWW URL space), or as a more abstract representation of concepts, distributed architectures, markets, or tasks.

Search The key component of how TrustMe conceptualizes a problem is that there is a concept of "distance between locations" and that agents' choices are defined (operationally) in terms of these distances. *Distance* can be interpreted as a traditional physical space, or on a more abstract level, such as time or similarity. Regardless of the particular interpretation, the general effect is that the problem is generally characterized as *search*, and search has an associated *effort* defined as a function of distance.[2] In TrustMe, there are three interpretations of distance and these are used as surrogates for three metrics of effort: simple count (of traversed locations), Euclidean (geometric distance), and logistic (non-linear count). Thus, distance matters, but you can define how it matters.

[1] For example, Constant, Sproull and Kiesler (1997) studies the advice patterns via e-mail of "weak ties" (strangers or mild acquaintances) and found that most of the information providers (responding to posted requests) did not know the person who posted the message. Cooperation, as social phenomena of optional advice provision, existed via electronic mail. Furthermore, Reeves and Nass (1998) provide evidence that under certain, but quite broad, circumstances even interactions between computers and humans constitute social interactions based on how humans react to those interactions.
[2] Search has a long and venerable history as both a distinct problem characterization as well as a metaphor in both cognitive science (e.g., Newell & Simon 1972) and computer science (e.g., Knuth 1998).

Agents. Each agent is *boundedly rational*; that is, each agent is architecturally constrained in primary ways in the specific context of the task: informationally and computationally.[3] The specific ways in which these agents are constrained are specified by the agents' *micro-architecture*.[4] These two types of bounds on rationality are realized in several ways in a typical TrustMe agent – and several of these bounds can be directly manipulated at the user interface.

TAG Models.

Underlying this simulation is a simple model of what we call "TAG models" of social interactions.[5] TAG models of social interaction are those that involve information dissemination within the context of task performance (advice), information dissemination regarding agent behavior with respect to advice (gossip), and submodels of believability of information those dissemination sources (trust) – Trust, Advice, and Gossip.

Trust. TrustMe supports five categories of trust models:

1. *Trusting*. These agents do not see events as sufficiently important to generate a response to alter trust behavior. They invariantly view other agents as honest and trust them.
2. *Distrusting*. These agents do not trust any other agent under any circumstances. All advice is ignored. These agents can be simply isolated performers or can actively disrupt the information quality of the group, depending on how you configure the options.
3. *Random Judgment*. In this model, a judgment of whether to trust the advice from an agent or not is solely based on a random choice from a uniform distribution. As opposed to the other models, this is a memoryless model with respect to social events. Each encounter with an agent's advice is independent of any other encounter.
4. *Forgiving*. These agents exhibit alteration of their trust in other agents, depending on options and situations. These alterations of trust are based on particular sequence of bad advice they have encountered when accepting the cooperation of other agents. TrustMe has four versions of Forgiving agents, each based on the number of bad advice messages it receives in a row for a particular agent, referred to as the tolerance level: 1, 2, 3 and 4. Once that particular limit is reached (e.g., 2 pieces of bad advice from a specific agent in a row), then a judgment of distrust is made. However a judgment of untrustworthiness is not an absorbing state. Agents that are not trusted can supply a series of good advice and redeem themselves. These are symmetric models, so if it takes n pieces of bad advice to be judged untrustworthy, then it takes n pieces of good advice to become fully trusted again.
5. *Unforgiving*. These agents exhibit similar alteration of their trust in agents, as these alterations of trust are based on particular sequence of advice they have encountered when accepting the cooperation of other agents – the tolerance level. However, once that particular limit is reached (e.g., 2 pieces of bad advice from a specific agent), then a judgment of untrustworthiness is made and a permanent disposition is made, which is not recoverable.

Advice. With respect to *advice*, there are two primary applications: generating advice, and believing advice. Trust models serve as filters in an overall advice resolution strategy that are applied before multiple resolution methods (random/maximum) are applied.

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[3] The strong form of bounded rationality was originally conceived to characterize the effects of a restricted rational agent on the assumptions and conclusions of economic and administrative theory (Simon 1976), and was highly influenced by research from sociology, social-psychology, and cognitive psychology. Bounded rationality ranges from strong forms that hypothesize the underlying cognitive (e.g., Newell 1990) or institutional (Cyert & March 1963) apparatus to less restrictive derivatives that address various organizational and economic issues at micro and macro levels.

[4] A *micro-architecture* is a description the components of the agent's deliberation mechanisms that contribute to the behaviors under study. Micro-architectures differ from full architectures, such as Soar (Newell 1990) in that they are not theories of full intelligent deliberation, but reflect on some level the dominant elements of interest that plausibly impact task behaviors in specific contexts (see induced simplicity hypothesis) Thus, TrustMe does not propose to be a generally intelligent architecture, but a model of a form of architecture that accounts for the behaviors under examination. They specify the assumed components of consequence for the task.

[5] See Prietula and Carley (2002).

Gossip. Gossip is the third element in the TAG model. Gossip functions as both a behavioral choice and as an organization construct, for it reflects a very real social mechanism of communication and control (e.g., norm enforcement). Current communication technologies alter the speed and scope of their distribution and (presumably) their organizational effect. Once whispered or dispensed on the telephone, gossip is now are broadcast real-time on firm's email or the nation-world Internet in seconds.

Gossip is a decision to generation a message regarding another agent, but there is also a decision on whether to believe gossip or not. In addition, what does gossip impact? Therefore, there are gossip *generation* rules, gossip *belief* rules, and gossip *impact* rules that can be selected for the agents.

Emotion. Finally, the current model is being expanded by the inclusion of the ACT emotion engine. Building upon a series of research efforts, we describe an expansion that takes into account emotional states capable of influencing, and being influenced by, agent behavior and task events. We adopt (and adapt) two theoretical models that can explain and predict emotional-cognitive aspects of agent behaviors. We also begin to craft a third theoretical framework that melds and extends the two to group emotional states and events (Prietula & Carley 1998).

