Practically Coordinating

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Abstract

To coordinate, intelligent agents might need to know something about themselves, about each other, about how others view themselves and others, and how others think others view themselves and others, and so on. Taken to an extreme, the amount of knowledge an agent might possess to coordinate its interactions with others might outstrip the agent's limited reasoning capacity (its available time, memory, etc.). Much of the work in studying and building multiagent systems has thus been devoted to developing practical techniques for achieving coordination, typically by limiting the knowledge available to or necessary for agents. This article categorizes techniques for keeping agents suitably ignorant so that they can practically coordinate, and gives a selective survey of examples of these techniques for illustration. *

Introduction

It has been said that ignorance is bliss. Certainly, people who know much (or think they know much) are sometimes subject to cockiness, confusion, paralysis, resignation, or other unpleasant states. Artificial agents can also suffer from knowing too much, and so it behooves us, as agent designers, to make sure that our agents are not overwhelmed with too much knowledge. The trick (or, ultimately, the engineering skill) is to design agents that have enough knowledge to act well in their environments, and no more knowledge than that, lest the knowledge over and above what is sufficient degrade the quality or timeliness of the actions.

The purpose of this article is to look more deeply at strategies for designing agents, and the strategies' methods of acquiring and using knowledge about agents, that make it practical for an agent to coordinate its actions with others. Before we begin, however, let me first be a little clearer about what I mean by the terms "agent" and "coordinate." In keeping with much of the current usage of the term, I will consider an agent to be an entity that is capable of acting in its environment to satisfy its desires. Thus, an agent is an entity to which it is convenient to ascribe characteristics such as: choices (capabilities for action); awareness (beliefs about the world); and preferences (over states of the world, often coming about as outcomes of its (and others') actions). In general, the set of actions available to an agent, and the set of possible worlds, could be infinitely large. To keep matters simpler, however, I will discretize them. We can capture these three characteristics in a variety of notations. For illustration purposes, let me here just represent them in terms of a payoff matrix, such as in Figure 1. Here, agent P can take actions A or B, has beliefs about whether the world is in state of affairs (SOA) 1 or 2, and prefers to take actions that lead to higher payoffs (the numbers inside the matrix). For example, P's actions might be to choose one of two doors, behind one of which is a lovely bouquet of flowers , the sight of which P values at 2 (Figure 1). If P guesses the wrong door, he does not get the reward of seeing the flowers, although he is still just as able to enjoy their aroma, so he breaks even (a reward of 0).

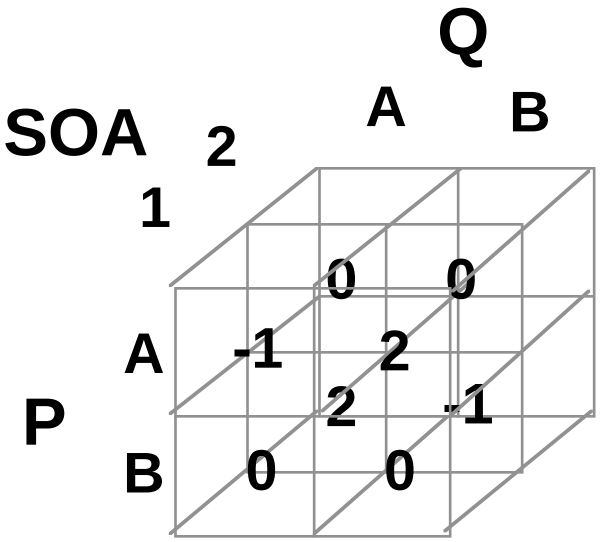
$$\begin{array}{cc|c|c} & & \multicolumn{2}{c}{\text{SOA}} \\ & & 1 & 2 \\ \hline \text{P} & \text{A} & 2 & 0 \\ \hline & \text{B} & 0 & 2 \\ \hline \end{array}$$

Agent P has a choice between doing A or B. The reward it receives is dependent on the state of affairs (SOA).

Figure 1: A Simple Decision Situation

When the outcomes of its choices can depend on the choices that other agents have made, are making, or will make, then an agent should consider the actions of those other agents when making its own choice. I will refer to this—the taking into account the choices of others when deciding what to do—as an agent *coordinating* with those others. "Coordination" is an overloaded term, possibly meaning either the process or the result of coordinating. I will use the former sense of the word. This has several advantages. For one thing, it removes value judgments that

* This work was supported, in part, by the National Science Foundation under PYI award IRI-9158473, by the NSF/DARPA/NASA Digital Library Initiative CERA IRI-9411287, by DARPA under contract DAAE-07-92-C-R012, and by a contract with Orincon Corp.



The payoff to P depends on its choice, the choice of Q, and the state of affairs (SOA). To decide on its choice, it should use whatever it knows to anticipate the choice of Q, and thus coordinate with that choice.

Figure 2: Coordination Problem

go along with evaluating whether a result is "coordinated." When such evaluations are needed to convey a sense of agents working to their mutual benefit, for example, I prefer a term like "cooperative" rather than "coordinated." By considering coordination as the process by which an agent takes into account the possible actions of others (uses those actions as "coordinates" to index into an outcome), we can determine whether an agent has coordinated without looking at other agents. Since coordination does not imply any mutuality, cooperative or competitive, it need not even be symmetric!

Returning to our simple example, what if P shared its world with Q? Now, it turns out that if P and Q choose the same door, the object (if any) behind the door is removed. Thus, if they both choose the door with the flowers, the flowers are removed and P is actually worse off (reward of -1), now being unable even to smell the flowers any longer. If Q opens the door with the flowers, then P's view is obstructed so P is no better nor worse off. From the perspective of P, therefore, it might do better to consider Q's likely choice when making its own decision, as shown in Figure 2, because P can benefit only when it chooses a different action than Q!

To make its decision, P needs to determine whether the state of affairs is 1 or 2, and whether Q is likely to do A or B, and then P should act accordingly. The degree of detail with which P should model Q would thus depend on how much P needs to know about Q to make an adequate prediction about Q's choice. Perhaps it is enough for P to have a probability associated with Q doing each of its actions. If Q were a degenerate agent, such as an agent that simply flips a coin to choose an action, then this might suffice. If Q's actions, however, are more dependent on the situation, then perhaps P needs probabilities for Q's actions conditioned on the state of affairs. For example, perhaps the aroma of flowers wafting from one of the rooms is quite discernible to P, and P has some statistics of how often Q takes action A versus B when P has sensed the aroma from that room before.

Of course, rather than relying on past statistics, P could use what it knows about Q's preferences. For example, if P thinks that Q likes flowers too (that is, P thinks that Q's preferences are just like P's in Figure 1), then P might conclude that Q will choose door A in SOA 1, and B in SOA2. P can use this to coordinate its decision with that of Q. It is also possible that P and Q might have different beliefs about the state of affairs (perhaps P thinks Q has a cold and cannot smell very well), and so to predict Q's likely action, P really should attempt to infer Q's probability distribution over the states of affairs.

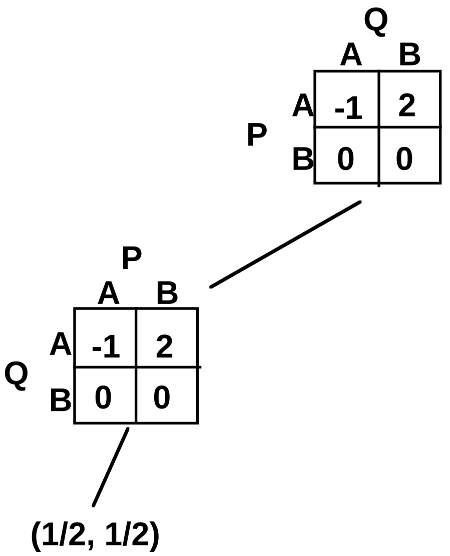
P could even believe that Q will consider P when making its own decision. Thus, P will need to model what it thinks Q's model of P is. To decide what to do, therefore, P will need to determine what it thinks Q will do, which in turn requires that P determines what it thinks Q will think that P will do, which in turn could require that P determines what it thinks Q thinks that P will think that Q will do, and so on. In principle, such nested models that agents have of each other could continue indefinitely.

