

CHAPTER ONE

Learning Along With Others

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Abstract

Unlike how most psychology experiments on learning operate, people learning to do a task typically do so in the context of other people learning to do the same task. In these situations, people take advantage of others' solutions, and may modify and extend these solutions, thereby affecting the solutions available to others. We are interested in

the group patterns that emerge when people can see and imitate the solutions, innovations, and choices of their peers over several rounds. In one series of experiments and computer simulations, we find that there is a systematic relation between the difficulty of a problem search space and the optimal social network for transmitting solutions. As the difficulty of finding optimal solutions in a search space increases, communication networks that preserve spatial neighborhoods perform best. Restricting people's access to others' solutions can help the group as a whole find good, hard-to-discover solutions. In other experiments with more complex search spaces, we find evidence for several heuristics governing individuals' decisions to imitate: imitating prevalent options, imitating options that become increasingly prevalent, imitating high-scoring options, imitating during the early stages of a multiround search process, and imitating solutions similar to one's own solution. Individuals who imitate tend to perform well, and more surprisingly, individuals also perform well when they are in groups with other individuals who imitate frequently. Taken together, our experiments on collective social learning reveal laboratory equivalents of prevalent social phenomena such as bandwagons, strategy convergence, inefficiencies in the collective coverage of a problem space, social dilemmas in exploration/exploitation, and reciprocal imitation.

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1. LEARNING WITHIN A COMMUNITY OF LEARNERS

From the procedures that many psychology experiments on learning use, one might get the impression that learning is typically a solitary affair. Experiment participants are often given an inductive learning task to perform in the seclusion of their own cubicle, with a minimum of instructions or advice. Participants are isolated from each other for reasons of good experimental control. If participants were able to “look over each others' shoulders” to see how others are solving the task, they might adopt their solutions, and cease to be an independent data point.

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In psychology, one researcher's confound is another researcher's object of study. We control variables because we expect them to exert a potentially large, contaminating influence on the topic under study. Psychologists may throw out the first 200 trials of a 2000 trial experiment because they want to observe stable performance, not performance affected by learning. Psychologists counterbalance the ordering of trials because of context, learning, and motivational effects. They run double-blind experiments to control for expectancies, goal-driven perception, and social influence. Of course, all of these experimental artifacts—context, learning, motivation, expectancies, motivated perception, and social influence—are also potent and important psychological phenomena deserving inquiry on their own.

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We believe that social learning is another such psychological phenomenon. By purposefully allowing participants to peer over their peers'

shoulders, allowing structured communication between participants trying to solve the same task, we can increase our understanding of how human learning often occurs.

p0025 As a species, humans are “obligatorily gregarious,” to use the zoo classification for species in which the individuals do not thrive unless they are living in a group of their own kind (Cacioppo & Patrick, 2008). We are typically surrounded by other people, and our degree of connectivity is rapidly increasing with the growing Internet, the increasing prevalence of mobile networked devices, and decreasing travel costs (Goldstone & Gureckis, 2009). As we try to solve problems in our everyday life, solutions from other people are readily at hand. This can be unfortunate when we are trying to form our own opinion about a movie, see an old television series without having its ending spoiled, or solve a difficult puzzle on our own without giving in to the sirens’ call of online solution sites. More often, though, we solve problems much better because we have access to others’ solutions.

p0030 A striking example of this is the speed with which software developers can now create highly sophisticated computer programs. The “open source software” community is committed to making software products, including the source code for the software, available to any interested party without restrictions (Lerner, Tirole, & Pathak, 2006). Due in part to this vibrant community, programmers now have a veritable smorgasbord of packages and libraries at their disposal when they are adding their own contributions to this collective repository. Previous software solutions are tweaked, adapted, and generalized to fit new needs, and developers frequently find it reinforcing, not aversive, when other developers use their solutions. Scientific progress in academic settings typically works in a similar fashion, with scientists benefiting tremendously from being in a community of other scientists who are making their methods, tools, analyses, theories, and experimental results available to others (Simon, 1957). In software development and science, not to mention music, art, sports, medicine, farming, and government, progress is radically expedited by innovators leveraging the work of others, learning from, and extending, previous solutions.

p0035 Outside of psychology experiment cubicles, learning typically takes place in a community of learners. Accordingly, we are interested in bringing back to the cubicles some of the essential elements of social learning. As experimental psychologists, we are loath to throw out the experimental control baby with the assumption of isolated learning bathwater. Our modus operandi has been to allow participants in laboratory experiments to

view each others' solutions and then to imitate and modify these solutions if they so choose. We do not allow participants to see or have open-ended conversations. Although these higher bandwidth channels of communication have produced important results (Ostrom, Gardener, & Walker, 1994), they are less amenable to the kind of computational modeling we develop in Section 3. Our participants have highly constrained communication possibilities. They can only view each others' solutions and the scores earned by those solutions. However, this minimal information exchange is still sufficient for creating emergent patterns of group convergence and collective coverage of a problem space that are commonly observed in real groups of interacting problem solvers.

s0015 **1.1. Parallel but Interactive Learning in Groups**

p0040 When we are solving problems, we are unlikely to be the only ones solving them. Common goals, skill sets, and motivations among the members of a group entail that people will typically be surrounded by people solving similar problems to themselves. This is true for other animals as well. Finding food, mates, and protection are problems shared by animals within the same group, and copying of solutions is frequently observed across many species (Hurley & Chater, 2005; Sumpter, 2010). The situation of learning along with others who are searching for good solutions to the same problems has unique but general group dynamic patterns that make it an important topic of study. One commonly observed group-level pattern is convergence, by which the members of a group adopt more similar solutions with passing rounds of solution exchange (Nowak, Szamrej, & Latané, 1990). For example, when members of a group can see the music selections made by others in the group, the entire group selects more similar music than when the members are not informed of each others' selections (Salganik, Dodds, & Watts, 2006; Salganik & Watts, 2009). A second pattern is that when people have only access to the solutions of their immediate neighbors, then spatially determined clusters of similar solutions arise (Latané & L'Herrou, 1996). A single region from within a larger group will often show substantial consensus in its members' solutions, but different regions may show striking diversity. These patterns of convergence and clustering, as well as others, will be explored in the experiments to be described.

p0045 The experiments described in this chapter focus on interactive, parallel problem-solving situations. By "parallel," we mean that each individual in the group is providing complete solutions to a problem, and that their rewards are based only on the quality of their own solutions. In other situations, the

members of a group coordinate such that the entire group generates a single solution to a problem (Kearns, Suri, & Montfort, 2006; Roberts & Goldstone, 2011). Both situations have real-world counterparts. Parallel problem solving is, perhaps, the more common situation, because it is implicated whenever individuals are self-interested and it is in their self-interest to imitate one another.

p0050 The “interactive” in “interactive, parallel problem solving” refers to the influence that problem solvers have on one another via the public nature of their solutions. For animals, the intentional signals or unintentional cues left by others can be used to find food and shelter (Sumpter, 2010). For companies, solutions are made publicly available when they are instantiated in commercially available products. For lobster harvesters in Maine, solutions to the problem of where to harvest to maximize one’s intake of lobsters are publicly available because of the presence of physical lobster traps (Acheson, 2003). For scientists, solutions are published in scholarly journals and presented at conferences, at which point the solutions may influence other scientists. A striking example of this last phenomenon is that estimates of physical constants in science tend to be inaccurate during early attempts to measure them. Subsequent attempts to measure the constants become more accurate, but they also tend to deviate systematically from the correct value in the direction of the earlier measurements (Henrion & Fischhoff, 1986). That is, new estimates of a physical constant tend to be distorted toward previous estimates. Historically, this pattern has been observed for the speed of light, Planck’s constant, the charge of an electron, the mass of an electron, and Avogadro’s number. In discussing systematic deviations in estimates of the charge of an electron, Feynman, Leighton, and Hutchings (1997) write, “Millikan measured the charge on an electron by an experiment with falling oil drops, and got an answer which we now know not to be quite right. It’s a little bit off because he had the incorrect value for the viscosity of air. It’s interesting to look at the history of measurements of the charge of an electron, after Millikan. If you plot them as a function of time, you find that one is a little bit bigger than Millikan’s, and the next one’s a little bit bigger than that, and the next one’s a little bit bigger than that, until finally they settle down to a number which is higher.” The fact that estimates of physical constants can be demonstrated to be influenced by previous estimates is noteworthy because each estimate is, in principle, being estimated solely on the basis of an experiment. Even when we use scientific methods and controls to shield ourselves from being influenced by others’ solutions, we cannot resist being influenced.

