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Experiments in Indirect Negotiation

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Abstract

The purpose of negotiation is to enable agents to coordinate their actions. Characterizing coordination in information-theoretic terms leads us to consider negotiation in the context of other processes that can transfer information among agents, such as those mediated by the environment. We illustrate these concepts using the Minority Game, an abstract model of resource allocation that achieves coordination without negotiation in the classical sense. Our work illustrates two important lessons. 1) Indirect (environmentally-mediated) negotiation can achieve agent coordination even without conventional negotiation. 2) The information flow between agents and the environment is likely to affect the dynamics of systems even when they use more conventional negotiation.

Introduction

The term "negotiation" is used to describe a wide array of interaction mechanisms among agents (Parunak 1999). While a precise definition is elusive, most attempts will refer to

1. iterative symbolic communication
2. among intelligent agents
3. leading to a coordinated course of action (e.g., distributing utilization across a set of constrained resources).

Research in this area usually begins with a focus on the first or second of these characteristics. The course of action that agents take in the "real world" is of interest as an outcome, but is not usually viewed in itself as a player that can participate in the negotiation process.

Some years ago, we became aware of the active role that the environment plays in negotiation when experimenting with an instance of the contract net for manufacturing control (Parunak 1987). After carefully proving that our protocol was deadlock-free, we ran it on a physical control system, and it promptly deadlocked. The negotiation in question concerned the movement of a physical part from one workstation to another. Our analysis of the protocol neglected the movement of the physical part itself. This movement conveyed information between the two workstations, and thus between the software agents that represented them. It represented an undocumented extension of our protocol, one that invalidated our proof and caused the system to deadlock. The arrival of the part at the receiving workstation gave that workstation information about the state of the system that it would not otherwise have had, namely, that the part had been delivered.

In general, the environment can contribute to coordination whenever the agents can sense its state and act accordingly. Whether changes in the environment result from agent actions or exogenous effects, the fact that the environment's state is common to all the agents enables it to increase their coordination.

Traditionally, the study of negotiation focuses on coordination by means of information flow directly from one agent to another. The mantra of situated robotics that "the world is its own best model" (Brooks 1991) suggests that the problem domain may deserve a more prominent role in the process. There are several motives for understanding the role of the environment in coordination, and learning to exploit it where possible.

- It supports open, heterogeneous societies of agents. The environment is by definition accessible to the agents that are negotiating about it. Any agent that wishes to deal with the domain must be able to sense and manipulate it. Thus the physics of the environment define common standards for agent interaction, in contrast with the more arbitrary standards programmers can impose on direct agent-to-agent communication.
- It integrates and reflects the state and dynamics of the overall problem-solving process at a global level that is only imperfectly visible in the internal models maintained by any of the agents. In particular, it captures high-order interaction effects that may escape the notice of any individual agent or *a priori* model maintained by an individual agent. For instance, assume agents A, B, C, and D are all interested in resource ℵ, but A and B know only of each other, as do C and D. The load on resource ℵ integrates information about the demands of all the agents that would otherwise not be available to them.
- It embeds domain constraints (e.g., resource limitations) directly in the reasoning process, without the need to identify and model them in advance.

Our research shows that significant coordination can be realized by relying on the problem environment to mediate agent decisions, without invoking direct symbolic communication among the agents. Pragmatically speaking, relying solely on such "indirect negotiation" is no more advisable than ignoring it as traditional "direct negotiation" does. Our objective in this paper is to emphasize two consequences of the flow of information through a shared environment.

1. This flow transmits environmental dynamics even to agents that negotiate conventionally, making it *necessary* for them to take it into account. (Our earlier experience with the contract net illustrates this point.)
2. This flow is rich enough that in some (restricted) cases it is *sufficient* to generate useful coordination.

Section 2 defines the sense in which we understand coordination using simple concepts of information theory, and summarizes the ways in which the environment can mediate the flow of information among agents needed to achieve coordination. Section 3 introduces an abstract model of indirect negotiation in resource allocation, shows how it can yield insights into this approach, and gives evidence that it can illuminate conventional negotiation as well. Section 4 summarizes the discussion.

An Information Theoretic View of Coordination

One way to measure the coordination among a group of agents is in terms of their joint information, otherwise known as their correlation entropy or mutual entropy. This perspective enables us to enumerate the ways in which this quantity can be increased, and thus survey the scope of mechanisms available for achieving coordination.