Recursive Modeling Method

What should an agent do in such circumstances? Well, one answer is that it should use everything that it knows to make a good decision. Using all of its knowledge means being able to represent the knowledge and to process it. For example, let us say that P clearly smells the flowers behind the door that would be opened with action A, so the decision it faces can be reduced to the matrix at the top of Figure 3. P is also certain that Q can smell the flowers and that Q values outcomes as does P, so P model's Q's decision situation at the second level of Figure 3. But P also believes that Q thinks P cannot smell the flowers (P only recently got over a cold, so does not expect Q to know this, for example), so P thinks Q will think P's choice will amount to randomly picking an action, represented at the bottom level of Figure 3 as (probability of choosing A, probability of choosing B).

A dynamic programming strategy, as used in RMM, the Recursive Modeling Method (Gmytrasiewicz and Durfee, 1995), can solve this decision problem by propagating from the leaves upward. P will believe that Q will take action A (since with P acting randomly Q will expect an average payoff of 1/2 for action A and 0 for action B), and so P would maximize its expected payoff by taking action B (with payoff 0, compared to expected payoff of -1 for action A).

Somehow, this outcome seems unsatisfactory. After all, P seemingly knows more about Q, and yet Q is likely to get the higher payoff. It is to Q's advantage that it is seen as



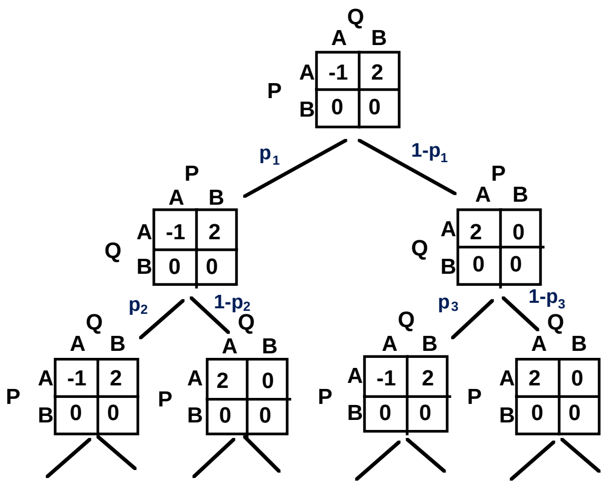
P models its decision situation (at the top), the situation it believes that Q is facing (in the middle), and the knowledge that it thinks that Q has of P (at the bottom). This last knowledge indicates that P thinks that Q thinks that P is equally likely to do A or B.

Figure 3: An Example RMM Hierarchy

ignorant by P![1] If P were to ignore its beliefs in Q's ignorance, then it might be more inclined to take action A, but of course if P's model is accurate, any increased probability in its taking action A only decreases P's expected payoff. It also drags Q's payoff down with it, but we assume that P would not care about this. (If misery loves company, then P might behave this way, but this implies that there is more to P's perceived payoffs that should be represented in its matrix.)

P might be able to improve its position if it were to (justifiably) change its knowledge state. For example, it might tell Q that it is now able to smell the flowers, which means that its model of Q's model of P should change. Now P's model of Q's model of P might include P's payoff matrix, which in turn means that P would have a model of Q's model of P's model of Q (at least) to predict how Q will think P will react to what it thinks Q will do! Obviously, the deeper P's knowledge about Q's knowledge about P's knowledge about .... the more extensive the representation and computation.

And the size of the nested models might not only be due to depth of knowledge but also breadth of possibilities. For example, what if some agents in the world were allergic to flowers? For such agents, the best outcome is if both agents choose the door with the flowers, so that the flowers are removed from the vicinity! Perhaps P is uncertain about whether Q is allergic or not, and about whether Q will think that P is allergic or not, and perhaps P even has beliefs deeper than that, yielding a representation such as the one in Figure 4.



In making its decision (top), P considers it possible that Q could see the situation in either of 2 ways (second level), and that for each of these Q will believe P could see the situation in either of 2 ways (third level), and so on.

Figure 4: A Branchy Nested Model

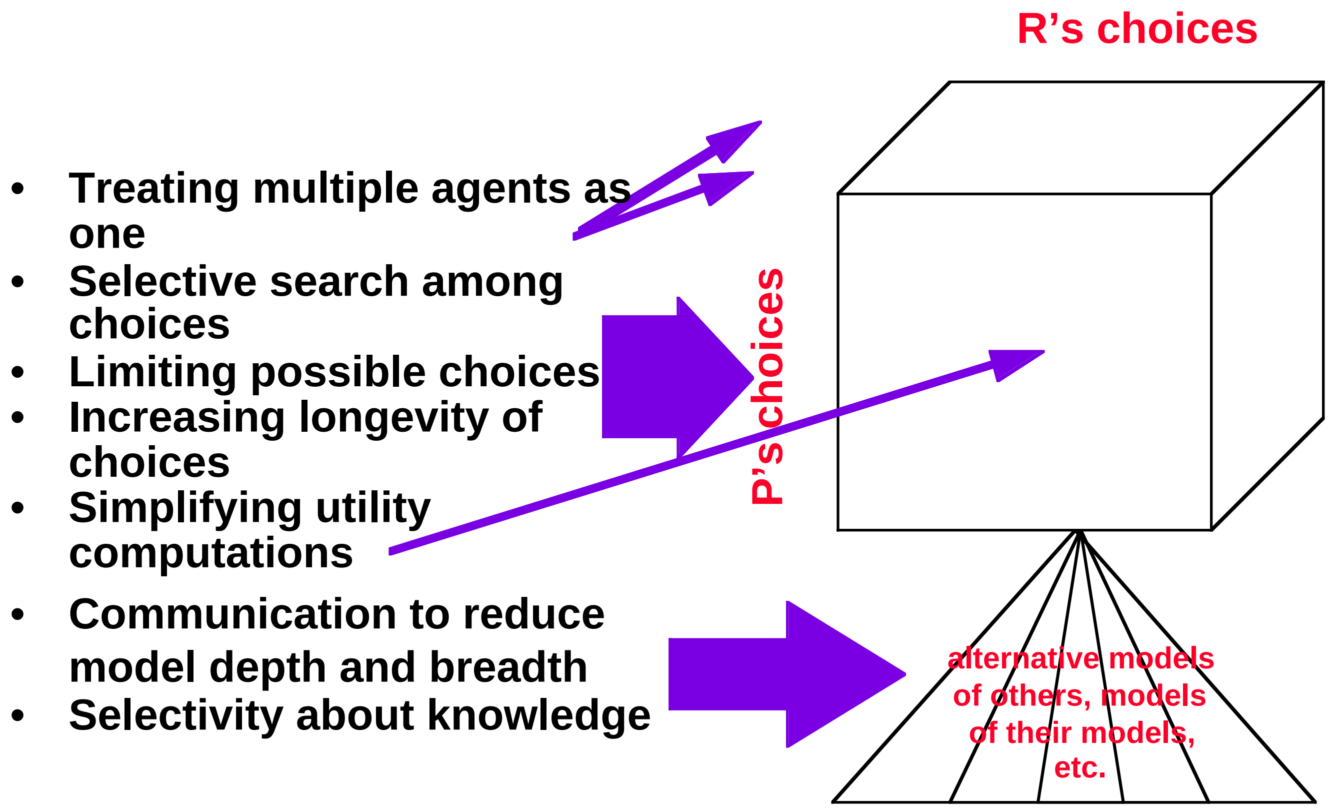
The uncertainty P has (or thinks Q has, or thinks Q thinks P has...) is represented in the branches. P believes that Q is not allergic to flowers with probability p_1. P believes that, if Q is not allergic, then Q will believe P is not allergic with probability p_2, but if Q is allergic, then it will believe P is not allergic with the possibly different probability p_3. And so on. In general, the branching factor can be much larger than 2. Moreover, the contents of the payoff matrices and the values of the probabilities can vary in principle, limited only by the knowledge available to an agent (since the hierarchy summarizes an agent's coordination knowledge). While in theory using all of the knowledge it has or might get will always lead to better (or at least no worse) decisions for an agent,[2] the costs of acquiring and using the knowledge must be considered to make the approach practical.

Keeping Coordination Practical

Using RMM as an example, consider the amount of reasoning that an agent might have to do. To consider each of the combinations of choices that the agents have, an agent needs to identify the choices (actions, plans) for each

[1] This is not unlike how seemingly oblivious drivers are given the right of way on the highway by more aware and defensive drivers.

[2] Recall, though, that while knowing more is better, it is not necessarily better to be known as knowing more. That is, it might be advantageous to be seen by others as being ignorant. There can be power in using knowledge that others do not know that you have! It is unlikely that the reverse (of not using knowledge that others know you have) will be a good idea.



