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Thinking in groups*

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Is cognition an exclusive property of the individual or can groups have a mind of their own? We explore this question from the perspective of complex adaptive systems. One of the principal insights from this line of work is that rules that govern behavior at one level of analysis (the individual) can cause qualitatively different behavior at higher levels (the group). We review a number of behavioral studies from our lab that demonstrate how groups of people interacting in real-time can self-organize into adaptive, problem-solving group structures. A number of principles are derived concerning the critical features of such "distributed" information processing systems. We suggest that while cognitive science has traditionally focused on the individual, cognitive processes may manifest at many levels including the emergent group-level behavior that results from the interaction of multiple agents and their environment.

Keywords: distributed cognition, emergence, complex adaptive systems, agent-based modeling, group problem solving, human foraging, social networks

1. Introduction

An implicit assumption made in cognitive science is that the individual is the critical unit of cognition. In recent years, the Distributed Cognition (DC) movement in psychology has arisen as a challenge to this assumption. Its adherents view the process of thinking as extending beyond the individual and instead as "distributed", either across the members of a group or in concert with objects and tools in the environment (Hutchins 1995a, 1995b). The DC perspective extends the boundaries of traditional cognitive science by including the larger network of ecological relations supporting the individual cognizer. However, one might reasonably question if such aggregate systems can themselves be productively viewed as cognitive, or if cognition is better understood from the perspective of the individual people comprising the system (cf. Harnad 2005).

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For example, when we say a group has "learned" something perhaps all we really mean is that some portion of the individuals in the group learned it.

There is an inherent tension between describing human groups in terms of the behavior of the individual versus the behavior of the aggregate. Focusing on the individual matches our personal experience. On a routine trip to the grocery store, we might be aware of the latest trend in the popularity of a breakfast cereal or the traffic on the way home, but we often have little sense of how our own goals or behavior might actually contribute to those phenomena. However, in even the most mundane daily activities, we become entwined in a network of aggregate social processes. Our cars contribute to the cyclic patterns of crowding and congestion on the highway (Helbing 2001) while our purchases interact with the consumption patterns of those around us to create trends and fashions (Gladwell 2000). These and other group-level phenomena such as rumors, the use of a standard currency, and the World Wide Web highlight the fact the behavior can be structured at levels beyond the individual.

Understanding the nature and cause of these types of group-level phenomena has been significantly advanced by the study of complex adaptive systems (Holland 1975; Resnick 1994; Kaufman 1996). One of the principal insights from this line of work is that rules that govern behavior at one level of analysis can cause qualitatively different behavior at higher levels. Thus, individual and group-level descriptions need not be in conflict. Armed with agent-based models, social scientists have developed detailed theories that explore how the low-level rules instantiated by interacting agents can account for organized patterns of behavior in the aggregate (Goldstone and Janssen 2005).

One of the most surprising results from this type of work is how the behavior of the group and the individuals in the group may diverge. For example, in the classic work of Thomas Shelling (1971), groups of agents who each have only a moderate bias towards living near members of their own "race" can give rise to extreme patterns of large-scale racial seggregation. Even though none of the agents wants to live in a completely segregated world, this is exactly the outcome of their individual actions and the cascade of reactions to those actions. Similarly, when a group must share a limited resource, egocentric individuals can cause all members of the group to be worse off than if they had acted in a more cooperative way (Axelrod 1984). These examples illustrate how attempts to understand individual behavior by observing the group can be misleading, as is trying to infer what the group will do based on the preferences of the individuals alone.

In our lab, we are interested in studying the collective behaviors that emerge when a large number of agents (both human and artificial) interact in a common world consisting largely of other agents. What are the critical properties of systems that exhibit interesting patterns of aggregate behavior? One critical feature seems to be that they are distributed, or spread across a set of multiple, interacting component units. In this sense, we consider the adaptive group-level behavior we observe in our work, and in the world at large, as a form of Distributed Cognition. Rather than tie cognition to first-person feeling as Harnad (2005) does, we (collectively, even more than we do individually) think that cognition is more productively construed in terms of adaptive problem solving. When a cockpit solves a navigation problem (Hutchins 1995b) or a university department successfully redefines its mission to fit changing times, we see these collective behaviors as evidence for adaptive information processing beyond the level of the individual human.