p0055 We cannot help being influenced by others because, in most situations, it is not the best policy to resist this influence. Social psychologists have historically stressed situations in which peer influences—from tacit learning to overt conformity—lead to impaired creativity (Kerr & Tindale, 2004), distorted judgments (Asch, 1956), or even dysfunctional actions (Milgram, 1974). However, in most cases, taking advantage of what others have discovered is a smart strategy. Imitating others' solutions is useful when people in a group tend to face similar challenges, when it is costly to explore a problem space on one's own, when the environment changes relatively slowly so that what was useful for one person will still probably be useful for another person, and when individual uncertainty is high (Boyd & Richerson, 1985, 2005).

s0020 **1.2. Bridging between Individual and Group Levels of Explanation**

p0060 We are interested in the consequences for the group when individuals learn to solve problems and know about each others' solutions. Accordingly, we do not follow the standard method used in social psychology of testing one participant in the company of experimenters' confederates who are scripted to respond in particular ways (Asch, 1956). Asch's method is well justified from the perspective of creating a well-controlled experimental environment for exploring factors affecting individual choices to imitate. However, the cost of constraining the judgments of all but one participant in a group is that the group dynamics of imitation cannot be revealed. The impact of individual imitation choices on the group's performance can best be discovered by allowing all participants in a decision-making task to be naturally and spontaneously influenced by one another. Understanding the group dynamics of imitation and innovation is one of the main goals of our study, and so we give all group members the opportunity to influence, and be influenced by, each other.

p0065 One result of our decision to let every group member influence every other group member is that the proper unit for our statistical analyses will be the group rather than the individual. Rather than trying to eliminate dependencies between individuals, we allow dependencies but then treat the entire set of interdependent components (e.g. participants in one experimental session) as the unit of analysis. This choice is based on a theoretical commitment that coherent group of people is often a highly useful level, even explanatorily indispensable, level of description (Goldstone & Ashpole, 2004; Theiner, Allen, & Goldstone, 2010). Understanding collective behavior requires theoretical constructs above the level of the individual. One

of the primary motivations for many agent-based models is to provide a theoretical bridge across different levels of description. Consider Schelling's (1971) classic "simulation studies" of segregation. Schelling created agents belonging to two classes (represented by dimes and pennies) that are reasonably tolerant of diversity and only move when they find themselves in a clear minority within their neighborhood, following a rule like "If fewer than 30% of my neighbors belong to my class, then I will move." Despite this overall tolerance, the agents still divide themselves into sharply segregated groups after a short time. What is surprising is that this occurs even though no individual in the system is motivated to live in such a highly segregated world. Although hardly a realistic model of migration, the model has been influential in contrasting group-level results (i.e. widespread segregation) and individual goals. If group-level constructs like segregation, wealth disparity, monetary flow, social network topology (Kennedy, 2009), and intellectual climate are eliminated, then many of the most surprising and useful theoretical claims for how individual-level incentives affect these constructs would no longer be possible. Not only would we miss out on truly bridging theories that show how individual behavior creates behaviors at a completely different level, but we would also lose much of our ability to predict and control social structures at scales that are meaningful for society.

p0070 Applying this moral to our experiment on social learning in groups, we will be explicitly interested in creating bridging explanation between explanations at the individual and group levels. One of our primary interests is in the consequences for the group as a whole when individuals engage in individual versus social learning. Many of the properties we measure at the group level are not even meaningful constructs at the individual level. These properties include the collective coverage of a problem space by the group, the diversity of solutions within a group, and the prevalence of reciprocal copying in which A copies B's solutions, tweaks them, and then B copies A back. The existence of these quantifiable properties at the group, but not individual, level helps to warrant the belief that multiple levels of organization must be posited for explanatory and predictive validity.

s0025 **1.3. Exploration and Exploitation**

p0075 One of the most important bridges between individual and group behaviors concerns individuals' chosen positions along an exploration-exploitation trade-off (Hills, Todd, & Goldstone, 2010; Roberts & Goldstone, 2006). Exploratory behavior introduces new solutions by searching in hitherto unknown regions of a problem space. It tends to be high risk because

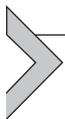
of the uncertainty about payoffs in unknown regions (Boyd & Richerson, 2005), but engaging in exploration can also have favorable long-term payoffs if the agent can take advantage of discovered bountiful resources for a prolonged period after the initial exploration (Sang, Todd, & Goldstone, 2011). Exploitation behavior involves taking advantage of solutions previously found, either by oneself or others. Rather than viewing exploration and exploitation as opposed to one another, they should be seen as reinforcing. The value of exploration is amplified exactly because the fruits of exploration are subsequently exploitable. In situations where there are few opportunities for subsequent exploitation, exploration is rarely a sound strategy. If there is only one chance remaining to harvest resources, exploration is usually a poor choice because there will not be any future opportunities to exploit what has been found. Exploitation is what makes exploration valuable.

p0080 Individual decisions to explore or exploit have powerful influences on the group's performance, and not always in a straightforward fashion. Exploiting the solutions of others through imitation is useful to the group because it allows effective innovations to spread. However, it can also reduce the group's overall ability to fully cover the range of potential solutions or options. As an example, of this reduced potential, Salganik and Watts (2009; Salganik, et al. 2006) allowed participants to download music from a site, sometimes with knowledge about the downloads made by their peers. By assembling participants into independent groups, they were able to measure whether separate "re-runnings of history" would have produced the same most popular songs, or whether different songs would arise as most popular because of rich-get-richer dynamics operating on initially haphazard choices. In fact, when participants had information about each others' download choices, then relatively imbalanced patterns of downloading arose, and some songs were downloaded far more often than others. For different groups, very different sets of songs became popular. The inequitable pattern of downloads compromised the groups' ability to collectively sample the full range of possible music. This is a classic example of choice copying reducing group performance by restricting the injection of new options. Other research has shown that early decision makers can have an undue influence on the group's behavior when subsequent decision makers are influenced by their own judgments as well as their predecessors' judgments (Bikhchandani, Hirshleifer, & Welch, 1992). Bettencourt (2009) formally models the importance of having sufficient independence among judges if the benefits of synergistic aggregation are to be achieved.

p0085 Individual decisions to explore bring in their own hazards for group performance. Exploration does inject new innovations from which the group can subsequently choose. However, the innovations come at the cost of underutilization and transmission of good solutions already at hand. If all members of a community are continually exploring new possibilities rather than taking advantage of existing solutions, then previous generations' solutions may be practically forgotten by newer generations. In the extreme, exploration without exploitation can halt the "cultural ratchet" that has been implicated in humans' unique ability to create lasting and improving cultural products (Tomasello, Kruger, & Ratner, 1993). This risk is not merely theoretical. Researchers have documented the collective forgetting of knowledge that would be useful for a community, such as an understanding of complex interactions among biological species in an ecosystem (Wolff, Medin, & Pankratz, 1999). Specific cultures, such as the Itza' Maya of Guatemala, have acquired over centuries knowledge of their natural world that is rapidly being left behind despite its continued relevance (Atran, Medin, & Ross, 2004).

p0090 Given the tradeoffs and interactions between exploration and exploitation, there will be no general solutions to the question of what percentage of one's time should be spent exploring versus exploiting. The answer to this question will depend on one's social orientation (whether one is seeking an optimal individual or group outcome), how many opportunities to seek solutions still remain, the complexity of the problem space, the density of one's social network, and the decisions that others are making to explore versus exploit.

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2. INNOVATION PROPAGATION IN A ONE-DIMENSIONAL PROBLEM SPACE

p0095 In social psychology, there has been a long and robust literature on conformity in groups (Cialdini & Goldstein, 2004; Sherif, 1935). The usual finding is that people conform to majorities in groups. To some degree, conformity is found because people desire to obtain social approval from others. For example, sometimes when people give their answers privately, they are less likely to conform to the group's opinion than when responding publicly (Deutsch & Gerard, 1955). However, at other times, the conformity runs deeper than this, and people continue to conform to the group's opinion even privately (Sherif, 1935). In our experiments and modeling, we are interested in the use of information provided by others even when social

approval motivations are minimized because the group members never meet one another and are anonymous.

p0100 Conformity to others' ideas has been a major field of research not only in social psychology but also in economics, political science, and sociology. It is common in models of collective action to make an individual's decision to participate based upon their expectations for how many other people will participate (Chwe, 1999). A common outcome of a collective "I'll do it if you do it" mentality is for "tipping points" to arise in which adding more participants to an action leads to a positive feedback cycle in which still more participants sign on, leading to an exponential increase in participation for a time (Gladwell, 2000). This behavior is a sensible policy both because the likelihood of success of an innovation depends upon its public adoption rate (Bullheimer, Dawid, & Zeller, 1998) and because other people may have privileged information unavailable to the individual making a choice. The potential cost of this bandwagon behavior is wasted time, money, and effort in adopting new innovations when existing solutions are as good or better. Furthermore, bandwagons entail redundant convergence on a single solution rather than continued broad search of a problem space (Rosenkopf & Abrahamson, 1999; Strang & Macy, 2001).