- Treating multiple agents as one
- Selective search among choices
- Limiting possible choices
- Increasing longevity of choices
- Simplifying utility computations
- Communication to reduce model depth and breadth
- Selectivity about knowledge

The outcome of P's actions depend on the actions of the other agents (Q and R in this figure, but in general this is n-dimensional). Anticipating their actions can require nested models of how they see the situation, how they think others see the situation, how they think others think that others see the situation, and so on. Making this tractable means limiting the number of nested models to reason over and decreasing the number of action combinations that P must consider.

Figure 5: Strategies for Making Coordination Practical

of the agents, and the outcomes (utilities) of each combination of choices for each of the possible environments. If we assume each of the *n* agents has *c* choices, then there are *cn* choices to identify for an environment. Since each choice can correspond to a planned course of action on the part of an agent, that means there are *cn* plans to formulate. And for each of the c^n combinations of plans, the outcome(s) of executing the plan combination must be predicted and assigned values (utilities). The above calculations only correspond to one view of the interaction by an agent. Given nested views of how an agent thinks that others think ... that others think about the interaction, there could be b^l such models to construct, where *b* is the branching factor caused by uncertainty (such as about allergies in the running example) and *l* is the depth of the nesting of models available to the agent.

As an agent knows more, therefore, it must in general do exponentially more computation. Since all practical agents have limits to the resources they can apply to make coordination decisions, it is in an agent’s (and an agent designer’s) best interests to maintain as much ignorance about the world and the agents that populate it as it can, while knowing enough to coordinate acceptably well with others. If we consider all the possible knowledge, as outlined within the RMM framework, there are numerous places where we could hope to trim down the knowledge being used (Figure 5). We can be selective about the nested knowledge we use, or even obviate its use by exploiting communication (bottom of the figure) We can simplify the utility calculations, trim down the number of options evaluated for each agent, or decrease the frequency of coordination decision making by coordinating over longer-lived choices (middle of figure). We can even reduce the dimensionality of an interaction by ignoring agents or viewing groups of agents as individuals (top of figure). In short, by considering places where an agent can simplify its coordination task by being selectively ignorant, we can make coordination practical. In the remainder of this article, I examine these strategies for practical coordination in more detail, considering examples of such methods. To provide a framework for the discussion, I will be working from the bottom of Figure 5 upward.

Limited Use of Nested Models

One method of keeping the computation in check is to prune away portions of the nested models, a technique familiar in minimax algorithms for game-playing programs. Pruning nested knowledge is somewhat different from game-playing reasoning, however, because unlike the latter which hypothesizes sequential possible physical game states, the nested knowledge captures what amounts to simultaneous perspectives on the parts of the agents. Thus, in game-playing, undesirable states can be pruned because rational agents will not act to get into those states. With nested models, however, the models exist regardless of their desirability; ignoring an unpleasant fact will not make it go away. For example, in the case where P believes Q does not know that P can smell the flowers, P might choose to ignore what it knows about Q, treating Q as equally likely to take either action (which is a natural way of terminating the recursive nesting when an agent is seen to have no information at a deeper level). If this were true, then P would take action A with an expected payoff of 1/2. But, in reality, action A will give P a payoff of -1, and P knew this but chose to ignore it.

The strategy, therefore, is to prune away possible nested knowledge that is not expected to change the strategy choice of the agent doing the reasoning (Russell & Wefald, 1991), rather than pruning undesirable states *per se*. For example, in Figure 4 at the second level right-hand side, Q, if allergic, has a weakly dominating strategy of taking action A (the only way it would ever do B is if it were convinced that A was going to do B, and even then Q would be indifferent between A and B). Thus, P might choose to not search down deeper in that branch, since it is unlikely that anything it discovers down there will change what it will expect "allergic-Q" to do. Our preliminary results employing such a strategy indicate that this approach holds promise, even for simple application domains. Vidal & Durfee (1995; 1996) show this in a simple pursuit task, where four "predator" agents placed in a grid world must surround a "prey." Given an uneven distribution of predators, they have to decide which will block the prey from which direction. An individual predator will thus seek to occupy the closest unoccupied side, but to decide which sides are likely candidates it needs to determine the sides that other predators are likely to occupy. But since this in turn depends on what sides they think others will occupy, and so on, the nesting can be fairly complicated. By using heuristic estimates (based on previous experience) about the impact of expanding different parts of the nested models, the agents in this problem domain can achieve a high level of cooperative behavior using only a judiciously-chosen subset of the nested models.

Using Regularities in Nested Models

Another way of simplifying the nested model computations is to take advantage of patterns in the nested structure to avoid rederiving the same information in different places. Figure 4 illustrates how regularities in knowledge can lead to patterns of similar models. Of course, if the knowledge is finite, then eventually some patterns must be broken. But a powerful simplifying assumption can be to purposely project the models beyond finitely available knowledge to infinite levels.[1] When this is done, fixpoint solutions can be discovered using often much simpler computational means. This has been a standard approach in game theory, for example, in identifying equilibrium solutions. Using the simple view of Figure 3 as an example, P might simplify its model by assuming that it and Q model each other identically, and that this is common knowledge (that is, that P knows that Q knows that P knows that Q knows that ... P and Q model each other identically, where the ... can go on infinitely deeply). Then, in the world where P smells and wants to see the flowers, it models Q as doing the same, and models Q as thinking P will do the same, and so on. The symmetric nature of this situation leads to P believing that it and Q will come up with identical strategies. In this case, for example, P might conclude that it and Q will have mixed strategies of taking action A with probability 1/3 and B with probability 2/3, yielding an expected payoff to each of 1/3.

Exploiting Observations

So far, we have considered how an agent, with its particular nested models about the coordination situation, can make its coordination reasoning more practical by transforming its nested knowledge into an approximate form that might require less reasoning effort. An extremely common means for transforming knowledge states, however, is to change the knowledge that agents have through observation.

Observations, for example, can be used for plan recognition. Based on the evidence provided by observations of another agent's actions, an agent can hypothesize the likely larger plans of which those actions are part (e.g., (Huber & Durfee, 1995; 1996)). With such hypotheses, the agent can then anticipate the future actions of the other agent, as being those that continue the inferred plans. When actions and plans are sufficiently unambiguous, this can obviate the need for nested models.

Observations also provide evidence to learning mechanisms so that agents can learn what actions others are prone to take in various situations. The literature on this subject is growing rapidly (e.g., (Weiss & Sen, 1996)). A fundamental challenge in this field is correlated with the notion of nested models: namely, while one agent is learning about others, they in turn are learning about it. This means that what an agent is learning is a moving target, since every time it learns something that changes how it responds to some situation(s), its new responses can in turn lead others to respond differently to the situation(s). This in turn could lead to the agent learning to respond yet differently, and so on.

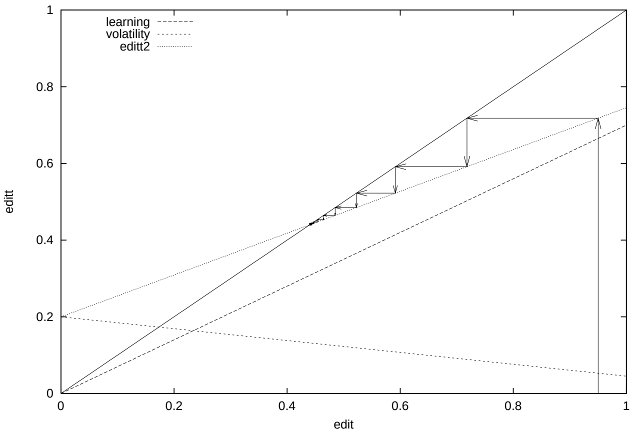
[1] Of course, if the agents truly do have infinitely deep knowledge, then this is not a simplifying assumption but rather a model of their true knowledge state. We address shortly the question of how such a knowledge state might come about.

It is conceivable that, in such circumstances, the learning never ends. In our running example, for instance, if P (who likes flowers) is paired up with a Q who is allergic in this game repeatedly, we can intuitively picture Q seeking to match P's choice (to eliminate the flowers from the world) while P seeks to make a different choice than Q. They could chase each other around the four combinations of actions *ad infinitum*, as first one changes, then the other does.

In general, a system reaches an equilibrium where the improvements it continues to make through learning are offset by the degradation to what it has already learned due to the volatility in what other agents are doing due to their learning. This notion is illustrated in **Error! Reference source not found.** which plots the error rate of an agent at time *t+1* given its error rate at time *t*, based on the combined learning capability (which tends to decrease error) and volatility (which tends to increase error). By characterizing learning capability and volatility (based on how coupled agents' actions are) for particular problems, we can build expectations of how practical it will be to use learning for coordination, as well as whether the system as a whole can ever learn to eliminate all errors (Vidal & Durfee, 1998).