Joint Information

At each time step, each agent (indexed by i) has access to any one of n_i actions $\{s_{i1}, s_{i2}, \ldots, s_{inj}\}$. We assume that an agent's actions are completely defined by its state, so that any of our definitions could be reposed in terms of states rather than actions without affecting the point, but we prefer to focus on the agent's actions because they, unlike its state, are externally visible. Let p_{ij} be the probability that agent i executes action s_{ij}.. One measure of the agent's behavior over time is its (Shannon) entropy, defined in the standard way as $H(a_i) = -\sum_{j=1}^{n_i} p_{ij} \log_2 p_{ij}$. Similarly, we can characterize the entropy of the overall system in terms of the various combinations of actions of the individual agents. For simplicity, we restrict our discussion to two agents, but the concepts can readily be extended to any number. The maximum total number of system actions is $n_1 * n_2$, p_j is now indexed over these joint actions, and the system entropy is $H(a_1, a_2) = -\sum_{j=1}^{n_1 * n_2} p_j \log_2 p_j$.

The system entropy is subadditive, $H(a_1,a_2) \leq H(a_1) + H(a_2)$. Equality obtains when the behaviors of the individual agents are statistically independent. When they are dependent, the system entropy is strictly less than the sum of the individual agent entropies, and the difference $I(a_1{:}a_2) \equiv H(a_1) + H(a_2) - H(a_1,a_2)$ is the mutual or joint entropy, sometimes called the joint information.

Now, agents coordinate when they seek to constrain their own actions in relation to those of other agents. It does not matter for our purposes whether this coordination is cooperative, competitive, or some mixture of the two. It will manifest itself in an increase of the system's joint information. One benefit of this perspective is that it permits us to distinguish the *fact* of coordination from the *mechanisms* used to achieve it.

For example, suppose that each of our two agents needs access to a widget to perform its duties. Suppose further that there are two widgets available, and (to simplify the computations) that each agent accesses each widget half of the time. Then the probability that agent a_1 is accessing widget 1 is $p_{1,1} = 0.5$, as is the probability that agent a_1 is accessing widget 2, the probability that agent a_2 is accessing widget 1, and the probability that agent a_2 is accessing widget 2. We further assume that a widget works better when only one agent is using it at a time.

Each individual agent entropy is $-2*0.5 \log_2(0.5) = 1.0$. At the system level, there are four possible joint actions: both agents accessing widget 1, both accessing widget 2, a_1 accessing widget 1 and a_2 widget 2, and *vice versa*. If the agents do not coordinate their activities, then each of these four possibilities is equally likely, with probability 0.25, and the system entropy is $-4*0.25 \log_2(0.25) = 2$, the sum of the individual agent entropies. If the agents manage to cooperate (whether by negotiating with each other or negotiating with the widgets, or consulting an oracle), they will avoid the joint actions in which they both choose the same widget. Now there are only two system actions, each with probability 0.5, and the system entropy is 1, less than the sum of the agent entropies. The difference, 1, is the joint information between the cooperating agents.

It is important to understand that coordination is not necessarily desirable. The agents would be just as coordinated, and would have the same joint information, if they always choose the same widget, but in this case productivity would be lower in the coordinated system than in the random one. Coordination is a useful concept, and joint information is a useful measure of coordination, but a worthwhile system must exhibit more than coordination and the resulting high joint information. We do not pursue this point further in this paper.

Increasing Joint Information

Once we view the *what* of coordination as increasing joint information, we can inquire into the *how*, the mechanisms that make it possible. Static mechanisms (e.g., hard-wired agent plans) do not accommodate changes in the real world. Agents will need to change their state dynamically in order to coordinate with other agents, and this change will require the movement of information across the agent's boundary. (We speculate that there may be a quantitative relationship among the joint information among a population of agents, the entropy of the domain, and the amount of information movement across the boundaries of the agents.)

Everything that lies outside the agent's boundary is its *environment*, and the options for this flow stem from the contents of this environment. Many agent architectures perceive the agent environment exclusively in terms of other agents. Other agents certainly are an important part of the environment, but it may include other entities as well. The environment may manifest its own state variables that can be sensed by the agents. Some, but not necessarily all, of these variables may be directly modifiable by the agents. In addition, the environment may support its own processes that couple its state variables and cause them to change over time. Thus we can distinguish three important components of the environment from the point of view of information flow among agents.

- Other agents are part of the environment.
- Endogenous environmental variables are those, such as resource loadings, whose values change over time depending on the actions taken by the agents. Some endogenous variables may be directly manipulated by agents, while others may be affected indirectly by changes that agents make to other variables, by way of environmental processes. For example, increased agent use of one resource may generate increased maintenance tasks that increase the utilization of another resource.
- Exogenous environmental variables are those, such as sunspots, whose values change over time independent of the actions of the agents.

Such an environment supports three forms of information flow that can affect coordination. We describe them in order from most conventional to least conventional.

1. Agents may communicate directly with one another, as in traditional negotiation.
2. Agents may make and sense changes to endogenous environmental variables. For example, if one agent consumes part of a shared resource, other agents accessing that resource will observe its reduced availability, and may modify their behavior accordingly. Even less directly, if one agent increases its use of resource A, thereby increasing its maintenance requirements, the loading on maintenance resource B may increase, thereby decreasing its availability to other agents who would like to access B directly.
3. Agents may jointly sense changes in a shared exogenous environmental variable (an "oracle"). The variable's dynamics are independent of agent actions, so it cannot move information between agents. But it may serve as a synchronizing signal that the agents use to coordinate their actions, and thus increase their joint information.