In what follows, we attempt to draw some lessons about the conditions under which the behavior of individual agents self-organize into adaptive group structures. First, we define what we see as some of the critical properties these systems. Then, we review a number of examples from our own lab where groups of people behave in adaptive ways and where the information processing achieved at the group level is qualitatively different from that of individuals in the group.

2. What makes something "distributed"?

Throughout science and engineering, there has been an intense interest in distributed systems. Biological evolution, nervous systems, the Internet, ant colonies, parallel computing systems, and traffic jams are all examples of distributed systems in action, and despite their considerable diversity there are a number of features they all share (Resnick 1994).

Perhaps most importantly, they are composed of identifiable units that can be used for different purposes and whose operation can be described independent of any particular context. Typically the operation of each unit depends on locally observable conditions rather than global information. The nodes in a computing cluster are all interchangeable, discrete systems which perform a number of functions independent of their inclusion in the network. Similarly, individual neurons in the brain have self-contained computational properties which depend largely on their local pattern of connectivity (Rumelhart and McClelland 1987). In human distributed systems, each person has their own set of perceptions, goals, and desires which can operate independently of the group. People are fairly independent because they can continue to function when isolated in the wilderness. To the extent that a person's functioning depends on their computer, desk, books, car, colleagues, and staff, their status as an independent information processing unit diminishes.

An implication of this characterization of units as structures independent of their context is that "unit-hood" is inherently graded. The status of a set of elements as a unit depends on two factors: the density of connections and dependencies among the set of elements, and the density of connections and dependencies between the elements within the set and elements outside of the set. The first factor decreases the unit-hood of the set of elements while the second factor increases its unit-hood. For example, a leading theory for the evolutionary origin of mitochondria and chloroplasts is that they were originally independent bacteria that became incorporated into the cytoplasm of cells, and once incorporated, conferred advantages for the cell because they allowed cellular respiration (mitochondria) and photosynthesis (chloroplasts) for energy production (Margulis 1970). We are less likely to view mitochondria as the individual units they once were because of their strong dependencies with other internal cell elements.

A second defining property of distributed systems is that the units are loosely coupled and can thus influence one another. This influence can take many forms. In computer systems this is the function of the network and communication protocol, while in human groups language, rhetoric, and social norms mediate interaction. Similarly, ants leave behind pheromone trails that other ants follow in order to find good foraging spots. However, other types of between-unit communication are more or less indirect. If we find out that a particular concert is sold out, a type of information has been transmitted from the individuals who bought the tickets to the individual wanting a ticket which may convey something about the perceived quality of the music.

A final property of distributed systems is that the pattern of connectivity between units is dynamic. If the elements of any system always belonged together, we would simply speak of them as one unit. Thus, in neural distributed system, synapse efficiencies, learning weights, or neurogenesis modulate new connection between units. In human groups, dynamic patterns of connectivity can be instantiated by changes to spatial or temporal proximity, or the pattern and strength of social relationships. In many cases, the pattern of connectivity can change considerably through time as individual units shift in and out of different groups.

The combination of these three properties is what makes distributed systems so interesting. For example, because of the loose coupling between units, the behavior of any single unit is contingent on the behavior of others.

The behavior of the group becomes the environment in which any single unit resides, thereby creating feedback loops of reactivity (i.e., because all the units around me do X, I will do Y which causes some of those units to do Z). In addition, due to the loose coupling and dynamic connectivity, distributed systems can implement a type of re-configurality. As units shift their allegiance between different groups, they allow cross fertilization. Units that have been influenced by their previous associations in turn bring these influences to bear on their subsequent interactions.