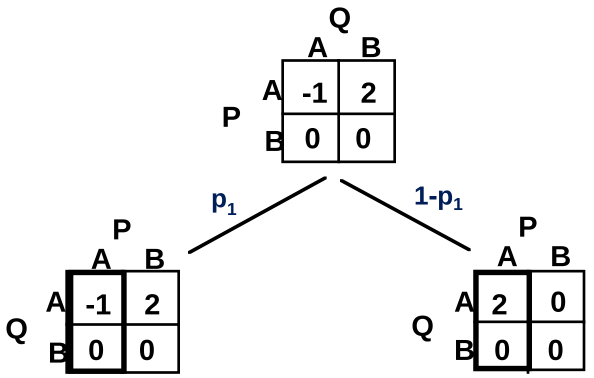
Using Communication

Communication is commonly used to obviate the need for nested models. For example, one approach has been for agents to explicitly tell each other about their intended actions (or at least about constraints on what those actions might be). Such an approach has formed the backbone of work in multiagent planning, for example, where agents separately form their own plans, and then communicate to identify possible conflicts or cooperative opportunities (Corkill, 1979; Georgeff, 1983; Durfee, 1988; Ephrati & Rosenschein, 1994).



The error rate at time t+1 based on the error rate at time t and the sum of the learning and volatility curves. The initially high error rate decreases, but cannot fall below .44 because further learning by this agent is offset by the fact that learning by other agents renders obsolete some things that were previously learned.

Figure 6: Error Progression.



When P tells Q that it will do action A, P can now truncate its model, since it need not reason about what Q will think P will do.

Figure 7: Truncated Hierarchy from Communication

The benefits of such communication are clear when captured in a nested model framework like RMM. By revealing information about itself, an agent simplifies its models of others, either by reducing uncertainty about the world (and hence reducing the branching factor) or uncertainty about what others will be doing (hence reducing the requisite modeling depth). For example, if P considers telling Q “I will do A,” then P would model the resultant mental situation as being truncated, since it knows exactly that Q will consequently expect P to pursue A (assuming that the message is certain to be delivered and believed (Gmytrasiewicz & Durfee, 1993)).

Looking at the resultant model (Figure 7), P can decide that its expected payoff in the knowledge state after sending the message is dependent on p_1. Specifically, it is $(3p_1\text{-}1)$. Clearly, being the first to commit to doing A is a good idea if Q is unlikely to be allergic, and a bad idea if Q is allergic. With probabilities in between, the question of whether the message is good for P depends on what P’s expected payoff was before sending it, and what it is afterward. P should send messages that cause the largest positive gains in its expected utility (Gmytrasiewicz *et al*, 1991).

Obviously, it might not be possible (or considered “fair”) for P simply to claim action A by being first. Nonetheless, communication can still benefit the agents if they have correlated preferences. That is, even with some randomization thrown in about who gets first choice, they can still avoid mutually poor outcomes (such as both choosing A, if neither is allergic). They could, for example, agree to abide by the flip of a fair coin, such that each now has an expected utility of 1, which is better than 1/3 which is what they would expect to get without communication.[1] And the case is even more obvious when both agents are allergic, where they both want to take the same action and get the same payoff! When possible, therefore, communication is often a very practical and effective tool for the agent coordination process!

Epistemic States for Well-Defined Coordination

In the previous section, we saw how a communicative act could be in the self-interest of an individual. Often, however, designers of multiagent systems also want to be able to claim particular properties for the collective decisions of the agents, such as stability, efficiency, and fairness (Durfee & Rosenschein, 1994). Thus, communication might be expected to change the agents' states of knowledge, as we have seen, to reach a state of knowledge from which certain properties must emerge.

For example, a recent trend in game-theoretic research has been to revisit notions of decision-theoretic rationality as embodied in game-playing agents, to understand better how rational agents would actually play a game, as opposed to analyzing a game independently of the agents, assuming basic rationality and common knowledge among the agents. Aumann and Brandenberger (1995), for example, investigate epistemic conditions for achieving Nash equilibria—that is, what must agents know if we are to be assured that their decisions will constitute a Nash equilibrium? While their analyses are too involved to detail here, and introduce problematic notions of common knowledge for cases involving more than two agents, we can get a flavor of how their ideas dovetail into those of AI by considering our ongoing two-agent case.

Recall that, in the previous subsection, P recognized that by telling Q about P's intention to take action A, P could increase its own expected payoff. Moreover, in this case, P got this higher payoff by doing what it had told Q it would do (it did not need to lie). If P is correct in its knowledge of Q's payoff matrices, of Q's rationality, and of Q's correctly receiving P's message, then P not only will take its part in a Nash equilibrium, but in fact knows that the agents are in a Nash equilibrium if it has itself been rational in choosing its action and truthful in revealing it.

A challenge of course lies in some of these nested knowledge assumptions. For example, P's projected knowledge state after sending the message (Figure 7) is predicated on knowing that, at the time of the door-opening decision, Q will have received, decoded, and incorporated P's message. P could require that Q acknowledge the message, and this acknowledgment could suffice, although more interesting kinds of coordination requiring infinitely nested (common) knowledge might require infinitely many acknowledgments in principle (Fagin *et al*, 1995). Alternatively, P could have more models of Q (for the combinations of hear/not-hear and allergic/not-allergic) with their associated probabilities.

As we have seen, it is often advantageous to agents if they can attain (and possibly help others attain) particular states of knowledge. When particular kinds of knowledge states tend to be advantageous repeatedly, agents can discover patterns of communication that tend to lead to these states. These patterns of communication form the basis of protocols. Practical coordination that is predicated upon communication usually embeds well-defined protocols into the agents to streamline the process of achieving knowledge states that are desirable for system-wide properties. Substantial efforts on the parts of multiagent system designers have gone into formulating, implementing, and testing such protocols (e.g. KQML (Cohen & Levesque, 1995, Mayfield *et al*, 1996)), so that agents reach agreement on issues such as task assignments (e.g. (Smith 1980, Rosenschein & Zlotkin, 1994)) and coordinated plans (e. g. (Durfee 1988; Ephrati & Rosenschein, 1994)).

Finally, is should be mentioned that overuse of protocols can be counter-productive. A protocol that keeps agents informed about each other is generally helpful, but it could happen that, when one agent changes its plans due to unexpected events, it tells others, who adjust their plans, and tell yet others who adjust their plans, and so on. Sometimes, this kind of chain reaction can trigger a large amount of communication and coordination reasoning, and therefore it only makes sense to do if the precipitating change was significant. Thus, part of the practical use of protocols is in deciding when it is better to say nothing at all (Durfee and Lesser, 1988).

Constraining Choices

So far, we have focused on methods for keeping the nested modeling tractable by using internal reasoning, learning, or selective communication to reduce the depth and/or breadth of the modeling space. Even if we were to reduce these drastically, however, it would not help if what little remained involved huge interaction representations. That is, in the form we've been focusing on, reducing the number of nested matrices will not help much if constructing even one such matrix is intractable. Recall that, in the worst case, every possible combination of the c choices for the n agents must be evaluated, meaning c^n evaluations.

Certainly, if the space is to be explored exhaustively, the set of choices must be finite. By constraining choices available to agents further, we can simplify the representations of interactions. In the most degenerate case, where each agent is given a single specific capability, an interaction is a matrix with only a single element (c=1 so c^n

[1] That is, by communicating the agents can be assured of taking complementary actions (one A, the other B), so one is sure of opening the right door (payoff of 2) and the other will get a payoff of 0. If each is equally likely to be in each of these circumstances, each has an expected (average) payoff of 1.

= 1)! This is an “assembly line” model of multiagent systems.

Organizational Structures

The idea of constraining the choices of agents has been part of multiagent systems for well over a decade in work that has tried to use notions of organizations and organizational roles as guidelines for coordinating agents (Corkill 1983). A description of an organization captures the preferences and responsibilities of its members, providing strong clues to the choices of actions the members might make. The organization might also impose prohibitions on certain kinds of actions, both for particular niches in the organization and for all members of the organization.[1] By embedding agents within an organization, their decisions are simplified (they have fewer choices and know that others have fewer options) and their dynamic coordination activities can be better directed. Among the challenges in designing an organization is determining how to decompose tasks into separate roles, so as to have reliable, inexpensive, and effective performance on the part of the organization.