A stock market illustrates the importance of information flows mediated by endogenous environmental variables. It affects both stock traders and business executives, in different ways. Traders (at least those who obey SEC regulations) do not negotiate directly with one another to coordinate which shares each will buy and sell. But when a trader offers for sale a share in one company, the offer tends to depress that company's share price, making the company more attractive to potential buyers. Thus information flows between traders through the environment of the stock market without direct negotiation. In contrast, business executives rely extensively on direct negotiation in reaching contracts with their customers and suppliers. However, they must also pay attention to indirect information flows, including those through the same stock market. For example, if a supplier's stock price drops precipitously, the supplier may not be able to raise needed capital, and in spite of its explicit promises in a negotiation, it may not be able to fulfill its obligations.

In some cases, it may be desirable to reserve the term "coordination" for joint information resulting from information flows among agents (cases 1 and 2 above), and use the more general term "correlation" when we wish to include case 3 as well. This refinement has subtle consequences that go beyond the scope of this paper, and we will explore it in another study.

The Minority Game and Extensions

These mechanisms can be made more concrete in the context of a simple abstract model of resource allocation. We first describe the basic game (Savit, Manuca, and Riolo 1999). We support our point that indirect negotiation is *sufficient* to achieve coordination in restricted settings by reporting on extensions that we and others have made. We support our point that taking indirect information flows into account is *necessary* by using it to illustrate a fundamental dynamic of resource allocation that is likely to affect systems using conventional negotiation.

Basic Minority Game

Consider an odd number N of agents (representing tasks) and two resources labeled 0 and 1. An agent might represent an incoming target, and the resources might be weapons platforms available to meet those threats. At each time step, each target agent chooses one of the weapon platforms. A platform is overloaded and unable to function if chosen by more than half of the agents. So each target assigned to the less-used platform at a time step receives a point, while each target on the overloaded platform gets nothing. Because agents prefer to be in the minority group, this model is called the "minority game."

Agents have access to endogenous environmental information in the form of a time series *G* of minority resource identifiers. That is, for any time step t, *G(t)* is 1 if resource 1 was less heavily loaded at t, and 0 if resource 0 was less heavily loaded. For example, if the minority resource alternates over the first ten rounds of the game, *G* would have the form '0101010101', where new rounds are recorded at the right.

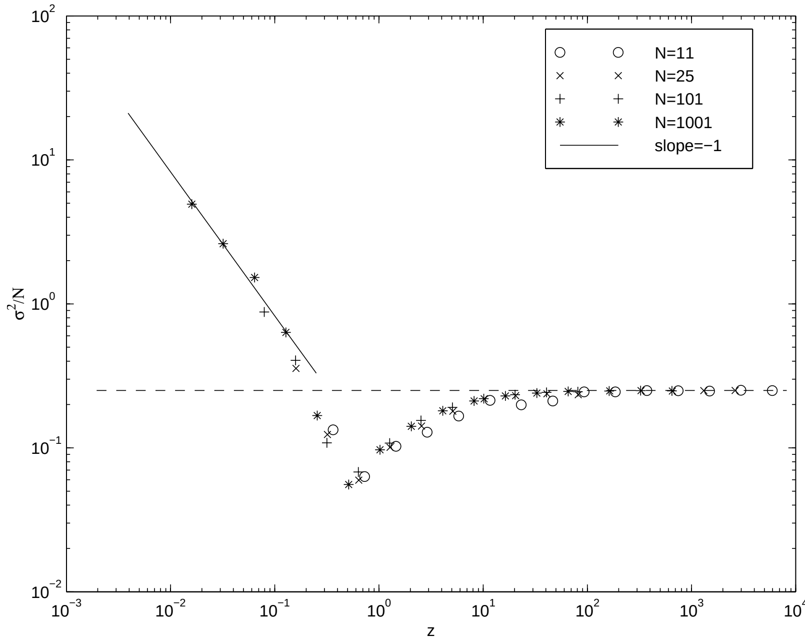

Figure 1: σ^2/N as a function of $z \equiv 2^m/N$.

Each agent has a fixed set of strategies. Each strategy tells its agent which resource to choose, depending on the most recent entries in the history *G*. A strategy of memory *m* is a table of 2^m rows and 2 columns. The left column contains all 2^m combinations of *m* 0's and 1's, and each entry in the right column is a 0 or a 1. To use a strategy of memory *m*, an agent observes which were the minority resources during the last *m* time steps of the game and finds that entry in the left column of the strategy. The corresponding entry in the right column contains that strategy's prediction of which resource (0 or 1) will be the minority during the current time step, and thus its recommendation of the agent's action. Table 1 shows an example of an *m*=3 strategy. To apply[47] this strategy to the example ten-step history outlined earlier, the agent extracts the last three digits of the history ('101'), finds that string in the sixth row of the strategy, and chooses action 1.