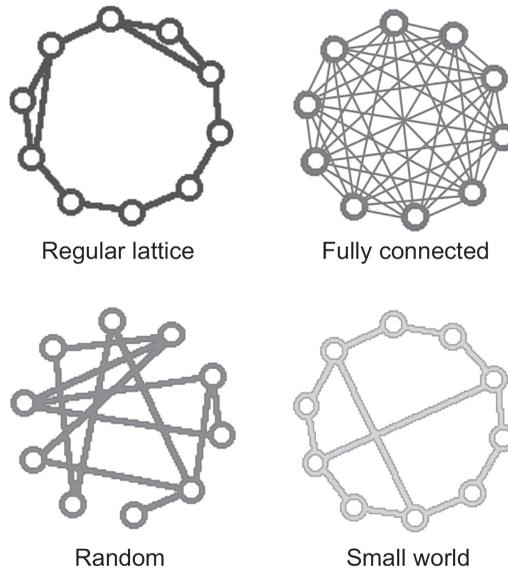
p0105 Our studies explore the diffusion of innovative ideas among a group of participants, each of whom is trying to individually find the best solution that they can to a search problem. The work fills an important gap in research. There are several promising computational models for how agents in a population exchange information (Axelrod, 1997; Kennedy & Eberhart, 2001; Nowak *et al.*, 1990). There is also excellent work in social psychology on how individuals conform or use information provided by others (Gigone & Hastie, 1996). Fieldwork also explores actual small groups of people engaged in cooperative problem solving (Arrow, McGrath, & Berdahl, 2000). However, there is very little work with laboratory-controlled conditions that explores the dynamics of a group of participants solving problems as they exchange information. One related study is Latané and L'Herrou's (1996) exploration of participants' sending e-mail messages to each other (Latané & Bourgeois, 1996) as they tried to predict which of two options their group would select. Over the course of message exchanges, neighboring participants in the network tended to adopt similar choices (consolidation), but there was also continued diversity of choices across the entire network. In contrast to this work, our research predominantly focuses on situations where participants are trying to find good solutions to a problem rather than trying to conform to their neighbors.

For example, farmers may discuss the benefits of various crop rotation techniques with their neighbors, and may be convinced to try a new one by a neighbor's success, but there is no reward to conforming to a neighbor's behavior in itself. Other research in this area has recently appeared (Lorenz, Rauhut, Schweitzer, & Helbing, 2011; Mason & Watts, 2011), and is likely to expand, given its relevance to parallel, independent collective search processes in businesses, the internet, and elsewhere.

s0035 **2.1. An Experimental Examination of Connectedness and Fitness Functions**

p0110 In creating an experimental paradigm for studying information dissemination, our desiderata were (1) a problem to solve with answers that vary continuously on a quantitative measure of quality, (2) a problem search space that is sufficiently large that no individual can cover it all in a reasonable amount of time, and (3) simple communications between participants that are amenable to computational modeling. We settled on a minimal search task in which participants guess numbers between 0 and 100 and the computer reveals to them how many points were obtained from the guess by consulting a hidden fitness function (Mason, Jones, & Goldstone, 2008). Additionally, random noise was added to the points earned, so that repeated sampling was necessary to accurately determine the underlying function relating guesses to scores. Over 15 rounds of guesses, participants try to maximize their earned points. Importantly, participants get feedback not only on how well their own guess fared but also on their neighbors' guesses. In this manner, participants can choose to imitate high-scoring guesses from their neighbors. We experimentally manipulated the network topology that determines who counts as neighbors, as well as the fitness function that converts guesses to earned points.

p0115 We created neighborhoods of participants according to random, regular lattice, fully connected, and small-world graphs. Examples of the graph topologies for groups of 10 participants are shown in Figure 1.1. In the random graph, connections are randomly created under the constraint that the resulting graph is connected—there is a path from every individual to every other individual. Random graphs have the property that individuals tend to be connected to other individuals via paths that do not require passing through many other individuals. This property has been popularized as the notion of “six degrees of separation” connecting any two people in the world, and has been experimentally supported (Dodds, Muhamad, & Watts, 2003; Milgram, 1967). More formally, the average path length connecting two



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Figure 1.1 Examples of the different network structures for groups of 10 participants from the experiment on collective search in a one-dimensional problem space (Mason *et al.*, 2008). Circles represent participants and lines indicate communication channels. For color version of this figure, the reader is referred to the online version of this book.

randomly selected nodes in a random graph is $\ln(N)/\ln(K)$, where N is the number of nodes and K is the average number of neighbors connected to each node. The regular lattice can be used to represent a group with an inherent spatial ordering such that people are connected to each other if and only if they are close to one other. The regular lattice also captures the notion of social “cliques” in that if there is no short path from A to Z , then there will be no direct connection from any of A ’s neighbors to any of Z ’s neighbors. In regular lattices, the average path required to connect two individuals requires going through $N/2K$ other individuals. Thus, the paths connecting people are much longer, on average, for lattice than random graphs.

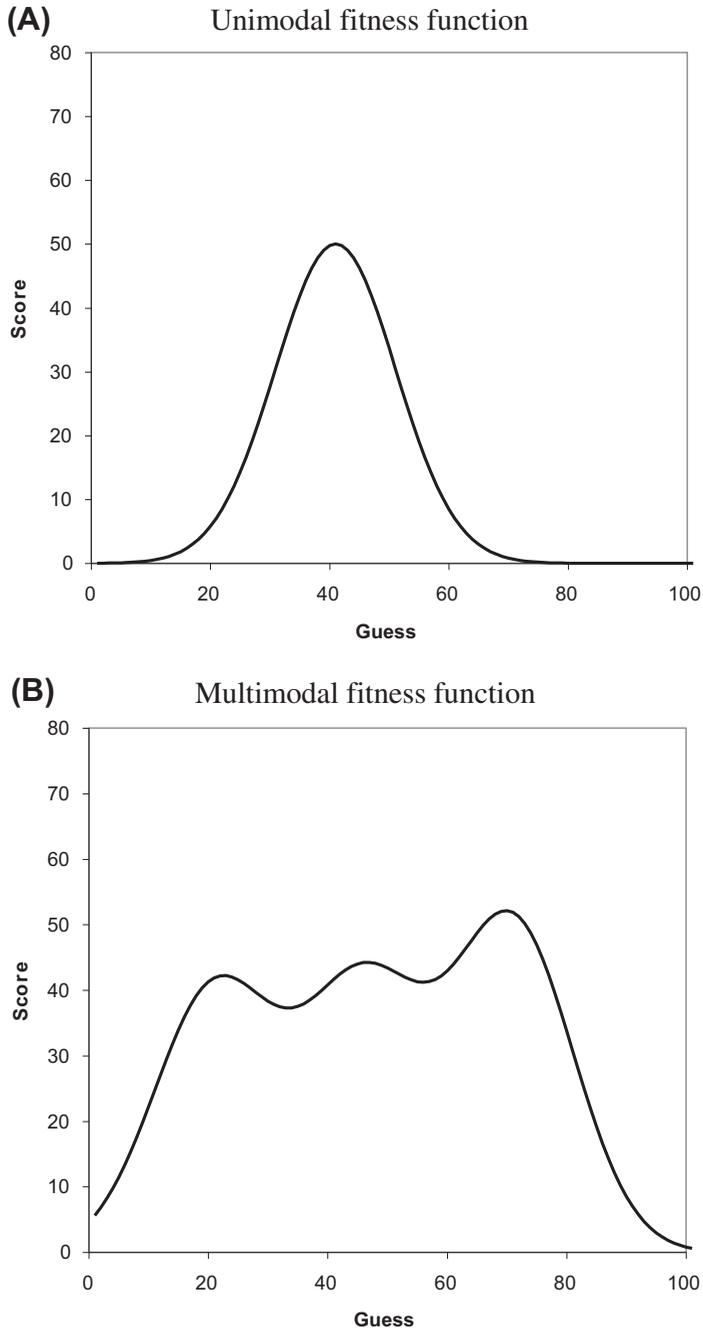
p0120 Random graphs have short paths, but unfortunately (from the perspective of realistic modeling of social phenomena) do not contain cliques. Lattices show cliques, but do not have short path lengths. Recently, considerable interest has been generated in networks that have both desirable properties, the so-called “small-world networks.” These networks can be formed by starting with a lattice and randomly rewiring (or adding new connections, in the case of our experiments and Figure 1.1) a small

number of connections (Watts & Strogatz, 1998). The result is a graph that still has cliques because nodes that are connected to the same node tend to be spatially close themselves, yet also have a short average path length. From an information processing perspective, these are attractive networks because the spatial structure of the networks allows information search to proceed systematically, and the short-cut paths allow the search to proceed quickly (Kleinberg, 2000). Notice, in Figure 1.1, that all three of the described networks have a total of 12 connections between 10 participants. Thus, if there is a difference in information dissemination in these networks, then it must be due to the topology, not density, of the connections. A fourth network, a fully connected graph, allowed every participant to see the guesses and outcomes of every other participant.

p0125 We compared two hidden functions for converting guessed numbers to points. The unimodal function has a single best solution that can always be eventually found with a hill-climbing method (Figure 1.2a). The trimodal function (Figure 1.2b) increased the difficulty of the search by introducing local maxima. A local maximum is a solution that is better than all of its immediate neighboring solutions, yet is not the best solution possible. Thus, a simple hill-climbing search might not find the best possible solution.