For example, consider hierarchical organizations for tasks such as information gathering. Given a query to answer, the query task can be decomposed and the (independent) query subtasks assigned. Let’s define the task granularity (γ) as the task execution time (τ) divided by the communication delay (δ). Then, given γ, the total number of primitive information gathering tasks (*N*), and the number of tasks (*m*) assigned to each leaf of the organization, we can derive the branching factor *k* for the balanced tree that minimizes response time (So & Durfee, 1996):

$$T(N,k,\gamma,m)=\left\{\begin{array}{l}(k+1)l\delta+(l+m)\tau \longrightarrow \gamma\leq 1\\ \\ 2l\delta+(kl+m)\tau \longrightarrow \gamma>1\end{array}\right\}$$

In the above, $l=log_k(N/m)$, and is the number of levels in the organization. The processing at the leaf level is simply to execute the primitive tasks and send the results of each back up the hierarchy. At the non-leaf levels, the agents receive larger tasks from above, break them into *k* subtasks, assign these subtasks sequentially to the *k* agents below, and then as results are returned they are synthesized (where integrating a received result requires τ time) and the composite result is sent back up the hierarchy once it is done.

Under this assumed organizational behavior, it is the case that, for *N*=32, *m*=2, and any γ, *k*=4 outperforms *k*=2 and *k*=16. Even in the space of such simple hierarchical organizations as these, therefore, the detailed design of the organization (the selection of parameter values for features such as the number of subordinates per manager) balances several considerations.

Organization and Runtime Coordination Codesign

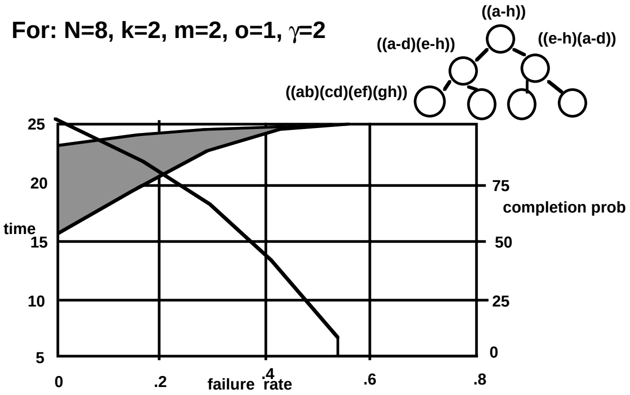
The above organization analysis assumes that each agent can reliably accomplish its task(s). A major challenge in organization design, in fact, is to design reliable organizations that can tolerate failures of some agents. To increase reliability, we typically introduce redundancy among the agents, so that each task is replicated at several agents. To the degree of replication, the task can still get done even if some agents fail. But redundancy also opens the door to possible inefficiencies, as agents can duplicate each others’ work in situations with few or no agent failures. Duplication of effort can be avoided if agents are able to coordinate dynamically at runtime, but this in turn incurs overhead and assumes sophisticated agents. So an important question in organization design is: How do different organizations make demands on the sophistication of agents that populate them?

To begin answering this question, we have defined **o-redundancy task assignment** by a parent to child in a tree-like organization as an assignment that tolerates the failure of *o* children. For example, 1-redundancy task assignment means that the organization is still assured of succeeding even if one of the “children” agents of each of the non-leaf agents fail. In a binary organization (*k*=2), 1-redundant task assignment means that all of the agents are responsible for all of the tasks, because in the worst case (when only one of every two children survives), there is a single “live” path to a single leaf! Since the failures are random, every single such path must lead to success, so every leaf agent will have every subtask. (See Figure 8 with tasks label with letters a, b, c... Note that tasks get grouped into subsets at deeper levels, where the ordering of subsets might imply a preferred ordering of subtask execution.) Fortunately, for larger values of *k*, redundancy need not be quite so total! (See Figure 9, where a leaf agent does not have all of the subtasks.)

For different levels of o-redundancy, along with the previously described parameters, we can measure an organization’s response time given that particular agents fail. We here define the agent failure rate as the proportion of agents that fail (although a richer model of independent failures is used elsewhere (Durfee & So, 1997)). Thus, with a failure rate of .4, an organization with 5 agents will have 2 failed agents. Whether the organization succeeds can depend on which of the agents fail (note that any simple hierarchical organization like the ones we have examined will fail if the top agent fails), and in some cases, the failure rate might force the violation of the degree of redundancy in the organization, and so the organization will be assured of failing to respond at all.

Thus, a particular organization will not have a deterministic response time, but rather will have a distribution over performance times, depending on which

[1] Note that prohibitions across the entire population equate to “conventions” or “social laws” (Shoham and Tennenholtz, 1995) which correspond to a specialized form of organization structure.

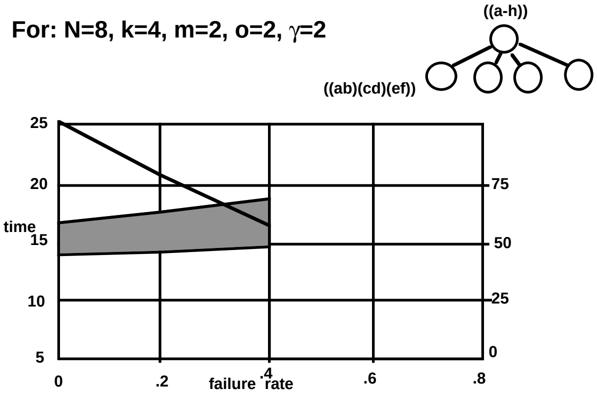


The organization (upper right) with 8 tasks overall (N=8), each non-leaf has 2 children (k=2), each leaf does 2 tasks (m=2), tasks are assigned so that even if 1 out of every pair of children fails, all the tasks still get done (o=1). The graph shows how variance in execution time decreases with greater agent failure rates, and how the probability of successful overall task completion decreases (scale on right side of graph).

Figure 8: Binary Tree Organization

agents fail and how the surviving agents order their tasks. If we assume random task ordering, we get behavior exemplified in Figure 8 and Figure 9. (These figures do not include response times for failed instances of organizations; for more on this see (Durfee & So, 1997).) Note how, in the first case (Figure 8), the distribution over runtimes (shaded region) narrows with increasing failure rate. This is because, as more agents fail, the differences in performance due to alternative orderings disappears since ultimately enough agents are gone that the remaining ones must complete all of their tasks anyway. This is not so in the second case (Figure 9); having less redundancy at the leaf agents means the performance distribution will be narrower, but it tends to widen with failures since there can be more reliance on results from agents who get their tasks later (assignments are made left to right). Broader distributions represent opportunities for improvements through runtime coordination (Durfee & So, 1997), which helps agents coordinate their orderings to do better than “random.” The second case also has a higher probability of completion for low agent failure rates, but does not degrade as gracefully as the first case as agent failure rate increases, as shown by the solid line in the graph giving completion probability (scale on the right side of the graphs).

The design of organizations is thus a balancing act between factors such as reliability, response time, and investment in runtime coordination technologies for the agents that populate the organization (Durfee & So, 1997). Again, recall that by embedding agents within an organization, their decisions are simplified (they have fewer choices and know that others have fewer options) and their dynamic coordination activities can be better directed.



The organization (upper right) with 8 tasks overall (N=8), the one non-leaf has 4 children (k=4), each leaf does 2 tasks (m=2), tasks are assigned so that even if 2 out of the four children fails, all the tasks still get done (o=2). The graph shows how variance in execution time decreases with greater agent failure rates, and how the probability of successful overall task completion decreases (scale on right side of graph).

Figure 9: Flat Tree Organization

Preference Simplification and Selective Search

As we have seen, overly constraining choices will impact the flexibility of agents to accommodate less than ideal circumstances, such as the failure of some agents within an organization. There are therefore limits to how much we want to make coordination practical by tying the hands of our agents - by keeping *c* small so that c^n stays small.

In this section we consider alternative strategies, such as only selectively examining some of the c^n combinations, or even just keeping *n* small. If some agents can be safely ignored, for example, the interaction can be greatly simplified. To say that an agent can be ignored means that the choices made by the agent have no (or negligible) impact on the perceived payoff that another gets from its choice of actions. Obviously, one way of realizing this is to structure the multiagent system in a way that maximizes independence, such as creating organizations with independent roles (e.g. no redundancy) so that agents would not need to consider what others had or would be doing when making their own decisions. Such systems have been called completely accurate, independent systems (Lesser & Corkill, 1981).