Distributed systems, then, are interesting because they exist at the *cusp* of unit-hood. Before the bacterium has been incorporated into the cell at all, it is simply an independent environmental influence on the cell. Once the mitochondrium loses its ability to make its own living in the world, it is no longer a unit by itself, but rather part of the eukaryotic cell unit. In between being a free-agent bacteria and a mitochondrial cog in the cellular wheel, the "bactondrial" is both independent and dependent on the cell. This status, we argue, is particularly important when it comes to cognitive systems. Computational complexity, in terms of being able to transmit information, is at its greatest for systems made of partially dependent elements. Sporns et al. (2004) have quantified the "information integration" of a system in terms of its total amount of mutual information. On the one hand, if a system's elements are completely independent, then information cannot be transmitted from one part of the system to another. On the other hand, if a system's elements are too tightly connected, then they all end up possessing the same information and communication is useless. Human nervous systems have apparently evolved so as to maximize the usefulness of neural communication (Sporns 2002). Similarly, we would argue that distributed systems incorporating people also adapt so as to create information-amplifying systems. Useful human collectives are those that promote robust information transmission across people yet avoid having everybody know the same things. Collectives that do this will maximize their computational capability.

Organization in such systems can be viewed from at least two levels: the operation of the collective, and the operation of the individual. These two levels need not be in conflict, although they are often not obviously related. By better understanding the operation of the individuals, one may derive considerable insight into the behaviors of the aggregate. Likewise, understanding the collective action of the group can give new insight into the behavior of the individuals.

3. Some case studies

Of course, simply being "distributed" in the sense just described in no way guarantees that any particular system will behave in any particular way. In some systems, the action of the group is quite simply the straightforward action of the individuals. However, in other systems new higher-level, emergent properties develop. In order to better understand what features encourage this process, our lab has developed an interactive computer platform which allows a large number of individuals (and agents) to interact in real-time.[1] Through this system we have been able to systematically study the effects of group behavior as it is driven by the environment, goals, perceptions, and motivations of individuals in the group. In what follows, we review a number of case studies from this work demonstrating the conditions under which adaptive group behavior can arise.

3.1 Group path formation

In one set of studies, we explored how individuals in a group are influenced by the choices and behaviors of their predecessors in the development of path or trail system (Goldstone, Jones, and Roberts, in press). Often times, there are advantages to choosing options which other's have already established as popular or useful. Early trail blazers through a jungle use machetes to make slow progress in building paths, progress that is capitalized on and extended by later trekkers, who may then widen the trail, then later put stones down, then gravel, then asphalt.

In our experiments, a small group of participants (6–12 people) interacted in real-time through a collaborative computer system. Each individual's task was to control a green triangle on the screen using the arrow keys on a keyboard and to direct it to a number of different goal positions on the screen. Navigation between these various goal states was complicated by a cost function which deducted points depending on where the participants moved. The number of points deducted on each step decreased as a function of the number of times that particular location had been stepped on by all participants of the game. Since the goal for each participant was to navigate to each location while losing the least number of points, they had to balance the advantage of short beeline paths between two destinations against the advantage given by traveling in regions that were popular with the group (i.e. established trails). The relative cost of each position in the virtual world was made visible to each participant by the color of each cell (higher cost cells were darker in the display, see Figure 1).

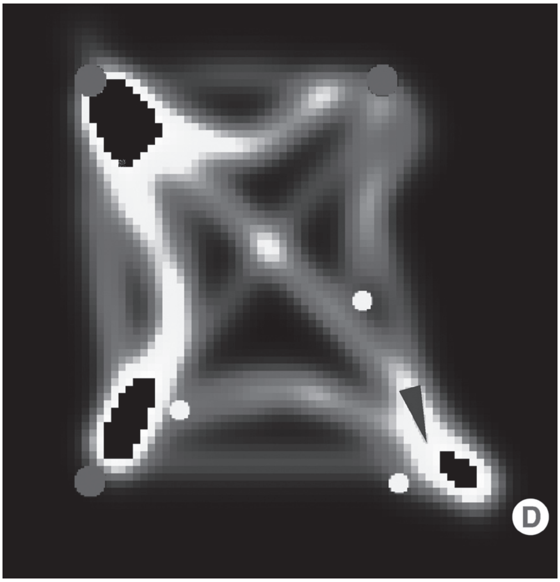

Figure 1. In this figure, the participants' own location is shown is shown by the dark grey triangle. The other agents are shown as small white circles, and the destinations are shown as the dark grey circles. The target destination for the participant is shown as a bright white circle labeled with the letter D, and the ease-of-travel of each location on the world is shown by its moment-by-moment brightness.