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A Work Practice Model of a Day in the Life Onboard the International Space Station

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Abstract

We present a model and simulation of the activities and work practices of astronauts onboard the ISS based on an agent-oriented approach. The model represents "a day in the life" of the ISS crew and is prepared in Brahms—an agent-oriented, activity-based language developed to model knowledge in situated action and learning in human activities.

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Acknowledgements: We acknowledge the contributions of many others, especially: Bill Clancey, Jeff Bradshaw, Ron van Hoof, Mike Scott, Reyna Jeffers, Debbie Prescott, Mike Shafto, Boris Brodsky, Julia Brodsky, Charis Kaskiris and Chin Seah.

A Work Practice Model of a Day in the Life Onboard the International Space Station

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The International Space Station (ISS) is one the most complex projects ever. Numerous interdependent constraints must be met in order to ensure productivity and crew safety. This requires planning efforts starting years before crew expeditions, and the use of sophisticated planning and scheduling tools.

Human work practice onboard the ISS, however, is not easily represented within traditional tools. Expedition ship logs highlight recurring discrepancies between planned crew activities and the reality of onboard life. In addition, scheduling constraints make it hard to replan onboard activities. The need emerges for tools able to model the work activities of astronauts onboard the ISS and their interactions with other humans and systems onboard and on earth.

In this paper we present our ongoing modeling of the work practice of the ISS crew using Brahms. Brahms is an agent-oriented, activity-based language developed to model people's situated action, communication, and collaboration. Brahms links knowledge-based models of activities with discrete-event simulation and an activity subsumption architecture (Sierhuis, 2001; Clancey et al., 1998). In Brahms, agents' behaviors are organized into activities, inherited from groups and located in time and space. In our model of "a day in the life" of the ISS crew we consider resource availability, human/machine interaction, scheduled and unscheduled activities, and the emergence of work practices onboard the station out of procedures developed by engineers and mission controllers.

Our model has two functions. One function is to provide an artifact (i.e. a simulation model) that can help us study and understand the way work is done onboard the ISS. As such, our Brahms model might be of help in creating new procedures for the ISS crew (for example, by predicting the time needed to implement activities never executed before), in assisting daily planning, in predicting behavior during emergencies, in future orientation and training of the ISS crew, and in developing human-centered robotic systems for the ISS (such as the Personal Satellite Assistant—see Bradshaw et al., in press—and the Robonaut—see Ambrose et al., 2001) that need to be aware of the activities and practices of the crew. A second and more abstract function of the model is to explore the use of Brahms in representing manned space missions. In this regard, Brahms can be considered an agent-based social simulation tool (Davidsson, 2002), and this model (and future Brahms models) could prove useful for internal NASA coordination of research and engineering.

The International Space Station

The ISS Alpha[1] opened for business on November 2nd, 2000, when Expedition Commander Bill Shepherd, Soyuz Commander Yuri Gidzenko, and Flight Engineer Sergey Krikalev opened the hatch between the Soyuz vehicle that had brought them in orbit and the Russian Service Module (one of the earliest components in the assembly of the ISS). That day represented the climax of years of preparation and planning during which the ISS objectives and procedures were defined. In this section we discuss the ISS goals, the activities of its crew, and their planning procedures.

The ISS was designed to provide an "Earth orbiting facility that houses experiment payloads, distributes resource utilities, and supports permanent human habitation for conducting research and science experiments in a microgravity environment." (NASA, 2001, p.1-1). To achieve this goal, several assembly flights of Shuttle, Soyuz, and Progress vehicles have been operated and several crew expeditions[2] have been onboard.

While crews from initial expeditions spent most of their time in assembly and maintenance activities, more recent expeditions have had more time to accomplish some of the research for which the ISS was created: experiments in areas such as life sciences, microgravity, and space sciences, as well as commercial product development and engineering technology. However, because of several constraints (cf. below), a crew of three spends most of its time maintaining the station rather than focusing on the research experiments that were originally planned. This creates a strain on the NASA ISS program and has caused scrutiny of its actual benefits, and consequently its funding.

In a typical day, each ISS crewmember divides his or her time between physical exercises, maintenance, experiments, as well as communications with ground, entertainment, and bio-needs related activities (e.g. rest, eating, etc.). Some of these activities are critical for the well being of the crew. Hence, the planned maintenance and research activities must be set around and scheduled after them. At the same time, several structural interdependent constraints must be met in order to ensure crew safety and productivity: thermal control, power, communications bandwidth, and other systems. These form a network of components that must be accurately timed and orchestrated around crew activities and needs.

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[1] The Expedition 1 crew had the privilege of naming the ISS. They named it "Alpha."

[2] At the time of writing, the fourth expedition is onboard. Each expedition is composed of three astronauts (Russian and American).

Coordinating human and technical constraints onboard the ISS is therefore a challenging task. Unlike other space missions, the ISS operates on "a continuous basis, with execution planning, logistics planning, and on-orbit operations occurring simultaneously for long periods of time" (NASA [1999], p. 1.1-1). Planning for crew expeditions starts months or even years before an expedition with the so-called strategic planning phase. This phase poses the basis for ground rules and constraints that are later used in other phases of the planning process. Tactical planning (which starts around 30 months before an expedition) defines the resources, priorities and objectives of an expedition. Pre-increment planning (starting 18 months before an expedition) defines the high level activities of an expedition and produces the reference material and the procedures (Operations Data Files and Systems Operations Data Files) necessary to implement the former. Finally, as the expedition begins, new "just-in-time" products are prepared, such as the weekly Onboard Short Term Plan (OSTP), to be executed on the ISS.

This elaborate planning process is necessary to meet the human and structural constraints discussed above. The planning complexity is such that the major planning rule for the ISS is: "Thou shalt not replan" (NASA [1999], p.2.1-21). What this means is that—with the exception of "unacceptable failures" and "job jar" items left to the self-organization of the crew—any activity that can not be performed at its allotted time will *not* be replanned in real-time. It will simply not be performed, "with the expectation that [it] will be rescheduled into the operational flow at some later date" (NASA [1999], p.2.1-21).