At the beginning of the game each agent is randomly assigned s (generally greater than one) of the 2^{2^m} possible strategies of memory *m*, with replacement. Thus the dimension of the strategy space occupied by agents with memory *m* is 2^m. An agent learns a cumulative performance rating for each of its strategies. Following each round of decisions, the agent updates the rating for each of its strategies by comparing that strategy's latest prediction with the current minority group. Then, in choosing its next move, it uses the strategy with the highest performance rating The agents can choose to play different strategies at different moments of the game in response to changes in their environment; that is, in response to new entries in the time series of minority groups as the game proceeds.

Table 1: An m=3 Strategy

m-string	Action
000	0
001	1
010	1
011	0
100	0
101	1
110	0
111	1

The total number of points awarded to the agents reflects the overall productivity of the system, since each point represents a task assigned to a resource that is not overloaded. This productivity varies with the amount or degree of detail of information used to coordinate the resource choices among the agents (reflected in the dimension of the strategy space). An indirect measure of this productivity leads to a universal form of the dependency.

Consider the time series of the number of agents assigned to resource 1. Because the game is symmetric, the mean of this time series will be close to 50% of the agents. The number of points awarded in a given step is bounded by this mean, since only agents on the minority resource are rewarded. If the variance σ^2 of the time series is small, most minorities will be close to half of the agents, and more points will be awarded over time than if σ^2 is large. So this variance (or equivalently, the variance of the time series of the number of points generated in each time step) will be inversely correlated with system productivity.

The number of agents *N* turns out to be an important normalization factor. Figure 1 plots σ^2/N as a function of $z \equiv 2^m/N$ on a log-log scale for various *N* and *m*. Thus scaled, the data fall on a curve that is universal in *N*. The horizontal dashed line reflects the value that σ^2/N would take if the agents assigned themselves randomly and with equal probability at each step. Let m_c be the value of m at which σ^2/N has its minimum. Then, the minimum of this curve is near $2^{m_c}/N \equiv z_C \cong 0.34$, and separates two different phases (Savit, Manuca, and Riolo 1997; Marsili, Challet, and Zecchina 1999)

For $z<z_c$ (reflecting low values of m and thus small strategy spaces), the system is in a phase in which system productivity is poor. In this phase agents exhibit a kind of herding behavior. About half the time a large proportion of the agents move to the same resource. Because there are relatively few strategies available, the choices that the agents have in response to the history string are limited, resulting in a kind of herding phenomenon. Thus on average the agents do worse than they would even by choosing randomly. As *m* increases to the critical point m_c, overall productivity increases because agents have a wider variety of strategies from which they can choose. This part of the curve is not surprising, since one might expect that a larger strategy space (measuring one aspect of increased agent sophistication) ought to lead to improved performance.

We are surprised, though, to find that as *z* increases beyond z_c, productivity falls off

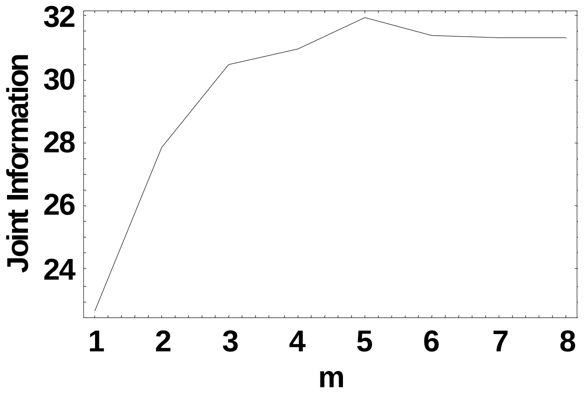

Figure 2: Joint Information in the Minority Game

until it approaches that achieved by agents making random choices. In this regime, the number of different environmental signals (2^m) is large compared with the number of agents, and thus with the number of dissimilar strategies that can be sampled. The time series contains structure that the agents cannot exploit, and their behavior is better described as exploratory. The productivity *decreases* as agent sophistication *increases*. System performance is greatest when the dimension of the strategy space from which the agents draw their strategies is on the order of the number of agents playing the game.

Around z_c the agents achieve a good utilization of resources. By basing their individual decisions on information that they collectively generate, the agents achieve a high level of coordination. This information develops over successive iterations of the system, and it is a form of indirect negotiation among the agents.