Over time, the participants combine their efforts to establish "trails" in this system just like the spontaneous paths that cut across the grassy areas on a university campus. One question of interest was if agents following the emergent paths of the group end up traveling less overall distance to reach to their respective destination (i.e. does the group find optimal path structures for connecting the destinations?). Fortunately, there is a relatively straightforward characterization of the shortest system of paths that connect any number of destinations called the Minimal Steiner Tree (MST). An example of MST solutions for two configurations of destination points is shown in Figure 2. The MST solution is the one that minimizes the total amount of "path" which is required to connect all the destinations in the configuration. In many configurations this is accomplished by adding some number of new, intermediate destinations to the configuration called Steiner Points.

The results showed that while groups did not necessarily find the best MST solution for any particular configuration, there were deviations from beeline paths towards what would be a MST solution. These pro-MST deviations were particularly common in places where the structure of the environment

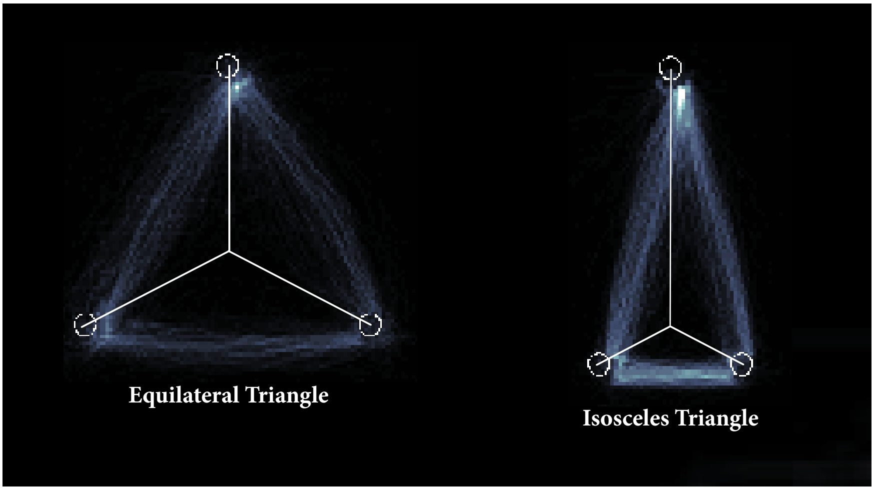

Figure 2. The cumulative steps taken on each cell for the Equilateral and Isosceles triangle configurations. The brightness of a location is proportional to the number of times that it was stepped on by all participants. The destinations are indicated by white circles. The shortest path system connecting the destinations is shown by the three white lines, and is known as the Minimal Steiner Tree.

encouraged path reuse such as in the isosceles triangle show in Figure 2. In comparison, the equilateral triangle arrangement of destinations showed relatively little deviation from the set of beeline paths. For the equilateral triangle, there is no incentive for a "pioneer" to move straight down from the top-most destination — it is dark and costly there. However, for the isosceles triangle arrangement, a participant moving from the top-most destination to the bottom-right destination might have an incentive to use the left pathway coming out of the top-most destination if, by chance, this path is somewhat bright because it has been recently traveled. Then, the participant will cut across at some point to the right-most city, thereby stepping in the middle territory. Once they have stepped in the middle region, it becomes somewhat more tempting for further travelers, who exploit and extend still further this middle, vertical trail (see Figure 2). The traveled path system for the isosceles triangle "zips up" over time. Participants originally start traveling by the beeline paths, but gradually step in the center regions, which causes still more steps in the center regions. Interestingly, the largest savings of distance for the Minimal Steiner Tree (shown as white lines in Figure 2) compared to the beeline paths is for the equilateral rather than isosceles triangle. Empirically, this is exactly the configuration that produces the fewest steps away from the beeline paths. Thus, having a strong group-level advantage for a path system is no guarantee that the group will find that path system.