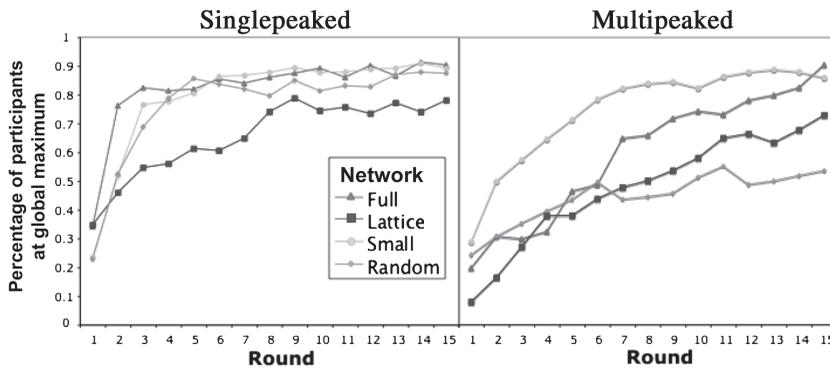
p0130 Twelve groups of Indiana University undergraduate students ranging in size from 7 to 18 people with a median of 14 people per group participated for partial course credit, for a total of 153 participants. Each group participated in eight experiments that consisted of every combination of the four network types (Figure 1.2) and two fitness functions (Figure 1.2). Participants were told to try to maximize their total number of points acquired over 15 rounds of number guessing, and that the same guess would be worth about the same number of points from round to round, but that a certain amount of randomness was added to the earned points. Participants were also told that they would see the guesses and points earned by some of the other participants, and that these others would also see the participants' guesses and earnings.

p0135 The results from this experiment are shown in Figure 1.3, expressed in terms of the percentage of participants within one-half standard deviation of the global maximum for a fitness function (similar results are found if "total points" is used as a dependent measure). Over the 15 rounds, increasingly many participants find the global maximum. For the unimodal function, the fully connected network finds the global maximum most quickly, and the advantage of the fully connected network over the other three networks is particularly striking for Rounds 2–4. Around Round 5, the



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Figure 1.2 Examples of the unimodal and multimodal fitness functions that convert guesses into obtained points.



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Figure 1.3 Percentage of participants within one standard deviation of the global maximum on each round for the unimodal and multimodal payout functions. For color version of this figure, the reader is referred to the online version of this book.

small-world network catches up to the performance level of the fully connected network, and for the rest of the rounds, these two network types continue to outperform the other two networks. This pattern of results is readily explainable in terms of the propensity of a network to disseminate innovations quickly. Innovations disseminate most quickly in the full network because every individual is informationally connected to every other individual.

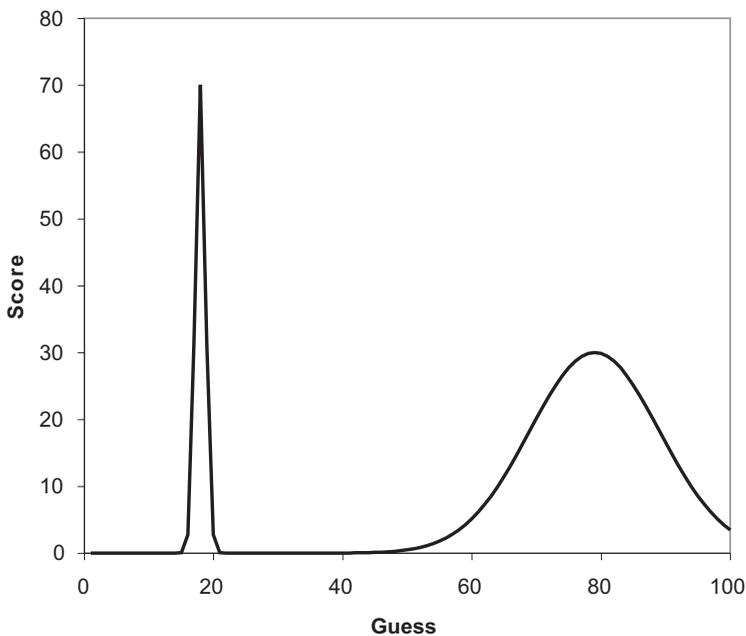
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For the multimodal payout function, the small-world network performs better than the fully connected network for the first six rounds. One account for its superiority over the full network is that the small-world network is able to thoroughly search the problem space. The fully connected groups frequently get stuck in local maxima because the groups prematurely converge on a good, but not great, solution. The small-world structure is an effective compromise between fully exploring a search space and also quickly disseminating good solutions once they are found. The most surprising aspect of these results is that the truism of “the more information, the better” is not supported. Giving each participant all of the results from all of the agents does not lead to the best group solution for the multimodal problem—the downside of this policy is that with the fully connected network, everybody ends up knowing the same information. Participants thereby become too like minded, acting like a single explorer, rather than a federation of independent explorers.

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The general point from this first experiment is that before one decides how to connect a group, one should know about the nature of the problem the group needs to solve. A candidate generalization is that the more

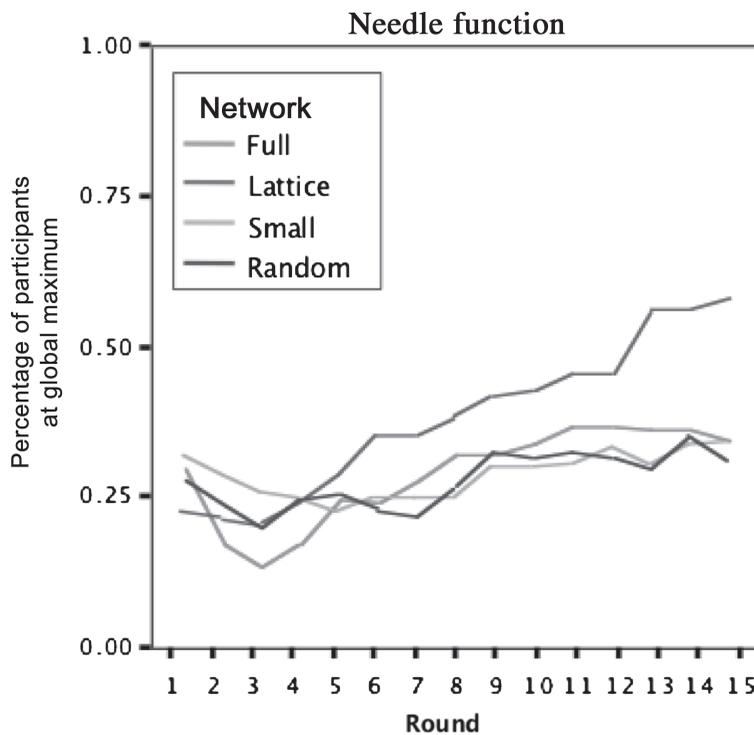
exploration a group needs to do, the more clustered and locally connected the network should be. Conversely, the more quickly a group needs to exploit emerging solutions, the more globally connected individuals should be. Problem spaces that require considerable exploration to find the global maximum should benefit from networks that have relatively well-isolated neighborhoods that can explore different regions of a problem space. To test this hypothesis, in a separate experiment, we tested the more difficult fitness function shown in Figure 1.4, which we call the needle function because of the thin and high global maximum and because finding this global maximum is a bit like finding a needle in a haystack. This function features one very broad local maximum, and one hard-to-find global maximum. We tested 12 groups of participants in needle functions like Figure 1.4, with each group connected in the same four network topologies we used before. For this function, Figure 1.5 shows that the lattice network performed better than the other three network types, starting by Round 7, if not earlier. The lattice network fosters the most exploration because of its spatially segregated