In more open systems, imposing such structure can be problematic, so alternative means are needed. One fundamental approach is to simplify the agents’ preference structure. Consider, for example, the following. In a robot delivery task, a robot R is indifferent to where other robots are, *except* when they are trying to be in the same place as R is at the same time. Thus, if we consider R’s interaction space, for most of the choice combinations, the payoff of the choice combination is the same as R’s payoff for its individual choice, except for a few points where R's payoff is strongly negative (a collision!). Reasoning about its choice of action, thus, could be viewed as prohibiting the bad combinations and acting independently otherwise. The notion of social laws (Shoham & Tennenholtz, 1995), for example, has this flavor of prohibiting actions that lead to failure states and otherwise allowing agents to ignore each other.

Satisficing

An even greater simplification can arise if each agent has only two levels of preference over outcomes of choices—*good* and *no good*. In effect, this reduces the search for an optimal choice of action to a satisficing search: as soon as a choice is found that is *good*, it is pointless to enumerate and evaluate other choices.

These strategies presuppose that agents know what choices to avoid. In some cases, off-line analyses of an application domain can yield a set of prohibitions, as has been done with social laws (Shoham & Tennenholtz, 1995). But runtime methods for searching for coordinated choices can exploit simplified preferences greatly. For example, in coordination approaches based on plan merging (e.g., Georgeff, 1983;, Ephrati & Rosenschein, 1994; Durfee & Lesser, 1991), agents begin by assuming that their choices are independent and thus each searches for plans that look best locally. These are then merged to detect conflicts, and if conflicts are found some agents might replan or simply revise (such as insert synchronization actions into) their original plans to remove the problem. Thus, rather than enumerating the whole interaction space (matrix), the agents selectively enumerate portions of the space until a satisfactory combination of local plans is found. Often, they perform a hill-climbing search, beginning from their combination of independently-derived local plans, and searching through successive perturbations of those plans until a satisfactory (conflict-free) combination is found (e.g., Durfee & Lesser, 1991).

This satisficing simplification of preferences to being *good* (enough) and *no good*, reduces the coordination process to a distributed constraint satisfaction problem (Yokoo *et al*, 1992, Conry *et al*, 1991, Sycara *et al*, 1991), where all satisfactory solutions are equally good. Much work in multiagent systems has benefited from this kind of simplification, taking advantage of algorithms for constraint satisfaction search to solve, for example, problems in distributed resource allocation and scheduling. There might be many possible strategies for conducting such a search, however, and the quality and cost of coordination might well depend on adopting an appropriate strategy given the current problem-solving context.

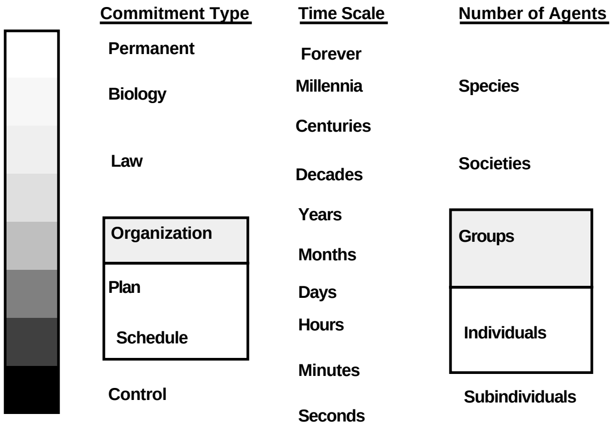
Negotiation

For example, in the application domain of distributed meeting scheduling, there could be several strategies for how agents go about searching through (negotiating over) possible meeting times to propose to each other (Sen & Durfee, 1995). Two (of many) possible strategies are to simply move through the available times chronologically and schedule a meeting as early as possible, or to find larger portions of the calendar that are relatively free, and then iteratively narrow down the times to find a meeting time. These strategies lead to calendars that look different, the latter tending to distribute meetings more evenly. In turn, the evolution of a calendar with one of the strategies eventually reaches a point where the other strategy becomes the better (more cost-effective) choice for further scheduling. As the calendar gets full toward the front from as-soon-as-possible scheduling, a fit-in-sparse-space strategy works better. As the fit-in-sparse-space strategy tends to make the calendar evenly dense (so there really are no spaces appreciably more sparse than others), the simpler soon-as-possible strategy becomes more cost-effective. Thus, not only does an agent's choice of strategy for searching the options impact the quality and cost of its schedule, but the agent also must be capable of adapting its strategy as circumstances change.

The iterative search through the space of joint decisions that we have described has many of the features that most people associate with the concept of *negotiation*. There are many possible strategies for making negotiation practical depending on the needs of an application, ranging from simplifying the preferences and adapting the search strategy (as outlined above), to simplifying the proposals (for example, using prices to summarize agents' current/future plans as in (Wellman, 1993; Lee & Durfee, 1995)), to using heuristics or past cases to generate new proposals based on feedback about prior proposals as in (Sycara 1989)), to exchanging intervals of proposals and narrowing down to solutions, and so on. In fact, because the term "negotiation" has been used to encompass so many more specific strategies like those just mentioned, the term has become much less technically meaningful; a challenge for the community is to more carefully characterize the different kinds of negotiation that have been studied, possibly (as suggested in this article) by focusing on how each kind attempts to make the coordination problem tractable.

Hierarchical Elaboration of Choices

So far, we have discussed approaches where agents can search through the space of individual actions to find good joint actions, such as working their way through proposed meeting times, and approaches where agents work within longer-term organizational guidelines that focus their behaviors. In fact, these strategies for coordination involve agents making commitments at different levels (at the schedule level versus at the organization level). Generally speaking, agents can make commitments along a spectrum of levels, which are differentiated mostly in terms of the lifetime of the commitment (or the frequency with which new commitments must be made) and in terms of the number of agents involved in the commitment, as broadly



As we work our way down, the time scale of commitments decreases, as does the number of agents participating in the commitment. The marked areas are the parts of commitment space focused on in this article.

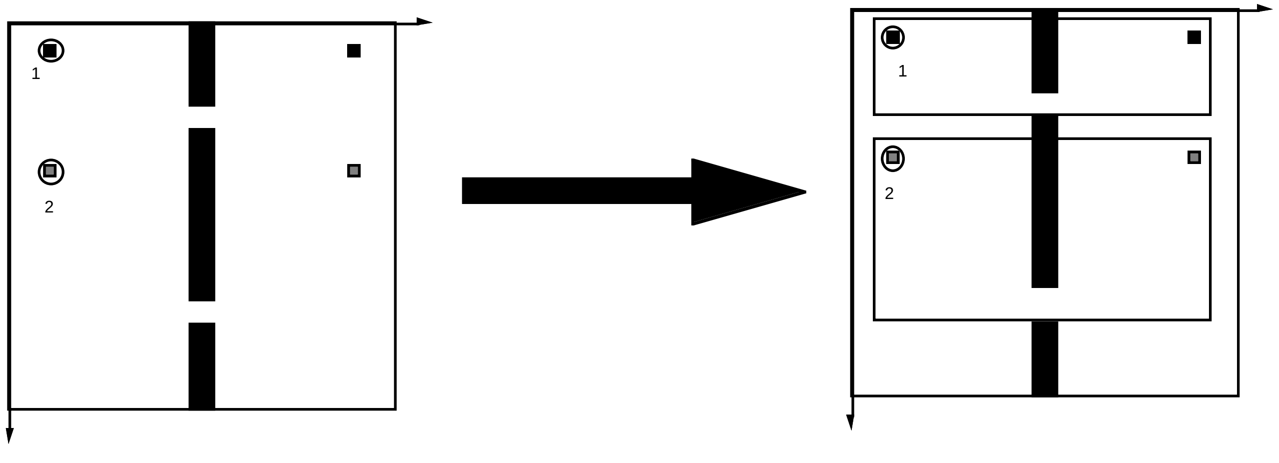
Figure 10: Commitment Spectrum

summarized in Figure 10. The frequency of coordination decisions is conveyed in the left column (darker is more frequent), along with the type of commitment and the time scale and number of agents involved. The emphasis in multiagent systems research is mostly in the areas “boxed”, with the gray areas being less fully explored. The choice of what kinds of commitment(s) agents should make to each other depends on the frequency of coordination activity, the requirements for coordination precision, the tolerance of coordination costs, and the flexibility that agents need to individually retain to cope with environmental changes.