In terms of our model of coordination as joint information, the Minority Game exhibits coordination at every finite value of *m*. Figure 2 shows the joint information in 30 replications of the Minority Game with 61 agents at each value of *m* from 1 through 8. The entropy of each agent is computed on the basis of its probability of choosing resource 0 or 1 at each step, while the entropy of the system is computed on the basis of the probability of a specific vector of 61 individual agent choices at a time step. The sum of individual agent entropies is in the range of 30-40, while the system entropy is in the range of 8-11, and the plot shows their difference. For these parameters, the phase transition (yielding maximum system productivity) occurs near $m = 5$. The values in Figure 2 are computed only for integer *m*, and the peak at $m = 5$ reflects the optimal coordination at the transition. It is important to recognize that the *nature* of the coordination among agents differs between the two phases of the system, with respect to issues such as the agents' (internal) choices among their strategies and their (external) choices of resources. Furthermore, Figure 1 measures an estimate of the overall system performance, while Figure 2 measures coordination, and while in this case the two are correlated, in general they need not be.

Extensions

The Minority Game shows that agents can coordinate without negotiating directly with one another, by interacting through a shared environment. One might suspect that this result is an artifact of the extremely simple form of the game. In fact, the main features of the game are robust under a wide range of extensions that have been studied (Challet 2000). This section discusses three such extensions.

Alternative Input Information. The agents use the time series *G* in two different decisions. First, at each time step, each agent updates its estimate of the performance of each of its strategies on the basis of the most recent entry in *G* (the outcome of the previous step). Thus *G* guides it in selecting which strategy to employ. Second, within that strategy, it selects its next move based on the most recent *m* entries in *G*. Several studies show that these two functions can be decoupled. In each case, agents must have access to the most recent outcome so that they can rank their strategies and thus know which strategy to use at each step. However, the string of *m* bits that is used with that strategy to pick a move need not be the global endogenous information *G*. It can be global exogenous information, endogenous information accessible only to a subgroup, or even endogenous information accessible only to a single agent.

Our discussion of coordination mechanisms in Section 2.2 suggested that agents can coordinate their activities on the basis of an exogenous environmental variable, one whose assignments over time are independent of their actions. One extension of the Minority Game (Cavagna 2000; Savit 2000) explores this approach. Agents use the most recent *m* entries in a random IID sequence to select the next action. The random sequence, by definition, contains no information about the state of the resources being allocated. However, it is common knowledge to all the agents, and so provides a synchronizing signal.

In another experiment (Paczuski, Bassler, and Corral 2000), agents rank their strategies based on the payoff they receive, but select actions based only on the choices of a subgroup of the other agents. This extension is important because it shows that the minority game dynamics are robust when one moves from decisions based on global information (in the basic game) to those made using local information. The agents now do not know which resource was actually in the minority at any moment, and they sample the decisions of only a local neighborhood of other agents. The global state of the system influences the agents' decisions only in determining their payoff, but this level of global feedback is present in any situated resource allocation system.

Private endogenous information can also generate coordination (de Cara, Pla, and Guinea 2000). In this experiment, each agent maintains a personal history of the resource that it chose at each time step, and uses the last *m* entries in this list to select actions from the top-ranked

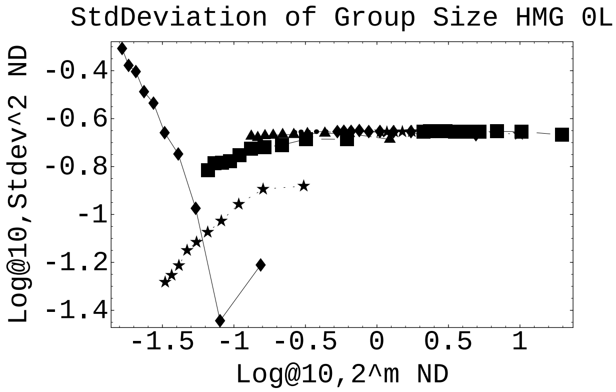

Figure 3: MG Normalization Applied to 3-Supplier Game

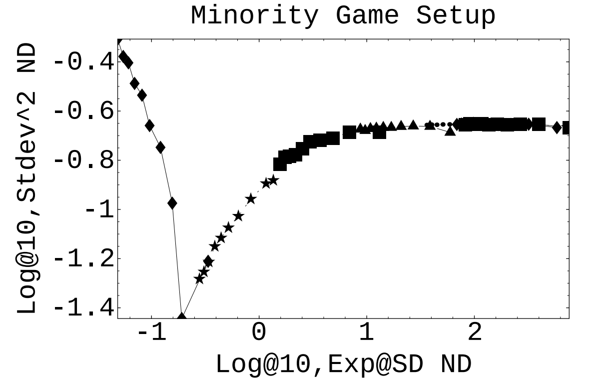

Figure 4: Entropy-Based Normalization of 3-Supplier Game

strategy. As before, strategies are ranked based on actual outcomes from the environment.

In all three cases (and the original game as well), as the agents reward their strategies, they are learning an individual response to a particular m-bit pattern that is maximally distinct from the responses of the other agents. The fact that the bit pattern is independent of the domain's dynamics does not reduce its usefulness as the trigger for the system's behavior. The information transfer among agents happens through the knowledge of the minority resource after each round of the game. Since the minority resource is selected by the aggregate choices of the agents, its identity provides a leakage of information from one agent to another, sufficient to coordinate their behavior.