To understand why subjects made the paths they did it is important to keep in mind that the environment in which the paths were formed was not simply the surface on which they "walked", but the interaction of the surface and the behavior others in the task. As individuals sometimes at random venture into new regions of the space, it becomes easier for subsequent agents to travel there. Only through a collective process of exploration and exploitation do agents arrive at a particular path solution. Our results showed how very slight modifications to the environment could encourage the group as a whole towards more optimal solutions. In particular, the structure of the isosceles triangles encouraged participants to move away from beeline paths by first fostering small steps away from the beeline paths, and then having subsequent travelers extend still further these deviations.

These results suggest that subtle changes to the structure of the environment and the incentives each agent responds to can have considerable influence on the group as a whole. Instead of using laws and strict barriers in order to control crowds, these less authoritarian methods of crowd control can be just as effective. For example, each year over 2.5 million people make their way across the Jamarat Bridge during their pilgrimage to Mecca. In 1990, as many as 1400 people were crushed to death by the massive crowd. Hughes (2003) applied methods from fluid dynamics to model the flow of pilgrims across the bridge and his models found that a series of barriers which helped to direct the density and speed of the crowd could effectively prevent congestion at dangerous spots.

3.2 Propagation of innovations

Related to the issue of how individuals build upon the work of others in constructing spatial paths is the propagation of innovations in more abstract domains. In solving problems, individuals often have to balance the cost of acquiring their own information against simply copying the successful behaviors of someone else (Bandura 1965). In order to understand the factors that influence the propagation of innovative solutions within a group, members of our lab have explored how groups pool and exchange information in order to solve an abstract problem (Mason, Jones, and Goldstone, in press).

Participants attempted to find the solution to a problem involving a simple, continuous number space. In each of 15 successive rounds, subjects guessed a number between 0 and 100 and were shown a numerical score as feedback that indicated how good their guess was according to a hidden evaluation function (see Figure 3). Each participant's goal was to maximize their own cumulative

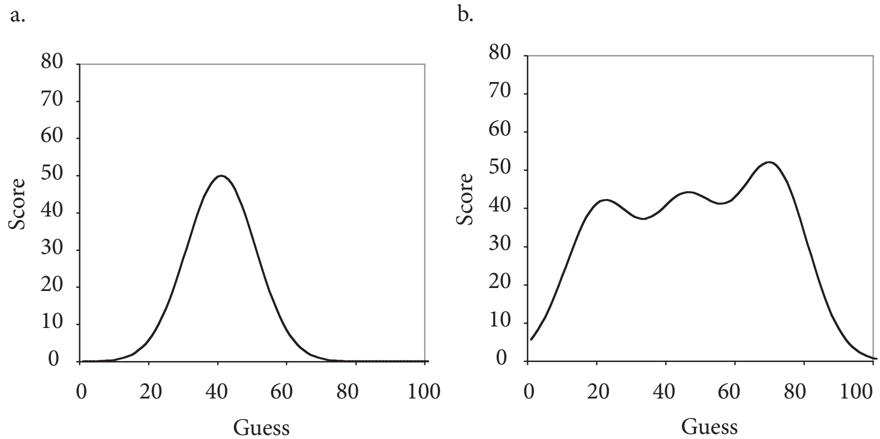

Figure 3. Examples of the (a) unimodal and (b) trimodal fitness functions which convert guessed numbers to scores.

number of points earned across the 15 rounds. In addition to receiving feedback about their own guesses, participants were also shown the guesses and scores of people who they were directly connected with. Thus on each round participants could explore near their own previous guesses, or switch to the successful guesses of people with whom they were connected.

The experiment manipulated two factors: the pattern of connections between individuals and the structure of the problem the individuals were to

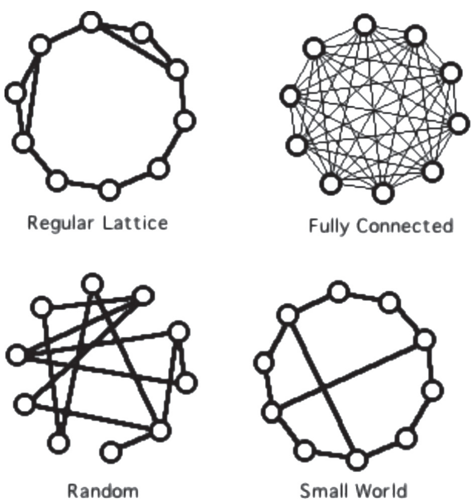

Figure 4. Examples of the different network structures for groups of 10 participants. Circles represent participants and lines indicate communication channels.