Considering this, it appears obvious that any unexpected event or discrepancy between the time allocated for a planned activity and the reality of onboard life will have far-reaching impacts on the completion and timeliness of crew activities, and therefore will drastically reduce efficiency and productivity onboard. Since such discrepancies are actually frequent (as the comparison between daily plans and actual ship logs shows), in order to develop tools to improve planning and efficiency it becomes important to study how crew work practices emerge from planned activities and written procedures. Our goal is to understand how the planned ISS activities and their written procedures fit the reality of onboard life, and more specifically to determine the work practices that evolved onboard since Expedition 1. To address these questions we chose an agent-based simulation approach and used the multiagent modeling and simulation language called Brahms.

The Brahms Language

Brahms is an Agent-Oriented Language (AOL) that has a well-defined syntax and semantics. A Brahms model can be used to simulate human organizations, for what-if experiments, for training, for "user models," or for driving intelligent assistants and robots (Sierhuis, 2001; Clancey et al., 1998). The run-time component—the virtual machine—can execute a Brahms model, also referred to as a simulation run.

Brahms is based on the idea of "situated action" (Suchman, 1987) and offers to the researcher a tool to represent and study the richness of activity theory and "work practice" (Clancey, in press; Sierhuis, 2001). A traditional task or functional analysis of work leaves out the logistics, especially how environmental conditions come to be detected and how problems are resolved. Without consideration of these factors, analysts cannot accurately model how work and information actually flow, nor can they properly design software agents that help automate human tasks or interact with people as their collaborators. For this goal, what is needed is a model that includes aspects of reasoning found in an information-processing model, plus aspects of geography, agent movement, and physical changes to the environment found in a multiagent simulation—such as interruptions, coordination, impasses, and so on. A model of work practice focuses on informal, circumstantial, and located behaviors by which synchronization occurs (such that the task contributions of humans and machines flow together to accomplish goals) and allows the researcher to capture (at least part of) the richness of activity theory (Clancey, in press).

The Brahms Modeling of the International Space Station

The ongoing effort to model the collaboration and work practice onboard the ISS in Brahms developed through three phases: 1) data gathering; 2) conceptual modeling; and 3) Brahms modeling. In the next subsections we discuss the research steps for achieving these goals.

The Data

We sought data to understand and represent a "day in the life" of the ISS crew. With this general objective in mind, in some cases we devoted more attention to specific activities and scenarios (such as the emergency scenario) that appeared of great relevance to our research objectives. We consulted ISS documentation and manuals, onboard procedures and flight rules, crew daily plans and ship logs, crew de-briefings, and particularly ISS crew videos. This information was interpreted, analyzed, and validated through interviews with astronauts, astronaut trainers, and flight controllers at Mission Control. While the day chosen for modeling was May 7th, 2001 (when Expedition 2 was onboard), we generalized the model so that we can simulate any possible day.

On a typical day (that does not involve EVAs) an ISS Crew member wakes up at 6.00 GMT and (after or before activities such as personal hygiene and breakfast) he or she reviews, on a laptop computer, the plan of the day. The scheduled activities include several sessions of physical exercises, communications with grounds, experiments and maintenance tasks. The crew executes these tasks by performing individual and collaborative activities, sometimes altering the order proposed by the mission planners, sometimes removing or inserting activities with or without previous coordination with Mission Control. At the end of their day, the astronauts have dinner together and then participate in some post-dinner activities, such as watching a movie, reading personal e-mail or a book.

One of the scenarios currently attracting our attention is an emergency scenario. We are gathering data about emergency procedures and the reactions of the crew and mission control during emergencies, with the goal of modeling emergencies under various conditions and predicting their outcome.

The Conceptual Model

In our analysis of the data gathered during the first phase of our research we attempted to recognize patterns in the crew activities and the emergence of work practice that are specific to onboard life. We generalized and represented the individual astronaut's daily behavioral patterns as learned and shared activities at the (conceptual) group level. For example, the activity of eating breakfast onboard the ISS is represented at the ISS Crew group-level. This way, all agents that are members of the ISS Crew "know" how to perform this activity. The group structure also allows us to represent differences between social, cultural and other type of communities (for example, the behavioral differences between American and Russian crewmembers, and between male and female crewmembers). In order to make our model reusable and applicable to any given day and scenario on the ISS, we represented procedures, daily plans, and flight rules as objects and conceptual objects in the model, that agents can access, have beliefs about, manipulate, and act upon. We categorized activities according to a two-by-two matrix, with the degree in which the activity was scheduled (scheduled vs. unscheduled activities) represented on one axis, and the uniqueness or repeatability (day-specific vs. recurrent activities) of the activity represented on the other axis.

The Brahms Model

In this section we discuss the current features of our model and we analyze the resulting simulation. We describe the *sub-models* of a Brahms model: the agent-, geography-, activity-, and knowledge model.

Agent Model: The Brahms Agent Model of the ISS includes both the ISS crew and ground controllers (Houston, Moscow, and Payload operations). Hierarchies and organizational structures are explicitly modeled; for example, different planning officers and flight controllers are modeled, each with their activities and responsibilities. The representation of group membership for the ISS crew agents reflects the different roles of the agents (e.g. ISS Commander; Flight Specialist; Soyuz Commander), their nationalities (Russian or American), their sex (male or female), as well as a grouping by type of activities they can perform (e.g. "BreakfastEaters").

Activity Model: The Brahms Activity Model of the ISS represents "a day in the life" of the ISS crew. Recurring activities (such as breakfast, lunch, physical exercise, and ground communication) are modeled as well as activities that are unique and only performed on a particular day (such as a specific experiment or a specific maintenance task). The model represents the onboard work practice as a combination of scheduled activities by mission control and unscheduled activities left to the discretion of the crew. The simulation of the model shows how the practice of onboard activities often diverges, both in timing and execution, from the originally scheduled activities and procedures: for example, delays caused by crew movement constraints, the search for tools and other items, and inability to share resources, or access to electronic procedures, are all represented in the model, and emerge during simulation.