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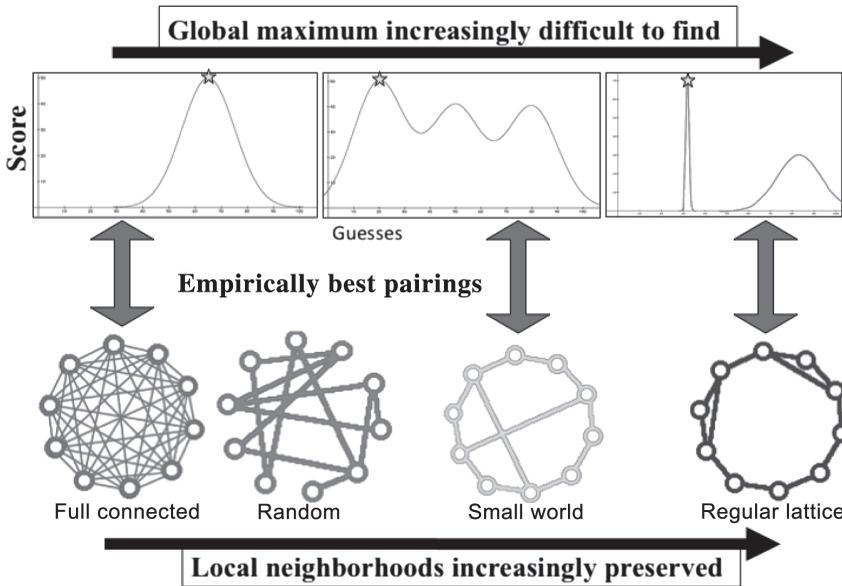
Figure 1.4 An example of the “needle” payout function. This function features one broad local maximum that is easy to find and one narrow global maximum that is difficult to find.

network neighborhoods. Exploration of the problem space is exactly what is needed for the needle function because of its hard-to-find global maximum. p0150 The three payout functions are ordered by the demands they place on broad exploration of a problem space. The benefit for exploration increases going from the unimodal to the multimodal to the needle function. In parallel, the network structures are ordered by their preservation of local cliques of nodes. Cliquishness increases going from full to small world to lattice networks. These two progressions are coordinated, as is shown in Figure 1.6, with both progressions going from the left to the right. The full network performs best with the unimodal function, the small-world network performs best with the multimodal function, and the lattice performs best with the needle function. In contrast to arguments for a general informational advantage of small-world networks (Watts & Strogatz, 1998), we find that what network is best depends on the kind of problem a group



f0030

Figure 1.5 Performance for the four network structures with the needle payout function. For this function, the lattice network performs better than the other three network types. For color version of this figure, the reader is referred to the online version of this book.



f0035

Figure 1.6 A summary of the empirical relationship between the difficulty of a problem search and the best-performing social network. As it becomes increasingly difficult to find the global maximum in a problem space (indicated by stars), the best-performing network has increasingly preserved local neighbors. Long-range connections are good for rapid diffusion of optimal solutions once they have been found, but risk premature convergence of the entire network onto good, but not optimal, solutions. For color version of this figure, the reader is referred to the online version of this book.

must solve (Lazer & Friedman, 2005). As broader exploration is needed to discover good solutions, increasingly cliquish networks are desirable.

s0040 **2.2. A Computational Model of Innovation Propagation**

p0155 We have developed an agent-based computational model of our experiments based on the premise that members of a group can choose to explore a problem space on their own or take advantage of the solutions found by others. In the model, called SSEC (for Self-, Social-, and Exploration-based Choices), every agent on every round probabilistically chooses between three strategies: using their own guess on the last round, using their neighbors' best guess on the last round, and randomly exploring. Each agent randomly chooses between these strategies, with the likelihood of each strategy based on its intrinsic bias and also its observed success. The model, thus, can be expressed as

$$p(C_x) = \frac{B_x S_x}{\sum_n B_n S_n},$$

where $p(C_x)$ is the probability of using Strategy x , B_x is the bias associated with the strategy, and S_x is the score obtained from the strategy. The participant's guess is then $G_x + N(\mu = 1, \sigma = 1)$, including normally distributed randomness to avoid perfect imitation, with G_x being the guess associated with Strategy x . When the random exploration strategy is selected, a uniform distribution is used to select the next guess. This model is motivated by the Particle Swarm Algorithm (Kennedy, Eberhart, & Shi, 2001). However, unlike the swarm algorithm, the SSEC model allows sudden jumps in guesses rather than smoothly changing patterns of oscillations around promising solutions. The experimental results showed that participants frequently jumped from one guess to a completely different guess, a behavior that the original Particle Swarm Algorithm does not accommodate.

p0160 The simplest version of this model, with mostly default parameter values for the biases, was able to accommodate some, if not all, of the trends in the results. In particular, we tested a version of the model in which B_1 (the bias for using one's own previous guess) is 1, B_2 (the bias for using one's neighbor's best-scoring guess) is 1, and B_3 (the bias for randomly exploring) is 0.1. This is essentially a one-parameter control of biases because B_1 and B_2 were constrained to be equal, and only the relative, not absolute value of B_3 matters given the choice model used to determine strategy choice. In addition, the value of σ that determines the mutation/drift rate for guesses was set to 3, and noise with a variance of 30 and a mean of 0 was added to the fitness function's output, just as it was to experimental scores. Each of the four network types was run 1000 times with each of the three fitness functions for 15 rounds of guessing and 15 agents per group. In this model, fully networked groups were best for the unimodal function, small-world groups were best for the small-world network, and latticed groups were best on the needle function. The model predictions are shown in Figure 1.7, and can be compared to the human results in Figure 1.3. The fit is not perfect, but even with no parameters optimized for fit to the human data, roughly similar trends are found for both the model and humans.

p0165 Given the promising results of this original set of simulations, we parametrically manipulated the network connectivity to continuously shift from a regular lattice with only local connectivity to a fully connected network in which every agent is directly connected to every other agent. This was achieved by connecting 15 agents via a lattice, and then adding a number of additional random connections between agents. As the number of random connections increases, the network initially transforms from a random network to a small-world network. Then, as the connectivity further increases,

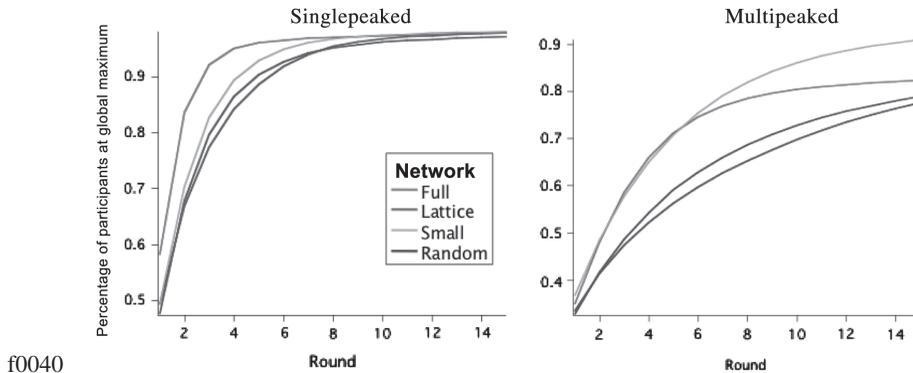


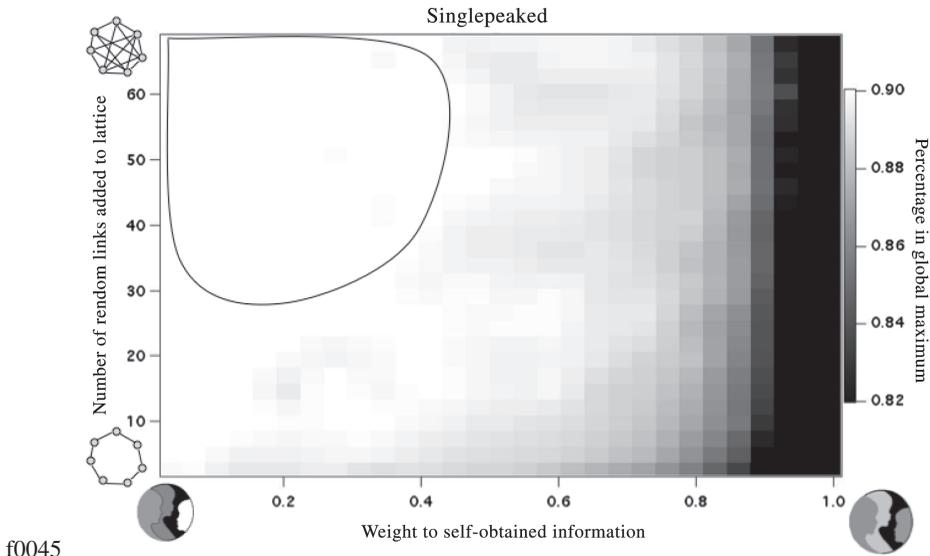
Figure 1.7 Simulations results for the SSEC model when given the single-peaked and mullepeaked fitness functions. For color version of this figure, the reader is referred to the online version of this book.

the network transforms from a small-world network to a fully connected network. If more information communicated in a network always increases group performance, then we expect better performance (shown by brightness in Figures 1.8–1.10) as connectivity increases.