An ongoing objective of our work is to represent the continuous spectrum of commitments in a single search space, to allow agents to move among models of individual and joint activity at different levels of (temporal) abstraction. Thus, the search for coordinated activity involves not only a search among alternatives at a particular abstraction level for specifying choices, but in fact a search through alternative levels of abstraction to find models of agents/actions that balance the costs and benefits of coordination appropriately.

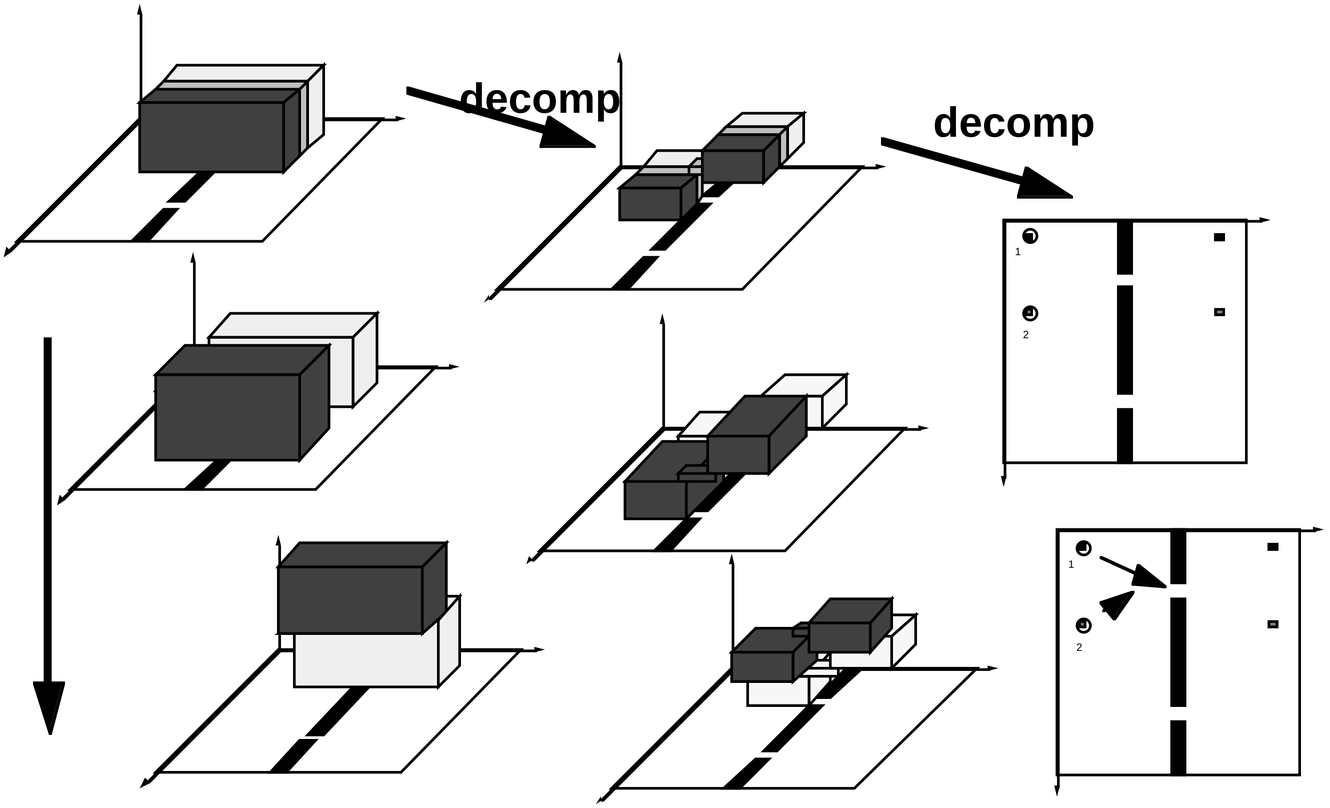
For example, consider 2 robots doing deliveries as in Figure 11 (left side). Since R1 always delivers to the top destination, and R2 to the bottom one, one strategy for coordinating is to statically assign resources (in this case, regions that contain the doors are most important). This leads to Figure 11 (right side), where R2 is always running around the long way. This “organizational” solution avoids any need for further coordination, but it can be inefficient, especially when R1 is not using its door, since R2 is still taking the long route.

For a particular delivery, R1 and R2 might consider their time/space needs, and identify that pushing their activities apart in space or time would suffice (Figure 12, left side). With temporal resolution, R2 waits until R1 is done before beginning to move to and through the central door. Or the robots could use information from this more abstract level to focus communication on exchanging more detailed information about the trouble spots. They could resolve the potential conflict at an intermediate level of abstraction; temporal resolution has R2 begin once R1 has cleared the door (Figure 12, middle column bottom). Or they could communicate more details (Figure 12, right side), where now R2 moves at the same time as R1, and stops just before the door to let R1 pass through first. Clearly, this last instance of coordination is crispest, but it is also the most expensive to arrive at and the least tolerant of failure, since the robots have less distance between them in general, so less room to avoid collisions if they deviate from planned paths.



Robot 1 delivers objects between the solid square locations (it is at one of those in the figure). Robot 2 similarly delivers between the shaded regions. One coordination decision could be to partition the space once and for all, such that each robot has complete control over its region (shown on the right).

Figure 11: An Organizational Solution



Treating coordination for only the next delivery, the agents represent their plans abstractly in terms of an x-y region over time. The most abstract representations (upper left) overlap, leading either to moving their activities apart in space or time (working downward in the figure), or exchanging more detailed views (moving to the right in the figure) to isolate more precisely where the conflicts could arise. At the most extreme right, the agents exchange detailed movement plans, and coordinate by shifting one of them very slightly in time to avoid collision in the doorway.

Figure 12: Alternative Levels of Abstraction

This example illustrates that coordination can go on at different abstraction levels, and that which level is right can be very situation-dependent. Thus, it is important to develop coordination techniques that can find the right level of detail. Moreover, in terms of the framework laid out in this paper—of thinking about strategies for limiting the knowledge being considered during coordination—the ability to represent situations abstractly is another way of reducing the number of choices (and choice combinations) being considered (lowers *c* in our earlier formulations). Protocols that allow the incremental elaboration of choices, moreover, can be based on such a representation, as another means for selectively exploring (and ignoring) options of agents (Durfee & Montgomery, 1991).

Of course, there are even more strategies for coordination even in a simple domain such as the robot delivery task. One interesting strategy is for the robots to move up a level—to see their tasks as part of a single, team task. By doing so, they can recognize alternative decompositions. For example, rather than decompose by items to deliver, they could decompose by spatial areas, leading to a solution where one robot picks up items at the source locations and drops them off at the doorway, and the other picks up at the doorway and delivers to the final destination. By seeing themselves as part of one team, the agents can coordinate to their mutual benefit (they can cooperate).

Using Teams to Simplify Coordination

We turn to one final strategy for keeping coordination practical that builds on both the ideas of using hierarchical abstractions and of ignoring agents or treating multiple agents as a single agent. Abstraction is a powerful tool for reducing complexity; for tasks that admit to abstraction such that subtasks can be elaborated independently, hierarchical distributed problem solving can solve an exponential problem in logarithmic time. That is, some problems admit to hierarchical decomposition, such as the Tower of Hanoi problem where solving the problem of moving a stack of disks off of the disk that needs to be moved can be solved separately from the problem of restacking smaller disks on top of the moved disk (Korf, 1987; Knoblock, 1991). Multiagent problem solving can construct a plan in logarithmic time,as long as the number of agents to solve the problem can grow with increasingly large problem sizes (Montgomery & Durfee, 1993).

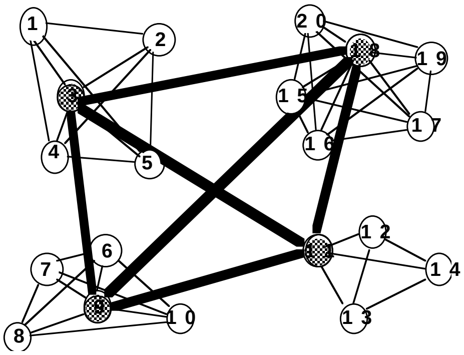
Even when strong assumptions of subtask independence do not hold, moreover, the use of abstraction can be beneficial. For example, in coordinating 20 delivery robots, having each communicate and coordinate with all of the others directly can lead to paralysis as each is overwhelmed with information. An alternative strategy is to have the agents break into teams, such that team leaders coordinate to divide (space and time) resources among the teams, and team members divide their allotment among themselves (Figure 13).