Geography Model: The Brahms Geography Model conceptualizes the geographical spaces within the *modules* of the ISS where the crew lives and works, with particular attention and detail for those locations where the astronauts spend most of their time (lab, crew quarters, etc). This means that some modules are represented with a higher degree of granularity than others. For example, the American Destiny module (which is used as the ISS laboratory) is modeled with internal locations for experiments (e.g. the Human Research Facility), the robotic arms controls, and physical exercise machines. Some of these locations, in turn, are decomposed into sub-areas—this allows modeling the locations of objects and other places within a particular area—for example, pliers and can-openers can be located inside boxes behind drawers of a module, or attached to hangers on the walls. This model of the ISS geography is instrumental to the representation of the astronauts' situated activities. For example, the model represents how the relative locations of the agents/astronauts inside a module and/or by the noise level in the background affect interaction and coordination.

Knowledge Model: The knowledge model represents what the agents can know about—have beliefs about—as well as their reasoning and/or problem-solving behavior—inference rules—which can be used to create new beliefs. We thus distinguish the agent's practice knowledge of how to perform activities and when (i.e. situation-action rules), from the definition of an agent's possible beliefs and its inference rules to create new beliefs or change existing beliefs. For example, the simulated astronauts learn the daily activities from the OSTP they read in the morning and access or refer to online procedure whenever they do not already know how to execute a particular activity—by reading the procedures (i.e. an activity) they will get beliefs (i.e. knowledge) about how to perform the OSTP activities. This makes the Brahms model highly reusable, because by changing the daily plan provided as an 'initial condition' of the model, and by adding new procedures taken from the real counterpart in the procedure documentation, the simulation can take completely different paths.

The Brahms model of "a day in the life" of the ISS crew is not "hard-coded," in the sense that the model does not encode only one specific day. Instead, we can simulate any "day in the life" by feeding a different daily plan as input into the model. The simulated agents (i.e. the Brahms agents that model the ISS crew) organize their day in a similar way to how the crew organizes its daily life in practice. The agents can react in (simulated) real time to the events of the day deciding whether there is a need to consult with Mission Control about a procedure or whether they can abandon the written procedure whenever there is a certain work around. For this reason, we believe that our ongoing efforts to model emergency scenarios might be of use to forecast potential outcomes of such eventualities under different scenarios. Given this, we believe that the simulation of a work practice model of "a day in the life" of can help the mission planners in creating short-term schedules.

Conclusions

We are developing an agent-based model of the work practices of the ISS crew. We use Brahms—an agent-oriented, activity-based language—to represent the ISS crew's situated action, communication, and collaboration during the course of their daily activities. In our modeling of the "day in the life" onboard the ISS we include resource availability, scheduled and unscheduled activities, and the emergence of work practices. In addition, we model human/machine interaction (such as the crew's use of their personal computers). In our continued research we are exploring the use of the ISS model as part of an environment for teamwork between the ISS crew and onboard collaborative software- and robotic agents, and as a short term planning and scheduling tool for mission planners.

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Simulating Information Growth & Diffusion in Agent Societies

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Abstract

The question of how to simultaneously promote growth and diffusion of information exhibits difficult yet pressing tradeoffs. Creation of new ideas is contingent on access to information source material; but maximizing incentives to create information often conflicts with maximizing availability after conception. Information flow systems depend on a distinctive set of factors including nonrivalry, incentives, agent rationality, topology, random interactions, access, productivity, and environments. Variations among these factors yield a diversity of emergent behaviors. In response to the complexity of practices and policies that explore information flow, we have developed an information growth and diffusion (IGD) simulator (http://si.umich.edu/~mvanalst/iShare).

This article describes several attractive properties of IGD and how it can be used to analyze information practices and policies. In particular, we describe (1) how tracking the entire flow of information is computationally expensive (2) how the IGD mechanism differs from prior art (3) how the simulator can emulate or "dock" certain kinds of models (4) how IGD functions as a research, teaching, and communications medium (5) how local structure is related to global factors via feedback mechanisms and (6) what open source approach we have taken to encourage future development.

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Key Words: Information, Diffusion, Agent Based Model, Incentive Systems, Simulation, Artificial Society

Acknowledgement: We are grateful to Misha Lipatov for valuable feedback.

Support: An NSF Career Award 9876233 has provided partial support for this research. Additional support has been provided by the University of Michigan, School of Information.

Simulating Information Growth & Diffusion in Agent Societies

Piotr Dollar, Paul Laskowski, and Marshall Van Alstyne

The question of how to simultaneously promote growth and diffusion of ideas exhibits difficult yet pressing tradeoffs. To economists, it concerns the relationship between economic health and incentives for sharing information. When does the stimulus to innovation, founded on a profit motive, collide with access to information source material, which exhibits properties of a public good? To the legal profession, it influences what types of ideas should be intellectual property. Is society collectively improved when rights to information are broader or narrower, longer or shorter? To computer scientists, this tension is manifest as a debate in the production of software. Is an open source or proprietary model superior? To policy analysts, growth and diffusion are related to furnishing information access. Are improved communications technologies enough to bring quality information to those who seek it, and if not, why not?

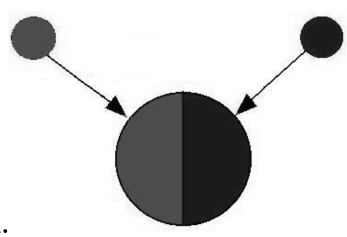
Information flow systems depend on a distinctive set of factors including nonrivalry, incentives, agent rationality, topology, random interactions, access, productivity, and environments. Variations among these factors yield a diversity of emergent behaviors. In response to the complexity of practices and policies that explore these factors, we have developed an information growth and diffusion (IGD) simulator (http://si.umich.edu/~mvanalst/iShare).