solve. There were four different network structures studied: full, lattice, random, and small world (see Figure 4). In the full network, every person was connected to every other person in the game. Thus, at the end of each round of the experiment, each participant had knowledge about the quality of the solution given by every other person. In the lattice condition, people were connected to only a small number of immediate neighbors. This network causes a large amount of local clustering in that a good solution found by one participant in one part of the graph must travel a long distance in order to reach people in other parts of the graph. In the random graph condition, people were connected randomly to other individuals. Random graphs have less clustering, and lower average path length between individuals, which speeds the flow of information compared to the lattice. The final condition was a small world network, which falls somewhere between the extremes of the highly structured lattice and the random graph (Watts and Strogatz 1998). Small world network combines high degrees of clustering with long range "short-cuts" which lower the average shortest-path length. The problem spaces, shown in Figure 3, were either unimodal (having one "best" solution) or trimodal (having two local maxima in addition to the globally best solution).

The principal factor of interest was how fast the group converged on the best solution, and how complete the convergence was (in terms of the percentage of individuals within some close proximity to the optimal solution). In the unimodal problem space, the networks with the shortest path average path length found the solution most quickly (i.e., the small world, random, and full networks). The full network converged upon the best solution most quickly of all. This matches the intuition that with such a simple problem, the group that can broadcast the solutions most effectively would perform best.

Performance in the trimodal problem space found a different pattern of results. In these sessions, the best solution was found faster, and by more individuals in the small-world condition compared to the full, random, or lattice networks. The structure of the trimodal problem space and the structure of small world networks align to help the group solve the problem. The large amount of clustering in the small world network allows for independent searching in different parts of the network enhancing the exploration of the problem space. On the other hand, the relatively short path length in the small-world networks allows the effective distribution of good solutions once they are found. In effect, the small-world network balances the competing demands of exploration versus exploitation.

Perhaps counter-intuitively, this result suggests that less information can actually be more when a group collectively searches a problem space. One hypothesis might have been that the full network would always have an advantage because it allows the most collaboration and exchange. However, the short path length and strong clustering of the small world network allowed for more regionally-based specialization within the overall group, leading to a more robust search of the entire problem by the group.

3.3 Human foraging behavior

Effective search is a critical part of human cognition. In the study just reviewed, search transpired in an abstract problem space. How do humans search for and exploit more concrete resources, and are there parallels between searches of spatial and abstract problem spaces (Hills 2006)? A final set of case studies conducted by members of our lab explored how humans search for and allocate themselves to resources (Goldstone and Ashpole 2004; Goldstone, Ashpole, and Roberts 2005).

As in the group path experiments, participants in these studies controlled a small character on the screen, however this time their goal was to collect resources which appeared at two different sites on the screen. Participants gained points for each piece of "food" they collected by stepping on it before any other person. The two resource pools had different experimenter-manipulated payoffs (50–50, 65–35, and 80–20). In addition, various conditions manipulated the information available to participants at any time. Participants could either see the location of other participants on the screen, the location of available food, both of these, or neither of these.

The question of interest was how the agents in the group would distribute themselves between these various resources. In biology there are models for how organism distribute themselves amongst a set of resources called the Ideal Free Distribution model (IFD) (Fretwell and Lucas 1972). Basically, this model predicts matching of agents to resources — if twice as much food is available at location A compared to location B, then the model predicts twice as many animals at location A compared to location B.

The results from these experiments found significant violations of the IFD model. In particular, in almost all conditions there was undermatching (i.e., if the resources were distributed 80/20, then participants distributed themselves 70/30). Undermatching implies that as a group, participants did not take advantage of the resources in an optimal way. The only exception to this was in the condition where resources were visible, but other agents were not. In this case, participants tended to overmatch (i.e. slightly more agents gravitated towards the more plentiful resource than predicted by the IFD model). Overall, the empirical results and associated computational modeling (Roberts and Goldstone 2005) indicate that people use knowledge of food density to move to lucrative regions, and use knowledge of the whereabouts of other foragers to distance themselves from crowds. However, we also found evidence for "bandwagon behavior" — when food was invisible but other participants were visible, then foragers used the appearance of other foragers as evidence that a region might be productive.