More than Two Suppliers. Most realistic resource allocation problems involve more than two resources. We have studied the dynamics of systems with three and four suppliers as well.

Figure 3 shows the results for three suppliers, scaled using the normalization factors applied in Figure 1. The various lines visible in the plot represent different values of m. The plot does show the same general structure as Figure 1 (performance worse than random at the left, asymptotic approach to random performance at the right, and better-than-random performance in between), but the data no longer fall on a curve that is universal in m. One might expect that the problem is due to the base 2 used in the factor $2^m/N$, since we have now moved from two to three suppliers, but a normalization based on $3^m/N$ fares no better.

An alternative normalization of the abscissa does restore the universal curve. For a given m, agents make their decisions based on strings of the history of length m. Count all distinct strings of length m in the history, and let p_i be the probability that the ith string appears. The (Shannon) input entropy (memory entropy) is then $S_{in} = - \sum p_i \log(p_i)$. Intuitively, S_{in} measures the range of uncertainty in the environment in which the agents act, or alternatively, the number of different signals to which the agents must coordinate. Figure 4 shows that normalizing the abscissa by e^S/N does (largely) restore the smooth curve. This normalization works for the two-supplier case as well. The original $2^m/N$ normalization for that case works because, to a first approximation, e^S/N is a fit to $2^m/N$.

Our theme is that endogenous environmental variables, such as the history G of outcomes, can effectively convey information among agents and thus enable them to coordinate their behavior. This refinement in the normalization reinforces this theme. The Shannon entropy is the basic element in the quantification of information flow, and its emergence in a universalizing normalization strongly suggests that the effect of G on the behavior of an individual agent should be understood in those terms.

Variable Payoffs and Partial Satisfaction. In each cycle of the standard minority game, each agent on the minority resource gains one point, while each agent on the overpopulated resource gets no points. Both of these conditions can be relaxed. Even the minority resource may become less effective as its population increases, leading to models with variable payoffs. In many resource allocation problems, an overloaded resource is not completely shut down, but can satisfy some of the agents that choose it, the partial satisfaction scenario.

In variable payoff games (Li, VanDeemen, and Savit 2000), the amount received by each agent on the minority resource is not constant, but depends on the population of the resource. We have explored two models for this variability. Let n be the population of the minority group, and let $r=n/N$. Then, we consider payoff functions of the form $A(r) \sim r^{-\alpha}$, and $A(r) \sim e^{-\gamma r}$, where $A(r)$ is the payoff to each member of a minority group with population $n = rN$. We have also explored payoff functions that depend on the difference in population between the majority and the minority group.

To model partial satisfaction, in addition to giving a point to each agent on the minority resource, we also give an award to a randomly selected subset of the agents on the overloaded resource(s). The size of the subset is equal to the capacity of the resource.

We have experimented with two different values for the amount of the reward. In one case, we give each agent in the rewarded subset a point, just as though that agent had selected a minority resource. In the other, we give each agent in the rewarded subset a fraction of a point, equal to the ratio between the resource's capacity and its population. We have also explored the effect of using fractional awards to rank strategies.

In all these cases, the basic dynamics of the game are unchanged. Performance is suboptimal when m is small, approaches the random payoff as m grows large, and is better-than-average in the intermediate region.

Summary of Extensions. The lesson we draw from the various extensions to the Minority Game that we and others have explored is that indirect negotiation can enable agents to coordinate their behavior, even when they do not negotiate directly with one another in the conventional sense. The basic game and its extensions have several common features, and these features bear comparison with conventional negotiation.

- The process is iterative. Agents cannot coordinate using endogenous environmental variables if they are playing a one-shot game. They must probe the environment with initial (possibly unproductive) actions in order to observe its behavior and adjust their actions accordingly. These initial actions are like proposals in conventional negotiation, and the environment's responses like counterproposals. Both direct and indirect negotiation are, in general, iterative activities.
- Various versions of the game may differ on the time series that agents use to select an action from a strategy, but in every case they use knowledge of the actual outcome of each round to rank their strategies for selection in the next round. That outcome is a parade example of an endogenous environmental variable, depending on the actions of the agents. Thus an agent that accesses it is receiving information about the actions of its peers. As in conventional negotiation, coordination depends on the exchange of information among the participating agents.
- Coordination (as measured by joint information) is ubiquitous, but its usefulness depends on agents' having the right amount of information, expressed in the length m of the substrings used to select actions from strategies. Too little information yields counterproductive herding behavior, and too much overloads the agents (cf. (Takashina and Watanabe 1996)). Both dynamics are credible in conventional negotiation as well. In most versions of the game, these substrings are drawn from the endogenous system-level history, fitting our interpretation of this history as the analog to the information flow among agents in a conventional negotiation protocol. However, the emergence of the same pattern when driven by other time series (such as exogenous environmental variables, or even private time series) strengthens the point of view that the information flow to the agents is a controlling factor in negotiation.