IGD is intended to support research and teaching in three ways: First, software libraries that manage network models will free researchers from starting anew each time a mathematical model is proposed, while speeding the process of inquiry. Second, a simulation environment will help scholars explore robust policies in the context of changes in preferences, technologies, and network structure. Immediate visualization of various propositions is far more effective at conveying new results than static text; standardized simulation will promote faster assimilation of ideas by a broader research community. Finally, tutorials demonstrating known results will be an effective and direct way to help introduce new students to the field. These educational benefits can extend to scholars outside the original reference discipline where an insight is first developed.

Distinctiveness of Information Economies

All agent-based models share certain unifying characteristics, but the problem of information flow exhibits its own distinctive set of behaviors. IGD is particularly well suited to dealing with this field. We briefly consider three examples of constraints that specifically affect information flow. First, we argue that exponentially many subsets are required to accurately model information flow.

Consider two agents that share knowledge with each other. Their knowledge stores should not be allowed to grow without bound by re-sharing the same information back and forth. Hence, to describe who has what information, three quantities must be specified: what amount of information each agent has a monopoly over, and what amount of information is held in common. As the number of agents increases, the number of subsets required to describe knowledge ownership increases exponentially. This approach is motivated by a paper by Van Alstyne and Brynjolfsson [Van Alstyne & Brynjolfsson, 1997].

a. 

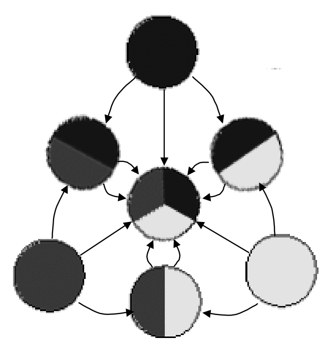
b. 

Figure 1: Knowledge sharing subsets for (a) two and (b) three agents

The IGD simulator can keep track of the knowledge unique to each subset of agents, including each subset that contains just one agent. That is, for every subset of agents, IGD records what amount of knowledge is owned by every agent in the subset, but by no agent outside the subset. This computation places no bound on the amount of knowledge that can be created by society. Alternatively, IGD can also treat knowledge as a collection of distinct facts and record which agents know which facts. This parallels the modeling of information as an agent genotype.

We next observe that in an information economy, the nature of interaction between people can have dramatic effects. Connections between people can differ in terms of their symmetry, their use for interacting with similar agents, what types of information flow across them, and how much information passes between agents. Connections can form due to deliberate actions of rational agents, or they can be exogenously determined, or they can indicate random interactions. Differences in willingness to share across connections can have a large impact on knowledge flow.

One specific instance of this compares Boston's route 128 to Silicon Valley, two high technology areas with different growth rates. Saxenian [Saxenian, 1994] presents a socio-economic explanation of why the California region, starting from the same size industrial base in 1975, had three times the employment growth and twenty five times the growth in market capitalization observed by 1990. The primary differences were attributed to several factors all related to greater information spillovers. Lower vertical integration allowed information to diffuse to buyers and sellers; less defense contracting reduced secrecy, and job-hopping and culture engendered a greater willingness to share with competitors.

The IGD simulator provides support for computing knowledge growth and flow in terms of connections between agents. Agents can connect to each other according to general societal structures, or they can choose their partners according to a suite of semi-rational strategies.

Finally, we consider the effect of geographic factors on information flow. Geographical, political, or language boundaries can limit what agents have access to what other agents. This can have dramatic effects on system behavior.

IGD agents can be placed on a 2-dimensional plane, in any one of several ordered structures or randomly. Users can then specify whom each agent has access to based on Euclidian distance. More precisely, setting access at some level, *a*, allows the average agent to connect to his *a* geographically nearest neighbors. As access increases, agents can connect to partners that are farther and farther away geographically. If access is set to the entire population size, access is universal and there is no geographical constraint at all. Increasing access simulates the effects of improved communication technologies on agent interaction. IGD allows us to explore the effects of access under a variety of agent preferences. We discover that the global behavior that results depends on the strategies that agents follow.

Utility of the IGD Simulator

The IGD simulator permits deep exploration of the relationship between local structure and global dynamics. At the agent level, users can specify agent connections manually, or as a function of the current system environment. These local connections determine how the system behaves on the global level. Furthermore, dynamic agent-choice strategies create a feedback mechanism that allows agents to alter their individual behaviors as the global environment changes through time.

The IGD simulator efficiently simulates a wide variety of agent-based models. This concept is one that Axtell, et al. have termed "alignment of computational models," or simply "model docking." [Axtell, et al., 1996] Put simply, model docking is the execution of one model with another model, or more generally, using two different models to simulate the same phenomenon in order to compare their results. The IGD simulator is designed to allow docking with a wide range of information models and to perform this task easily.

The simulator's docking ability has three main benefits. First, existing models can be replicated in IGD. We have completed this task successfully with a wide variety of models including [Carley '91; March '91; Van Alstyne & Brynjolfsson '97; and Watts & Strogatz '98]. Replication is an important part of scientific inquiry. It allows the robustness of results to be tested under a variety of inputs and assumptions.

Second, IGD allows researchers to efficiently implement new models for study. Implementing models in IGD is intuitive and requires no programming skill. Maximum flexibility is provided by the IGD simulator's system of production functions. Production functions are expressions that a researcher inputs into the IGD simulator. They describe how every component of every state vector in society changes in every time interval. Production functions are entered into the simulator in a format similar to LISP and can include mathematical operators, but also looping statements and variable declarations, giving them high flexibility. The production functions take all the knowledge components in society as inputs, as well as the connections that each agent has.

Once a model is written and ready to be run, the IGD simulator eases the process of debugging and analyzing the model. Many types of data are generated automatically and can be examined at any time, or can be graphed to show their history. These graphs are visual aids that should give the user a general idea of the behavior (or misbehavior) of the model. Production functions can be altered and new data can be gathered without the need for any recompiling of code.