Because team members must summarize their requests for team leaders, and then team leaders must pass revised team constraints back to the members, the property of subtask independence does not hold. Yet, despite this, as illustrated for a particular case in Figure 14, the use of team-level abstraction can allow coordination costs to grow more slowly as the task becomes harder than if the individuals had to coordinate with every other agent (Montgomery & Durfee, 1993).

Summary and Future Work

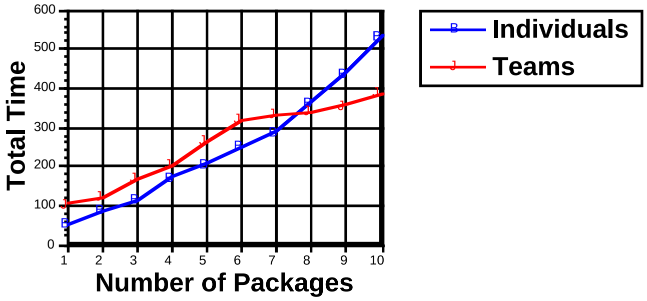
To summarize, what we have seen is that, considering all of the knowledge that an agent might have, completely thoughtful coordination might be impractical for most applications. Making coordination practical therefore means finding ways to *not* use some of the possible knowledge---to either be, or pretend to be, blissfully ignorant about some aspects of the multiagent situation (Figure 15). I would claim, in fact, that the bulk of coordination research has been in developing techniques to do exactly that. The large number of techniques out there seems to me to be a reflection of the number of ways that people have found to ignore, simplify, or implicitly design away aspects of agent models to make coordination tractable. Different application domains have tended to be sensitive to ignorance of different things; hence, in general coordination techniques appear to be tied to application domains.

My hope is that this is really not the case, but that the coordination techniques are tied instead to what is safe to ignore in different domains. By characterizing coordination techniques in terms of how they reckon with the potential intractability of the coordination task, as I have done here with a small (shamelessly biased) subset of techniques, I hope to encourage further examination of previous and ongoing work (of which there is too much to comprehensively list) to understand it not in terms of how techniques match a particular application domain, but rather how they fit a class of domains that admit to---or even thrive on---certain kinds of ignorance that allow coordination to be practical.



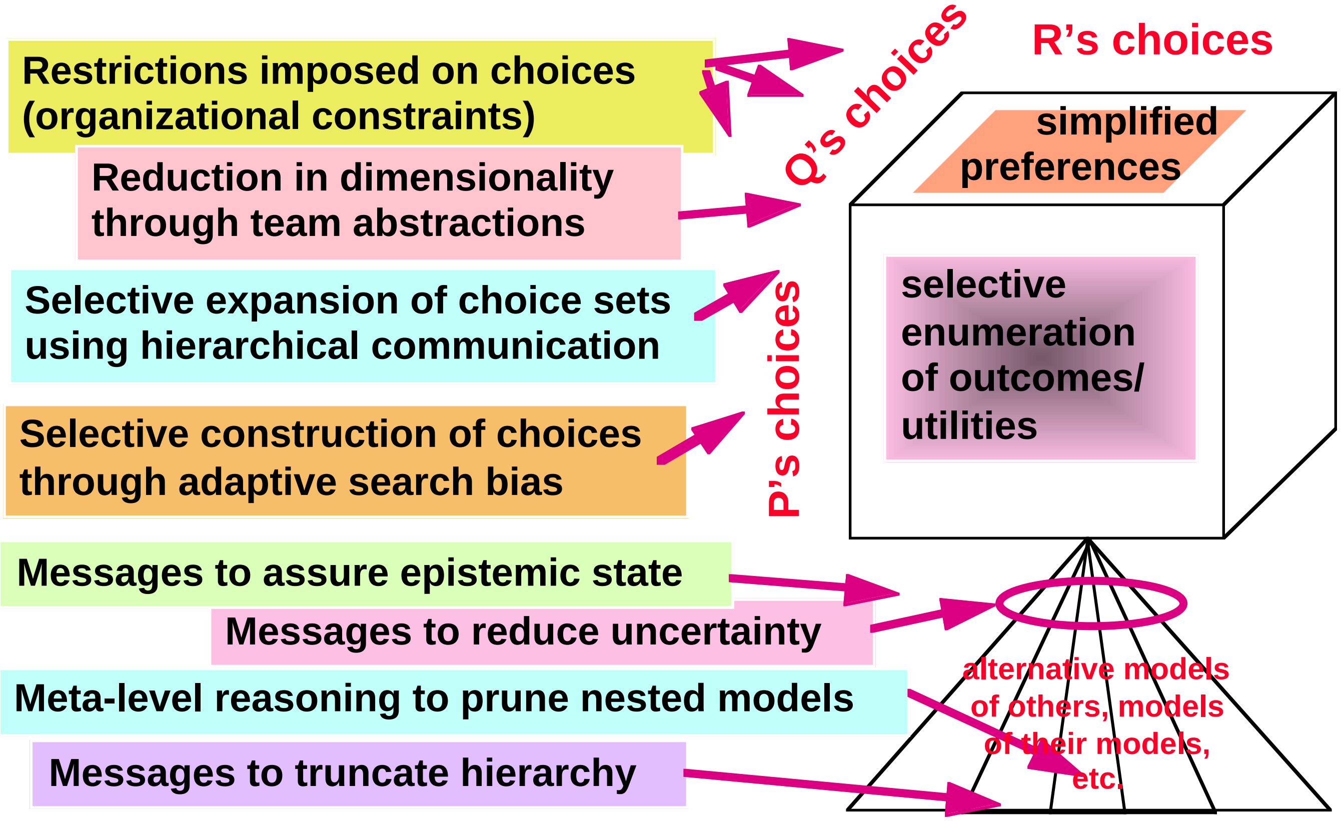
Nodes are clustered into 4 teams, and one member of each team acts as a "leader" and coordinates with the leaders of the other teams.

Figure 13: Example Team Hierarchy



The total time to complete deliveries is plotted as the number of packages to be delivered (where their start and destination locations are randomly generated) grows. With a small number of deliveries, it is faster for agents to coordinate as individuals, since the number of potential conflicts (collisions) is small, than to incur the overhead of working through a team hierarchy. However, as the number of deliveries rises, it eventually becomes more cost effective to decouple much of the search by using teams despite the added overhead.

Figure 14: Experimental Results on Team Deliveries


Restrictions imposed on choices (organizational constraints)
Reduction in dimensionality through team abstractions
Selective expansion of choice sets using hierarchical communication
Selective construction of choices through adaptive search bias
Messages to assure epistemic state
Messages to reduce uncertainty
Meta-level reasoning to prune nested models
Messages to truncate hierarchy
Q's choices
R's choices
P's choices
simplified preferences
selective enumeration of outcomes/ utilities
alternative models of others, models of their models, etc.

A summary of the techniques described for making coordination more practical, indicating what parts of the coordination problem they affect .

Figure 15: Strategies for Practical Coordination

Further Reading

Computational approaches to coordination among artificial intelligence systems have been a focus of work in the distributed artificial intelligence and multi-agent systems community for many years. Numerous collections of research results in the field exist, ranging from classic papers (Bond & Gasser, 1988) to the papers in the International Conferences on Multi-Agent Systems (Lesser, 1995; Takoro, 1996; Demazeau, 1998) and the Autonomous Agents conferences (Johnson, 1997; Sycara & Wooldridge, 1998). There are in-depth treatments on the design of mechanisms that lead to multiagent systems that exhibit desirable properties (e.g., Rosenschein & Zlotkin, 1994), on computational organization theory, (e.g., Prietula, et al, 1998), and on theories of nested agent knowledge (Fagin, et al., 1995). Recently, the field has matured to the point where textbook-level treatments have begun to appear (O'Hare & Jennings, 1996; Weiss, 1998), and a journal entitled Autonomous Agents and Multi-Agent Systems is now being published.

Acknowledgments

My thanks to my current and former students, whose investigations have contributed important pieces to the overall puzzle still taking shape in this article. Their names are sprinkled liberally in the references that follow. Piotr Gmytrasiewicz and Sandip Sen specifically gave helpful suggestions about this article. This article is a revised and extended version of an invited paper presented at the International Conference on Multi-Agent Systems (ICMAS) in 1995. I would like to thank my colleagues in Israel---Jeff Rosenschein, Sarit Kraus, and Moshe Tennenholtz---for feedback on the early formulation of this paper, and members of the MAS community at large since ICMAS-95 for their thoughts.

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