Independently, we manipulated the relative weight given to information obtained from oneself compared to others. Keeping B_3 constant at 0.1, we varied B_1 from 0 to 1 and set B_2 equal to $(1-B_1)$. Thus, we varied the degree to which each agent’s guesses are based on their own previous guess compared to others’ guesses. In Figures 1.8–1.10, as we go from the left to the right, we go from “sheepish” agents that base their guesses completely on others’ guesses (and an occasional random guess) to “mavericks” that always continue using their own solutions without any influence of others.

Figures 1.8–1.10 show that the influences of connectivity and agent independence are not constant, but rather depend on the shape of the problem space. For the easy-to-solve unimodal problem, Figure 1.8 shows that group performance increases monotonically with both increased reliance on others’ information and increased connectivity. Both trends can be explained by the fast propagation of innovations obtained when agents follow their best peers, and have many peers to follow. For single-peaked problems, there are no local maxima and so no concern with hasty collective convergence on suboptimal solutions.

For the three-peaked function (Figure 1.9), optimal group performance involves intermediate levels of both connectivity and self-reliance. These two factors trade-off with one another such that increases in connectivity can be offset by decreases in conformity. Networks that have only local

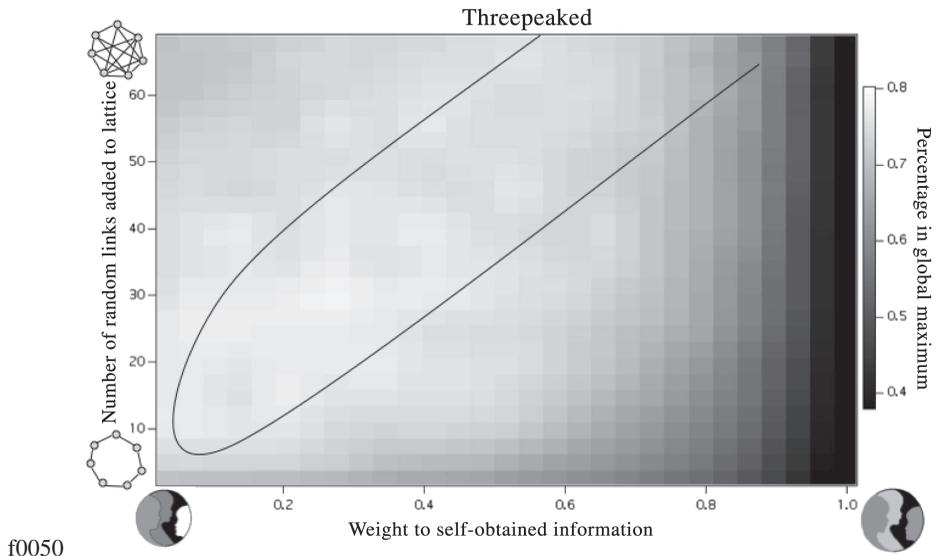


f0045

Figure 1.8 Group performance for the single-peaked function. This graph shows the interaction between the bias for self- versus other-obtained information and the number of random links added to a regular lattice. Group performance is measured by the percentage of individuals within one standard deviation of the global maximum of the fitness function. The brightness of each square indicates the group’s performance after 15 rounds of number guessing. The area of the parameter space that produces the best performance is outlined in black. For this simple problem space, group performance increases monotonically with increased reliance on others’ information and network connectivity. For color version of this figure, the reader is referred to the online version of this book.

connectivity and self-reliant individuals perform relatively poorly because good solutions are inefficiently spread. Conversely, networks that have global connectivity and conformist individuals also perform poorly because the group frequently converges on local rather than global maxima. Good group performance is found when a group can both search a problem space for good solutions, and yet spread those solutions quickly once they are found. This is achieved when conformist individuals communicate over a sparsely connected network, or when self-reliant individuals communicate over a more broadly connected network. If one is able to engineer a social network, then one’s target network should depend on both the problem and “personalities” (mavericks vs. sheep) of the nodes in the network.

p0185 For the trickier needle function (Figure 1.10), the best-performing networks are pushed even further in the direction of increasing self-reliance and decreasing connectivity. Consistent with our empirical results, the



f0050

Figure 1.9 Group performance for the multimodal function. The best performance is found for a combination of using self- and other-obtained information, and for intermediate levels of network connectivity. As the degree of connectivity increases, best group performance is achieved by decreasing reliance on others' guesses. For color version of this figure, the reader is referred to the online version of this book.

needle function requires more exploration, and both limiting connectivity and increasing self-reliance promote independent exploration of group members. As with the three-peaked function, there is a trade-off between network connectivity and individual self-reliance.

p0190 A major conclusion from both the experiments and modeling is that propagating more information is not always good for the group. Full access to what everybody else in a group is doing can lead human and computational agents to prematurely converge on suboptimal local maxima (Lazer & Friedman, 2005). Networks that preserve spatial neighborhoods promote exploration, and this can explain why the full network is the best network for the single-peaked function, the small-world network and its intermediate level of connectivity does best with the three-peaked function, and the lattice function with no long-range connections does best with the difficult needle function.

p0195 Although more information is not always better as far as the group goes, it is always in the best interest of individuals to use all the information at their disposal. Accordingly, our innovation propagation paradigm provides an unexpected example of a social dilemma (Goldstone & Janssen, 2005; Ostrom *et al.*, 1994). Individuals, looking out for their own self-interest, will

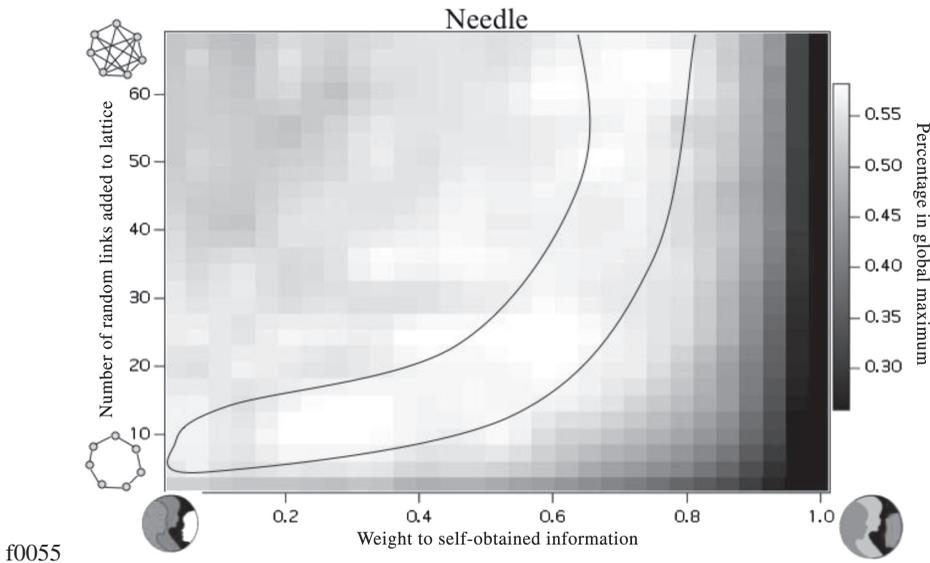


Figure 1.10 Group performance for the needle function. This function benefits from even greater reliance on self-obtained information and decreased global network connectivity, as shown by rightward and downward displacement of the best-performing ridge of the parameter space. For color version of this figure, the reader is referred to the online version of this book.

seek out as much information from others as possible, but this can inhibit the group as a whole from widely exploring a search space. Thus, in the present situation, obtaining information from as many peers as possible is noncooperative behavior even though it involves conformity. Searching a problem space on one's own is cooperative in the sense of allowing the group as a whole to collect the most points possible, by avoiding local maxima. Our simulations show that every individual agent is best off linking to as many other people as possible. Agents with relatively many links outperform those with relatively few links. However, if every agent links maximally to every other agent, then the entire group does not perform well due to premature convergence on good, but not optimal, solutions. Sensitivity to this conflict between individual and group interests may help in the design of adaptive social networks. Designing for the greater common good may sometimes entail placing limits on individuals' ability to connect with each other. Problems with difficult, hard-to-find solutions often drive people to look to others for hints and clues, but these are exactly the kinds of problems for which limited, local connectivity is advantageous.