Perhaps the most interesting empirical result has been oscillations in the harvesting rate of the resources pools across time, particularly when participants had no knowledge of the location of either other foragers or of available food. Fourier analysis revealed strong fluctuations in the utilization of a particular pool in the range of 50 seconds per cycle. These waves of crowding were caused by correlated dynamics in the decision making of individual agents. Initially, an appealing resource patch would become overcrowded with foragers. This crowding would lead to relatively low payouts to the individuals in the crowd. This, in turn, led to an extensive migration out of the patch, making the patch, once again, attractively underused, thereby completing one cycle of population flow. These cycles were not found when other foragers were visible because the temptation to leave an over-harvested resource pool would be tempered by the realization that several others have already begun the migration to the less crowded pool. The irony of the waves of crowding in the conditions with invisible foragers is that participants are highly motivated to avoid traveling with the mob. This individual-level motivation for each forager to be in the minority is exactly what leads the group to travel as a mob!

4. Lessons learned

There are a number of lesson learned from these experiments:

People are a large part of people's environments

Consistent with the DC perspective, the behavior of individuals is influenced and supported by an environment composed of other people. In each of our experiments, the behavior of most individuals followed that of the group, despite the fact that people were free to act however they wanted. Rather than build their own trails, or seek their own problem solutions people naturally take advantage of the behavior of others when devising their own actions.

The interaction between individuals in our experiments was not always direct. The biologist Pierre-Paul Grassé (1959) developed the notion of "stigmergy": how organisms often communicate indirectly by modifying their local environment. This type of communication was prevalent in our studies where the tracks left by early travelers invited later travelers to follow. Similarly, in the forager experiments, the waves of oscillation between foraging spots occurred when individuals, by virtue of over-harvesting their local environment, changed its intrinsic value to the group.

Divide and conquer: Exploration and exploitation in groups
In many systems, effective management depends on leaders who delegate necessary tasks to their subordinates. However, our experiments show conditions in which a group may spontaneously organize into an effective problem solving structure without centralized control. In searching a hidden problem space with local maxima, groups connected by small world networks naturally took advantage of their distributed nature to both explore and exploit the problem domain. Given that the tension between exploration and exploitation in learning systems is a common challenge facing intelligent systems (Sutton and Barto 1998), it is interesting that our groups were able to arrive at solutions which balanced the two.

More information isn't always better
The amount of information that individual agents have access to clearly influences the efficiency of the group. When both resources and other agents were invisible, the groups in the foraging experiments made less optimal use of the food distributions than when more information was provided. However, more information is not always better. In the group problem solving experiments, the small world network provided more robust search abilities than did the full networks. Here less information encouraged independence between individual agents that greatly enhanced group performance in a complex problem with multiple local maxima.

Influencing groups by bottom-up pressures rather than top-down rules
Finally, our experiments suggest new ways for control the behavior of groups. The most common method of crowd control is through direct orders or laws. If we wish to direct pedestrian traffic, for example, we may institute rules or physical barriers that prohibit certain movements. Rather than enforcing restrictive laws or boundaries, minor changes to the incentives of even a few individuals can cause radical changes in the group. For example, in our path formation experiments, even without instituting physical or abstract barriers, it may be possible to indirectly control collective behavior with substantial efficacy. The

"Active Walker" model in biophysics (Helbing, Keltsch, and Molnár 1997) does a good job of explaining and predicting our empirical results. In this model, walkers move to destinations, and as they take steps, they affect their environment, facilitating travel for subsequent walkers. Walkers compromise between taking the shortest way to their destination and using existing, strong trails. Two critical parameters of this model are how quickly the influence of a step dissipates, and how visible the strengths of trails are to walkers. As influence dissipation becomes more rapid, and as path visibility increases, the agents collectively form better approximations to the optimal Minimal Steiner Tree path systems. For situations where conserving the total amount of pathway is desirable (e.g. when vegetation must be cut down to create the paths), planners should explore ways of increasing path visibility, the efficacy of steps, or path decay. Given the empirical success of the Active Walker model with our groups of people, varying its parameters becomes a potentially useful way of not only predicting, but controlling the growth of spontaneous paths.