Finally, IGD applies broadly to a comparative study of models. To motivate this discussion, note that while simulation is a powerful tool for conducting scientific inquiry, it has certain drawbacks. By definition, a model is an approximation, or simplification, of a real system, and is based on a collection of assumptions. It has been noted that model builders face a not-uncommon embarrassment when another modeler discovers widely different results under alternative reasonable assumptions [Sterman, 1988]. What is needed is a method for recognizing faulty models, and identifying what models are special cases or generalities of other models. In the IGD simulator, different models can be run side-by-side. Parameters can be easily altered and the changes in behavior can immediately be seen in the built in graphs. Relationships can be identified between different parameters and between different models. In this way, the IGD simulator makes it easier than ever to identify what assumptions dictate model behavior, reject fragile behaviors, and compare models to determine which is the most appropriate for answering different questions. Additionally, perhaps the largest obstacle to creating a real comparative study of models is the large amount of time required to implement each one. The IGD simulator aims to make this process easy, so that model behavior can be studied in the context of other models and their underlying assumptions.

IGD Target Audiences

We designed the IGD simulator both to be a foundation on which to study and compare particular models, and also a communications tool, with resources for demonstrating the properties of different models through interactive tutorials. These tutorials can deal with a wide array of topics and combine text with visual aids and hands-on experiments. The audiences that can use these features include students, teachers, and researchers. Each of these groups will use a different scope of the simulator's functions and capabilities.

Students will benefit from the simulator's ability to clearly demonstrate information phenomena. The interaction between social structure and information flow can be very complex and difficult to illustrate. The IGD simulator provides a visual and hands-on method of understanding these complex relationships.

Teachers may use the tool's scripting capability to develop new scenarios based on existing structure. In this mode, alternately configured and differentially endowed societies can be created and saved, then recalled easily for assigned exercises. This involves choices among elements of a general-purpose structure in order to present a coherent lesson.

Finally, researchers will make use of the full capabilities of the IGD simulator. They will also have access to the source code and will therefore be able to alter and develop new structure, adapting it to their own novel research questions. The IGD simulator is an open source project, and was constructed with future additions in mind. The source code is fully modular, and the basic structures are made to be as versatile as possible. Figure 2 contains a graphical representation of the program structure.

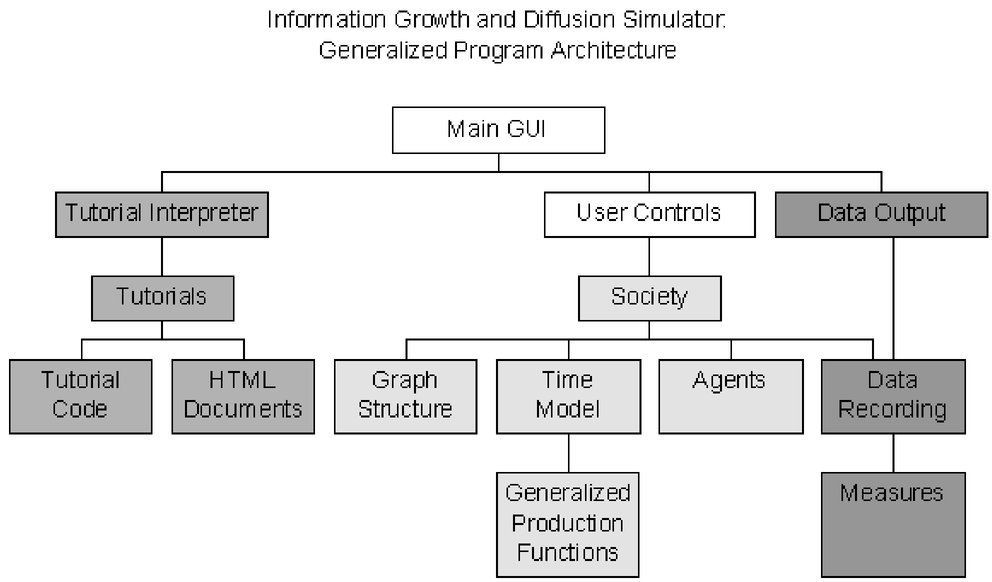


Figure 2: IGD Program Architecture

Often times, upgrading the program only involves adding a few modules and doesn't require an understanding of the entire program structure. The code is written in the popular Java (Sun Microsystems) programming language, which is particularly adept at creating clean, modular code. If a researcher has frequent modeling needs, the initial investment of basic familiarity with the code will enable easy upgrading.

To facilitate formation of an open source community, the simulator will be released under a modified or blended open source license. The rights of anyone submitting an extension are increased to allow for a brief proprietary or commercial interest of up to one year. Both firms and scholars are invited to submit their research, tutorials, and model extensions for peer review and subsequent inclusion. Upon inclusion, other scholars may build upon the tool set subject to a *temporary* commercial interest of the author who submits extensions.

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Choice Interaction and Organizational Structure

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Abstract

We examine how a firm's formal organizational structure affects its ability to cope with interdependent decisions. An agent-based simulation, in which firms struggle to discover good sets of decisions, allows us to examine four coordinating mechanisms that have rarely been analyzed jointly: the grouping of related decisions under a single subordinate, a vertical hierarchy that reviews proposals from subordinates, firm-level incentives, and managers who are able to process more information. We find that organizational structure affects long-term performance by influencing the number and nature of "sticking points"—configurations of choices the organization will not change. We identify each of the four coordinating mechanisms as a force that either encourages firms to explore a broad set of alternatives or stabilizes firms around existing choices. Successful firms strike a balance between exploration and stability. The need to balance exploration and stability generates interdependencies among the coordinating mechanisms. As a result, firms sometimes benefit from seemingly harmful features: avoidable decision interdependence between departments, a passive CEO, or subordinates of limited ability. We further examine how appropriate organizational design depends on the underlying pattern of interaction among decisions. When interactions are pervasive, successful organizations employ coordinating mechanisms that promote broad exploration.

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Key Words: organizational design, interdependent decisions, coordinating mechanisms, sticking points

Acknowledgement: We are grateful to the Mack Center for Technological Innovation and the Division of Research of Harvard Business School for generous funding.