p0200 This analysis of the conflict between the good of the individual and group becomes particularly relevant when we turn to situations where people can choose their connectivity, rather than having it imposed. Pursuing experimental paradigms in which people can create their own social networks would be valuable as connecting with both the mathematical literature on the evolution of networks (Dorogovtsev & Mendes, 2003) and the social science literature on coalition formation (Kahan & Rapoport, 1984). In many naturally occurring groups, people have some choice in who they will share information with, and what information they will reveal. From our perspective on human groups as complex systems, one of the interesting issues will be to study the global efficiency of information transmission in self-organized networks, and how incentives to individuals can be structured so that globally advantageous networks emerge.

s0045



3. COLLECTIVE LEARNING IN HIGHER-DIMENSIONAL PROBLEM SPACES

p0205 One dissatisfaction with the initial experimental paradigm is that the problem space is not particularly complex. For some fitness functions in the first experiment, it was difficult for participants to discover the global maximum, but this was due to the limited number of guessing rounds and the narrow basin of attraction for the global maximum. The second experiment was designed to provide a better experimental analog to a collective search situation in which members of a community are generating novel innovations to a relatively open-ended problem. Scientists coming up with new experimental paradigms, sports teams coming up with new plays, and artists coming up with new styles are all engaged in a search for innovations with a problem space that is impossible for a single individual to cover by themselves over a realistic time period. We chose an experimental paradigm most closely resembling the last of these situations, in which participants see drawings created by others as they create their own (Wisdom & Goldstone, 2011). Unlike a community of artists, we incorporated a simple, objective measure of the quality of drawings, so that we could inform participants of the quality of each others' solution. Unlike the first experiment, we only incorporated a fully connected network in which every participant could see every other solution on every round. The fully connected network seems like a natural, minimally assumptive default network, and offers the greatest potential influence of others on one's own decisions.

p0210 Using this paradigm, we were interested in describing individuals' strategies for imitating and innovating, and the consequences of these strategies for the group as a whole. For example, in the relatively constrained problem space of the first experiment, we found a tension between individual and group outcomes, with imitation being good for the individual but bad for the group. If this is replicated in the current experiment, it will suggest some generality to the social dilemma of innovation. If not, it will suggest a relation between the nature of a problem space and the existence of social dilemmas.

p0215 More generally, the collective drawing task allows us to observe participants' strategies for innovating and imitating. There are possible strategies related both to *which* participants' drawing to imitate and *when* to imitate (Laland, 2004). We might expect for participants to imitate other drawings that are scoring well, and that are scoring better than their own drawings (Rendell et al., 2010). It is also possible that drawings will be imitated that are already relatively similar to an imitator's current drawing, if the imitator finds it difficult or risky to blend potentially incompatible solutions. Participants might be expected to imitate more at the beginning of a set of rounds, when their uncertainty is the greatest, when their scores are relatively poor, and when there is a diverse range of possible solutions (Galef & Laland, 2005).

s0050 **3.1. The "Draw the Mystery Picture" Task**

p0220 With these predictions in mind, 145 participants were distributed into 39 groups ranging in sizes from 1 to 9. The participants' task was a round-based picture-matching puzzle game with score feedback given after each round. The goal picture that participants attempted to match was a randomly generated spline quantized to a grid of square pixels. The participants' game board was a grid of the same dimensions as the goal picture, with each square initially colored white. The color of each square on the game board could be toggled between black and white by clicking it with the mouse. Each participant's display included their own game board and the most recent score (given as the number of squares, both black and white, marked correctly out of the total number of squares on the board), their neighbors' game boards and scores, and indications of the current round in the game and the amount of time remaining in the current round (Figure 1.11). Players could copy a neighbor's most recent solution to their own at any time during the game by clicking the chosen neighbor's board with the mouse. Each game consisted of 24 rounds of 10 s each. After the last round in each

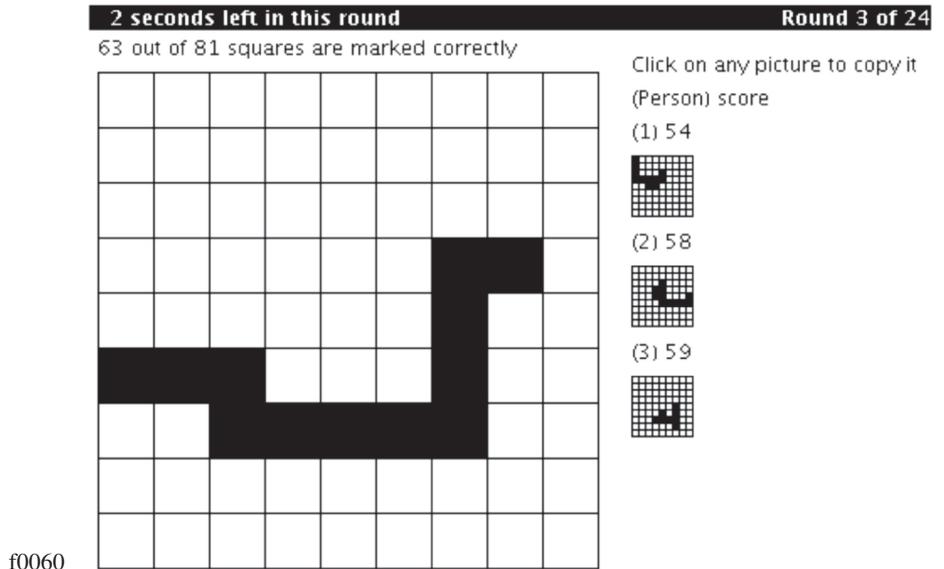


Figure 1.11 Screenshot of a participant's display in experiment 2. The participant's own created picture is the large image to the left. All other participants' pictures from the previous round, and the scores earned by these pictures, are shown to the right.

game, participants were shown their guesses and scores for each round, along with the goal picture, and a button to click when they were ready to begin the next condition. Participants were instructed to maximize their scores over all rounds by matching the hidden goal picture as closely as possible.

p0225 A participant's *score* in each round was defined as a cell-by-cell comparison (overlap) between the participant's guess for that round and the hidden goal picture (i.e. the number of cells which the two pictures had in common), divided by the total number of squares in the goal picture, to give a percentage that could be compared between conditions of varying grid size (Figure 1.12). This same overlap measure was used to determine the similarity between two different drawings. An *improvement* was defined as an instance of a participant obtaining a score higher than all prior scores of all players within a particular condition. *Turnover* for each round (after the first) was a measure of the amount of change between a participant's guesses over successive rounds. It was defined conversely to similarity, except that the two pictures compared were the participant's guesses from the current and previous round. A participant was regarded to be imitating another participant in a particular round if the participant's guess was closer to the most similar neighbor's previous guess than to the participant's own previous

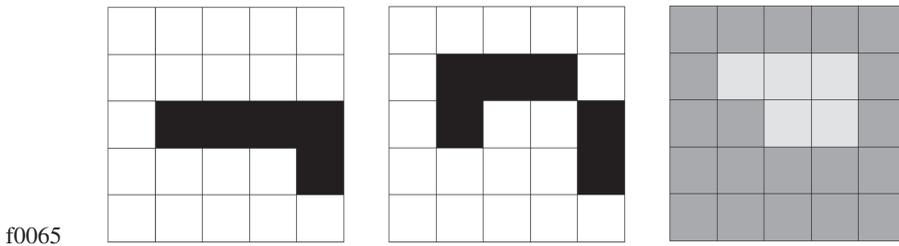


Figure 1.12 Determination of the similarity of two solutions. The left and middle pictures have the same black/white state for 20 out of 25 squares, shown in dark gray on the rightmost image, and so they have a similarity of 80%.