In sum, the persistence of the emergence of coordination under a wide variety of extensions supports our sufficiency claim. Information flow through a shared environment is strong enough to yield coordination among agents even in the absence of conventional negotiation, in appropriately designed systems. This conclusion is strengthened by early results from an experiment currently underway that measures the dynamics of humans choosing between two groups on the basis of history with the objective of selecting the minority group. Unlike our simple model, they are not constrained to a single choice of m or even to look-up table strategies, and they are free to change their decision rule whenever they choose. In spite of these variations, and in the absence of any direct messages among the players, the preliminary results clearly show the emergence of cooperation (Savit 2001).

Phase Transition in N vs C

Our necessity claim is that conventional negotiation is not immune to information flowing through the environment. As we found in our contract net application, the information exchanged indirectly between agents through the environment may impact the behavior of systems that do not rely on these mechanisms as their main means of coordination.

Our experiments with the Minority Game have shown an effect that we expect will fall in this category. The standard Minority Game constrains the total capacity C of the suppliers (the sum of their individual capacities) $C = N - 1$ and explores the effect of varying m. In more general resource allocation problems, demand and capacity may vary more widely with relation to one another. Thus we have explored configurations that depart from this constraint. The example discussed in this section explores a system with two resources with total capacity 24, over the range $N \in [15,50]$ and $m \in [1,8]$. When $N = 25$, this configuration corresponds to the Minority Game.

Figure 5 shows the mean award rate (the number of agents receiving a point in each turn) over the space $N \times m$. For $N < 25$, the award rate approaches 1, indicating that the agents are able to distribute themselves evenly over the available resources. This result is in itself non-trivial, and indicates that the strategy mechanism is in fact capable of leveling load across resources when the system is operating

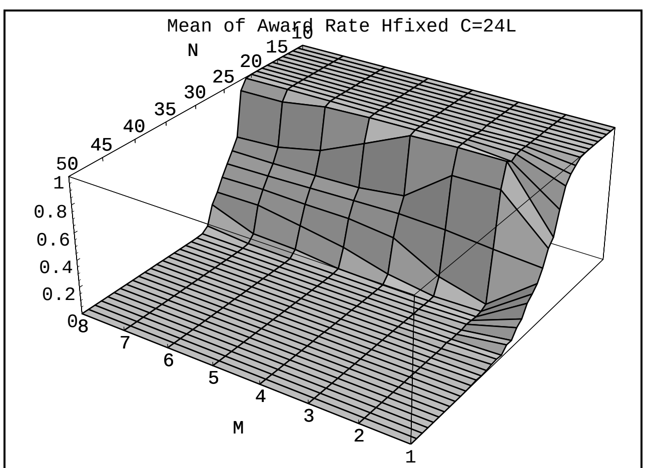

Figure 5: Mean Award Rate as Function of Load

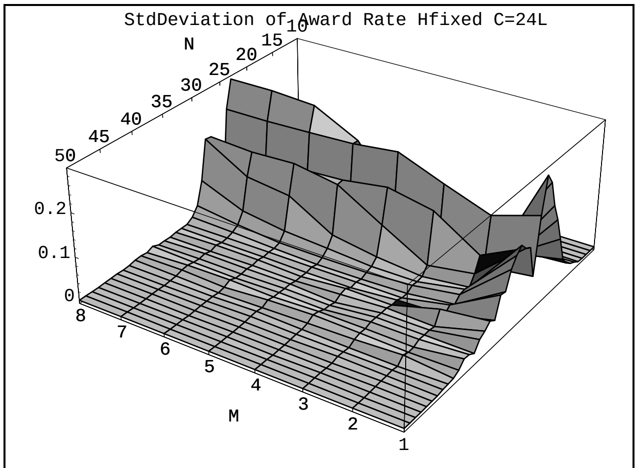

Figure 6: Standard Deviation in Award Rate

under capacity. As the load increases and *N* grows greater than the total system capacity, the award rate falls to zero. Around *N* = *C*, the award rate is about 50%.

Figure 6 shows the standard deviation of the award rate over this same space. It peaks around *N* = 25, the configuration of the standard Minority Game. This plot shows that when the system is far from capacity in either direction, its behavior will be relatively stable and predictable. When it approaches the point where capacity and demand are closely balanced, system performance becomes more complex.

It is instructive to compare Figure 5 and Figure 6 with the lower and upper regions, respectively, of Figure 7 (after (Mitchell, Selman, and Levesque 1992)). This plot represents a phase transition in constraint satisfaction problems. For a given number of variables *N* and number of clauses *L*, an instance of random 3-SAT is produced by randomly generating *L* clauses of length 3. Each clause is produced by randomly choosing a set of 3 variables from the set of *N* available, and negating each with probability 0.5.