Choice Interaction and Organizational Structure
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In firms of even modest size, interdependent decisions are allocated to distinct managers. One manager is given the right and responsibility to make production decisions, for instance, while another makes marketing choices—despite the fact that production and marketing decisions affect one another. One manager controls one product line while a second manager controls another, even though the two product lines may share a factory or a sales force. Formal organizational design is, at its essence, a process of breaking interdependent decisions into bundles commonly known as jobs, assigning individuals to those jobs, and arranging some means to coordinate individual action.

Students of organizational design have considered a number of mechanisms that promote coordination across interdependent decisions (Galbraith, 1973; Mintzberg, 1979; Nadler & Tushman, 1997). In this paper, we develop a model that permits us to explore the workings of, and the relationships among, four especially prominent elements of formal organizational design.

1. *Decomposition* is the grouping of decisions so that, as far as possible, related decisions are under the purview of a single manager

2. The *vertical hierarchy* connects the decomposed parts and deals with interactions that remain after decomposition. A vertical hierarchy might consist, for instance, of a CEO who sits above distinct product divisions, reviewing and integrating their decisions.

3. *Firm-level incentives* encourage managers to act for the good of the overall organization rather than pursue the parochial interests of their divisions or departments.

4. Finally, we examine the role of *managerial ability*. Interdependent managerial tasks must be divided into jobs in part because individual managers are limited in their ability to process information and consider alternatives. A natural approach to improve coordination, then, is to hire smarter managers.

These four are not an exhaustive list of the coordinating mechanisms that organizational designers have considered and employed. However they do cover the important classes of mechanisms in the literature on formal organizational architecture. We model these coordinating mechanisms and the underlying pattern of interaction using an agent-based simulation model derived from research on complex adaptive systems. This approach enables us to look simultaneously at all four coordinating mechanisms, distinguishing our work from prior papers that have examined only one or two mechanisms at a time. In our model, firms with different organizational features face a long series of decision problems. For each decision problem, each firm attempts to find a good solution, that is, an effective set of choices. Decisions within each decision problem interact with one another in a manner controlled by the modeler. The management team of each firm consists of a very simple hierarchy: a CEO and two subordinate managers. Each subordinate manager has purview over a subset of the organization's decisions, a "department." Starting from a particular configuration of choices, each manager considers altering the decisions under his command, evaluates the alternatives in light of an incentive system, and makes recommendations to the CEO. The CEO reviews the proposals and accepts the pair of proposals—one from each manager—that will serve the firm best. In choosing the best pair of choices, she has the prerogative to overrule either or both of her subordinates and maintain the status quo.

Modeled firms differ in their structures: how they allocate decisions to subordinates; how active a role the CEO takes; how much information managers convey up the vertical hierarchy; and whether managers are rewarded for departmental success or the performance of the firm as a whole. Organizations also differ in the cognitive abilities of their CEOs and managers. By comparing the performance levels of firms with different structures across a large number of decision problems, we can isolate how the distinct coordinating mechanisms affect the ability of a firm to cope with interrelated decisions.

The results of our modeling effort focus on interdependencies in two senses. First, we show that the underlying pattern of interaction among decisions has a profound effect on the efficacy of these coordinating mechanisms.

Second, we find that the mechanisms interact with one another in ways that are surprising at first but have reasonable explanations. We observe, for instance, a) when the interactions among decisions span departmental borders, hiring smarter subordinates may undermine firm performance; b) when a firm has a capable CEO, it may be beneficial to intentionally leave interdependencies between departments; c) given certain patterns of interaction among decisions and low levels of managerial ability, it may be better to have a CEO who blindly rubberstamps the proposals of subordinates than to have one who actively exercises discretion. Such interdependencies among coordinating mechanisms are consistent with a longstanding observation in the literature on organizational design, that the fit among elements of an organization's architecture is as important for success as the disposition of any individual element (Mintzberg, 1979: 216-220).

We interpret our results in terms of a firm's search in a space of possibilities, using the landscape conceptualization that has become popular in certain formal models of organizational search (Kauffman, 1995; Levinthal, 1997; Levinthal & Warglien, 1999; Gavetti & Levinthal, 2000; Ghemawat & Levinthal, 2000; Rivkin, 2000; Fleming & Sorenson, 2001). A mapping from firm decisions to payoffs creates a landscape in the space of decisions. Firms can be conceived of as trying to attain and sustain a high spot on such a landscape—a combination of decisions that, together, yield a high payoff. When decisions interact richly, such landscapes become rugged with numerous local peaks. From a local peak, no single decision can be changed in a way that improves the firm's payoff.

Organizational design, we argue, affects firm performance by altering firms' search behavior on the landscapes they face. A firm typically gravitates on its landscape toward a "sticking point"—a configuration of choices from which it will not change. Importantly, sticking points may or may not be local peaks; there exist local peaks that are not sticking points and sticking points that are not local peaks. Organizational design affects long-term performance by two primary channels. First, it alters the nature of a firm's sticking points—the number of such points and the payoffs associated with them. Second, it influences the likelihood that a firm will actually reach such a stable configuration of choices.

In our simulations, organizations with the most effective designs balance exploration and exploitation (March, 1991). Early on they are able to explore their landscapes broadly. Having found a good set of decisions, they are able to stabilize around that set rather than wander incessantly. In landscape terms, they find good points and also stick to those points. We find that specific organizational characteristics are associated with exploration and stability. Roughly speaking, firms with interdependencies between departments, decentralized decision-making, department-based incentives, and smart subordinates tend to explore broadly. Firms with completely decomposed decisions, strong vertical hierarchies, firm-level incentives, and departmental managers of modest abilities tend to be good exploiters; they stabilize around sets of decisions rather than wander. These tendencies create interdependencies among elements of organizational design. Often a firm must offset one element's push toward exploration with another's pull toward stability. Prior models of organizational search tend to overlook such interdependencies because they often grant "stability for free": that is, they assume that firms which discover good decisions through exploration can lock-in on those decisions forever. Contrary to this assumption, we illustrate that organizational structures which enable discovery may undermine lock-in.