Collective behavior is potentially more controllable than isolated individual behavior because of the strong influences among the individuals' behavior. A small pressure can often be magnified by the positive feedback involved in individuals following other individuals (Dorigo et al. 2000). This has important implications and warnings for public policy. On one hand, the incentives given to individuals do have important impact on the behavior of the group. Thus, tax policies that encourage certain behaviors can lead to desired social changes. On the other hand, the relationship between the individual biases and group-level behavior is often not obvious. In the group path formation experiments, despite incentives to cooperatively lay down efficient trails, the groups tended not to find the optimal solution. Agent-based modeling provides a new avenue for exploring the implication of various government policies on the emergent behavior of collectives (Epstein and Axtell 1996).

5. Conclusions

Earlier we brought forward a number of features we believe characterize distributed systems. In particular, we argued that distributed systems that strike a critical balance between the dependence and independence of their units would exhibit unique information processing characteristics. This characterization is well exemplified by the reviewed findings. By manipulating the pattern of connectivity between individuals in the group problem solving experiment, we found that the most robust group search strategies came when people were connected in small-world networks, which balance strong local dependencies against global connectivity. Similarly, the most optimal group paths were formed when the structure of the environment encouraged path re-use (i.e., the isosceles configuration) and thus interactions between the path histories of separate individuals following their own goals. When there was little chance for overlap, such as in the equilateral configuration, the group tended to be less efficient and instead simply reflected the expected paths of non-interacting agents. By being only partially dependent, elements avoid becoming redundant. The dangers of redundancy are well illustrated by the tendency of people connected via a full network to converge on sub-optimal local maxima. The price of everybody being connected to everybody else directly is that a federation of explorers comes to behave as a single explorer.

Perhaps most importantly, the studies reviewed show several dissociations between individual- and group-level behavior. For example, the individual foragers in a group with other invisible foragers are motivated to be in as underpopulated a resource pool as possible. This motivation leads them, perversely enough, to travel in crowds. In the group search problem when individuals can see everybody else's scores they end up converging quickly on a single solution, rather than exploring the full range of solutions. The result is that individual attempts to maximize points earned lead to poor group performance. In these examples, individual actions have unanticipated and undesirable consequences for the group's behavior.

The lessons we found in our work have implications for how distributed systems should be designed, deployed, and controlled. Unlike traditional top-down systems, apparently innocuous design decisions may greatly affect global behavior in distributed systems. For example, maintaining a critical level of independence for individual units is important for teams, committees, and economies in order to most effectively search a complex problem space. The often non-intuitive relationship between individual motivations and group behavior highlight the importance in building computational models to test the impact of particular design decisions. As computational simulations become increasingly realistic, they will serve as increasingly useful test-beds for exploring the potential consequences of public policies that have complex, non-linear dynamics.

Let us return to the question of whether our experiments demonstrate genuine distributed *cognition*. We have no way of assessing Harnad's (2005) criterion that the group actually *feels* something, any more than a neuron can assess whether its human owner feels. However, our experiments demonstrate how the behavior of interacting groups of people may organize into an adaptive, problem solving structure. This creative, adaptive problem solving behavior is a key characteristic of cognitive processing, and so it is not unreasonable to consider such group behavior a form of distributed cognition. The solutions of our groups varied in quality. The collective travelers do not ever form Minimal Steiner Trees while the foragers actually do distribute themselves with considerable efficiency to resources. However, regardless of the quality of solutions, the important point is that the group-level behavior can be evaluated separately from the individual-level behavior. It has a life of its own.

The complex systems framework provides a powerful tool for understanding the behavior of a diverse set of natural systems, including cognition. The idea that systems composed of loosely coupled, but well defined units can self-organize into systematic behaviors at higher levels of analysis closely parallels the ethos of Distributed Cognition which seeks descriptions of cognition at both the level of the individual and the group. Understanding how these two levels of description mutually reinforce each other is an important step toward richer theories of many natural phenomena.

Notes

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1. Participate online at http://groups.psych.indiana.edu/

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