Two metrics in this system are of interest: the number of calls to the atomic constraint resolution procedure needed to determine whether a given problem instance is or is not satisfiable (reflecting the computational complexity of the given problem instance), and the probability that such an instance is indeed satisfiable (estimated as the fraction of a population of randomly generated instances that are found to be satisfiable). Figure 7 plots these two metrics as a function of L/N.

The lower plot shows that as the number of clauses increases for given *N*, the probability that the problem is satisfiable drops. This behavior is expected: as additional clauses are added, the likelihood increases that the problem will be overconstrained.

The upper plot shows that the computational effort needed to determine whether an instance is or is not satisfiable (reported as the median of 500 trials) is low for instances with either very few or very many clauses, and peaks around *L*/*N* = 4.3.

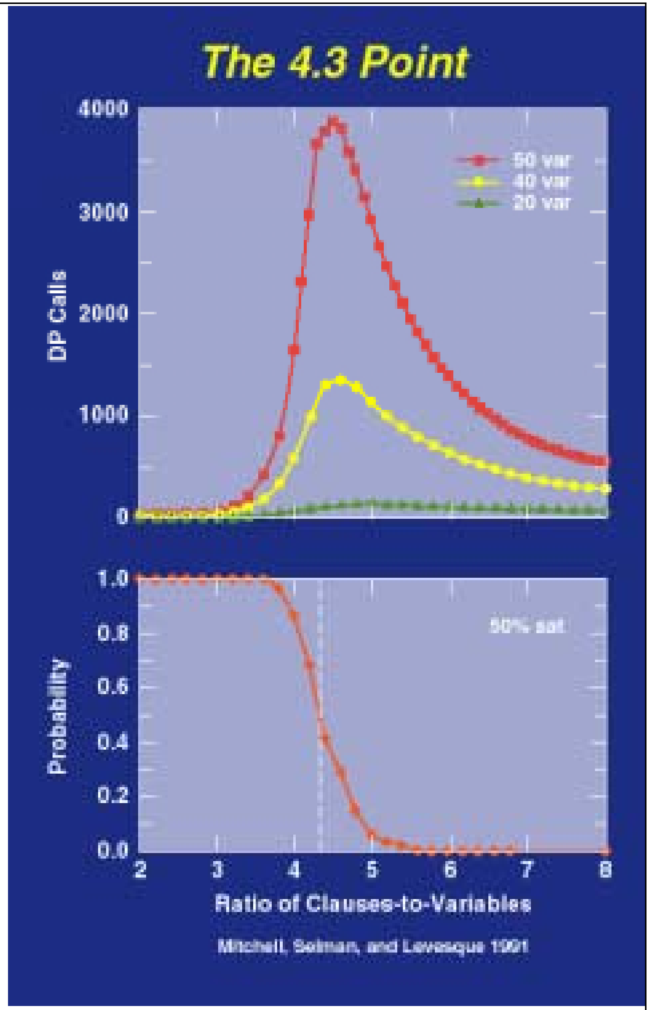

Figure 7: Phase Transition in 3-SAT

The computational effort peaks just at the point where the probability of satisfiability is 50%. If almost all instances are either satisfiable or unsatisfiable, it doesn't take long to find either a solution or an irreconcilable pair of clauses. However, in the intermediate region, a much larger proportion of the domain must be examined.

The similarity between the two systems is important. Both cases distinguish a region in which solutions are abundant and easy from a region in which they are rare. In both cases, the transition between these two regions is marked by a peak in an undesirable system measure (variability in award rate in the Minority Game; calls to the solver in 3-SAT). The similarity suggests that this signature is not an artifact of the indirect negotiation used in the Minority Game, but reflects a general property of any system that is close to its capacity. In particular, we expect that whatever negotiation mechanism is used to address a resource allocation problem, its behavior will degrade in some observable way in the region where load is about equal to capacity. The way in which this degradation is manifested may depend on the mechanisms being used. In some systems, it may take the form of high variability in the results achieved. Other systems may achieve low variability, but at the expense of more protracted negotiations. The point is, a closely constrained environment has intrinsic dynamics, and the flow of information between the environment and the agents that interact with it will impose its dynamics on those agents, whatever the negotiation mechanisms being used.

Summary

Many negotiating systems manipulate a shared environment, such as a set of shared resources. In such a setting, information flows among the negotiating agents not only through the explicit messages of their protocols, but also through the changes that they both make and sense in the environment. Our experiments with a simple abstract model of resource allocation teach two important lessons about this information flow.

1. It can be used as a form of "indirect negotiation" to coordinate the actions of agents even in the absence of more traditional direct negotiation.
2. Because information flows between agents and the environment, the behavior of the agents may reflect the intrinsic dynamics of the environment, independent of the explicit coordination mechanisms with which the designer has endowed the agents.

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