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UMIE-2002: U-Mart International Experiment 2002
- What We have Learnt from the Virtual Market -

U-Mart Organizing Committee [*], U-Mart System Technical Committee [†]

Abstract

U-Mart is a joint project to research a virtual stock market, in which any pre-registered agents are able to participate via local and/or wide-area networks. The aim of the project is to provide a forum (1) in which multiple agents of both computer programs and human traders participate in the auction and compete in the market, and (2) where research on market structure analysis is carried out. In this paper, we describe the concept , the system specification of U-Mart and discuss its future research in the context of economics, computer sciences and artificial intelligence. In addition, we report the results of "U-Mart International Experiment 2002 (UMIE2002)", an international open experiment of the U-Mart at CMOT Conference held in Carnegie Melon University in June 2002 .

Introduction and U-Mart System Configuration

The U-Mart project is a research program for developing an open type artificial market system called U-Mart as a common test bed for interdisciplinary study of economics and computer science. As an artificial market system, U-Mart has two important features. One is that U-Mart treats futures of an existing stock index in virtual space. Thus, it provides the artificial market with relationship to real economy, and with adequate complexity and reality. The other feature of the U-Mart is its open structure. U-Mart allows participation of user-defined trading strategies both as software agents and as manual trading by human. Thus, we can involve existing trading strategies used by actual traders, learning/adaptation/evolution techniques for software agents, and play/learning by human in the artificial market.

In this project, we provide "U-Mart Server" which process inquiries and orders from "U-Mart clients" via computer networks. The server and the clients communicate each other via "Simple Virtual Market Protocol (SVMP)". The U-Mart server collects orders given by agents, decides the market price, and pays or receives the price to/from the agents. Therefore the U-Mart server works like a real market, except for the fact that real cash is not transferred, that is, the results of trades are just registered in the server and that trade histories and final results will be open to all participants.

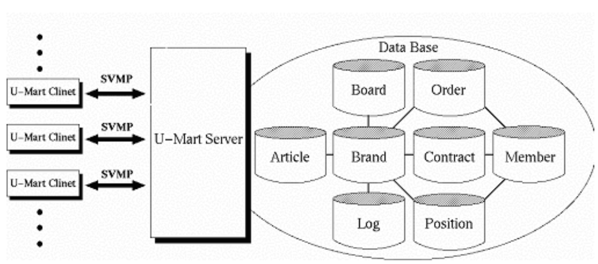

Figure 1: Composition of U-Mart experimental system

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Figure 1 shows the system configuration of the U-Mart experimental system. The system consists of a virtual market server and trader clients. The clients communicate with the server by Simple Virtual Market Protocol (SVMP). SVMP is character-based protocol equipped on TCP/IP protocol. This means that the server and clients can be developed separately and the system has platform-free characteristics.

U-Mart server contains a transaction processing component, a communication component and a database component. PostgreSQL is used for a database management system. The current version of the U-Mart system is implemented in Java language.

Outline of U-Mart International Experiment 2002

The U-Mart project has successfully held two domestic open experiments as contests of trading agents in Japan (Pre U-Mart 2000 and U-Mart 2001), and possibility of this approach is confirmed. The U-Mart system is also used as an effective education tool both in schools of economics and computer science in several universities in Japan.

Based on the above experience, we have decided to have an international open experiment of the U-Mart: "U-Mart International Experiment 2002(UMIE2002)" at 2002 CMOT Conference held in Carnegie Melon University in June 2002. Our web site is: http://www.casos.ece.cmu.edu/conference2002/index.html.

The aims of this experiment are:

- to share an artificial market system as a common test bed for agent-based simulation,
- to share variation of trading strategies, and methodologies for developing them for artificial market study, and
- to know complex behavior of the market consisting of agents having various trading strategies.

The UMIE2002 calls for participation of trading software agents during these three months. With submitted agents, a demonstrative contest is held at the site of the conference. Also, the committee carries out intensive experiments with the submitted agents for various market situations in advance, and the results are reported at CMOT conference. Furthermore, all the codes and documents of the submitted agents also will be shared by all the participants for further study on the artificial market.

Developers' Kit for U-Mart Trading Agents

To let the participants easily develop their own software agents, we provide the developers' kit for U-Mart trading agents, which includes:

- Documents of the U-Mart system,
- Description of the contest specification of UMIE2002,
- The U-Mart server,
- Java API for client programs,
- Sample agents using the API,
- GUI clients for manual trading and monitoring,
- Standalone U-Mart simulator for developers,
- Sample trading strategies for the standalone simulators, and
- Wrapper program to make the strategy developed with the standalone a kit U-Mart client.

All the documents are in English, and all the programs are coded in Java (JDK 1.2 or later).

To obtain the kit, send e-mail identifying

1. Name,
2. Affiliation,
3. Postal Address,
4. Telephone and FAX (with country code), and
5. e-mail

to XYZ@u-mart.econ.kyoto-u.ac.jp for registration. After completion of the registration, the U-Mart developer's kit will be sent. The registered person is also added to the mailing list of the UMIE2002 for communication on the experiment and software. Registration is required just to send the kit, and it doesn't automatically means participation to UMIE2002.

With all the submitted agents, we will carry out U-Mart experiments in advance, and the results will be reported in the CMOT conference with some actual demonstration. We also require that both the submitted agents and their descriptions will be open to public for the further study.

What We Have Learnt So Far and Future Issues

The U-Mart experiments so far have shown the promises to construct a variety of machine agents and clarified the strategic differences between human and machine agents. We continue this study program forward by integrating the knowledge obtained from both type of agent simulations.

It is also interesting that the results indicated the usefulness of the U-Mart system as an educational tool for both economics and information science.

So far, we have carried out similar experiments several times with software agents, human agents, and their mixtures. These experiments have further revealed that (1) in most cases, the heavy rises and falls phenomenon occurs, although the design of the trading market is very simple and natural, (2) the market are stable if all the agents are very conservative and not aggressive in the trading volumes, (3) the random agents have an important role in the trading and they often become winners, and (4) no powerful agents (including humans!) could not be implemented. This means that the research on multiagent learning has still remained immature status. We must clearly determine the concepts of multiagent learning and their abilities.

Appendix

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