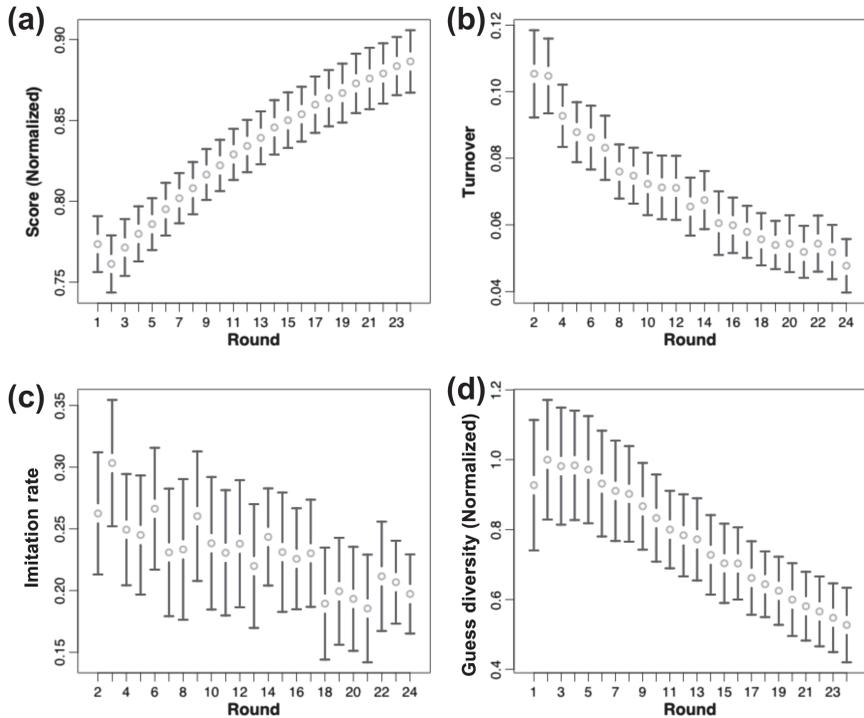
guess. *Diversity* (a measure of the spread of group members' guesses over the problem space within a particular round) was defined as follows:

$$D_r = 1 - \frac{\sum_s \sum_p \text{majority}(G_{spr})}{S_{\text{tot}} P_{\text{tot}}},$$

where G_{spr} is the binary value (black or white) of square s in the guess of participant p in round r , S_{tot} is the total number of squares in the game board, P_{tot} is the total number of participants in the group, and *majority* is a binary function that conveys whether the value of G_{spr} is in agreement with the majority of participants in the group for that square in that round (0 = not in majority, 1 = in majority). Diversity as defined above is constrained to be within the 0–1 range, and higher values of diversity indicate more deviation of individuals' guesses from the majority guesses.

s0055 3.2. Major Results and Implications

p0230 Overall, the average guess turnover rate per round was 7.3% of the game board, and participants engaged in imitation on 25.8% of guesses. In the aggregate, participants achieved final scores that had 89.3% agreement with the best score. Scores reliably improved with passing rounds. Turnover rate, guess diversity, and imitation rate all decreased with passing rounds, as participants converged on better drawings. All these effects are shown in Figure 1.13. In addition to these effects, increasing group size was associated with higher individual performance as well as higher imitation rate, presumably because more peers offered participants more options for imitation. Nearly all instances of imitation were of those with higher scores than the imitator's, implying that, like other animal species (Templeton & Giraldeau, 1996), people are biased toward



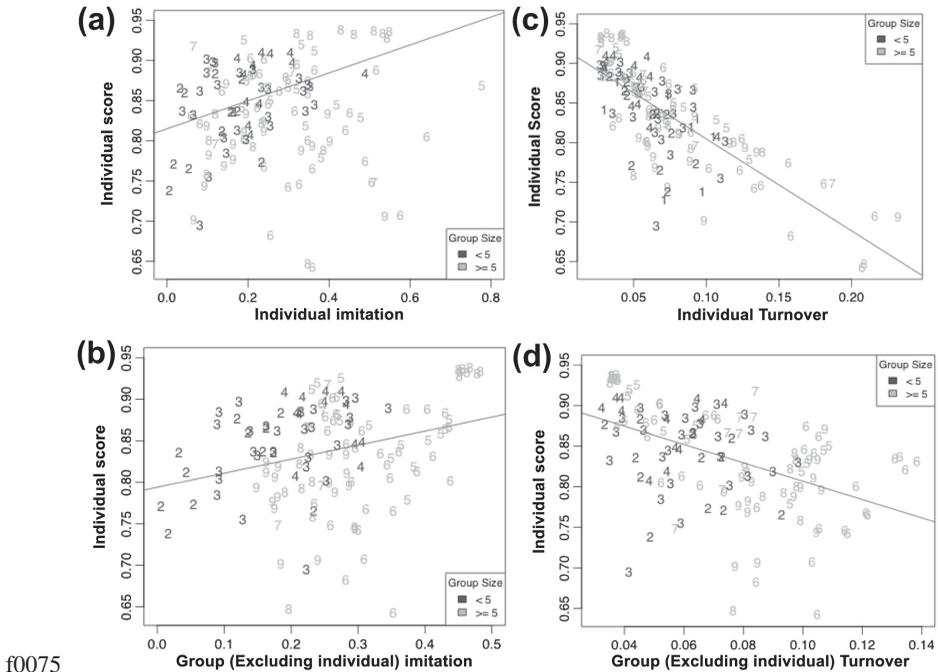
f0070

Figure 1.13 Results from experiment 2: (a) mean score increased, while (b) turnover, (c) imitation rate, and (d) guess diversity decreased as more rounds were played within a game. For color version of this figure, the reader is referred to the online version of this book.

imitating better-performing peers. The bias toward imitating the best-scoring peer was sizeable for small groups, but less pronounced for large groups, probably because participants were informationally overloaded by too many options.

p0235

To further investigate the relationship between strategy and performance, we performed regression analyses of score versus mean rates of imitation and turnover for individuals and groups. A linear regression of mean individual score versus mean individual imitation rate showed a significant positive relationship for individuals in group sizes of ≤ 4 , but none in groups of ≥ 5 (Figure 1.14a). Figure 1.14b shows that across all group sizes, there was a significant positive relationship between an individual's score and the mean imitation rate of all other group members, excluding the individual. That is, regardless of what an individual did, she/he was likely to have a higher score if the others in her/his group imitated more often. Figure 1.14c and d show a strong negative relationship between score and mean turnover. As one's



f0075

Figure 1.14 Results from experiment 2: (a) for smaller groups (<5 participants), higher imitation rates led to higher scores; however, these relationships did not hold for larger groups. (b) For all group sizes, regardless of a particular individual’s imitation rate, the individual’s score tended to increase as the imitation rate of others in the group increased. (c, d) Higher scores were associated with lower turnover rates. For color version of this figure, the reader is referred to the online version of this book.

peers turnover their guesses more, one’s own score tends to be lower. The results from Figure 1.14c and d stand in striking contrast to the results from the simpler search space of the first experiment, in which adding opportunities for imitation (by letting every participant see every other participant) increased individual performance but decreased group performance.

p0240

Figure 1.15 shows a comparison between the similarity of imitators’ most recent guesses to those which they imitated, and to those which they did not imitate. The analysis revealed that there was significantly greater similarity to imitated guesses than to nonimitated guesses (77.7% for imitated vs. 72.3% for nonimitated). In other words, imitation tended to be biased toward guesses that were more similar to the imitator’s own prior guess. This difference held over all rounds within a game (Figure 1.15b), even though mean guess diversity decreased such that solutions generally converged (Figure 1.13d).

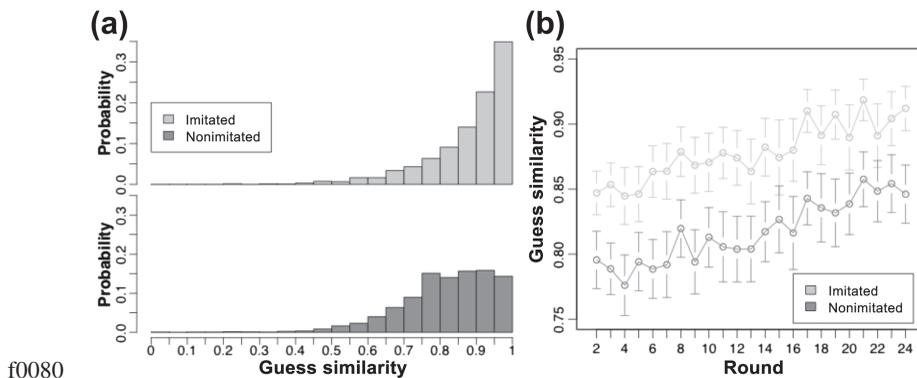


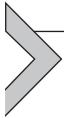
Figure 1.15 Similarity bias for imitation. (a) The probability of an imitation/nonimitation event occurring, as a function of the similarity between a participant's and peers' solutions. Imitators' previous guesses showed greater similarity to the guesses they imitated than to those they did not imitate. (b) The bias toward imitating more similar guesses was consistent across all rounds in a game. For color version of this figure, the reader is referred to the online version of this book.

p0245 Overall, participants' solutions improved over rounds through the use of fairly conservative strategies, as evidenced by the low mean turnover rate. Rather than large, revolutionary changes, participants made small, incremental improvements by changing only a few cells, typically just one. These small changes allowed participants to make accurate comparative inferences about their effects on score. Participants' rates of imitation and general turnover decreased across rounds, and the imitation that did occur was biased toward more similar solutions. This entrenchment of solutions carried over to the group level as well, shown by the decreasing group solution diversity across rounds.

p0250 The association of higher scores with greater imitation rates at both the individual and group levels shows that imitation is not always harmful to innovation and performance improvements. The rate of imitation was about the same among solutions that were improvements and nonimprovements, suggesting that improvements were often achieved by imitating a relatively successful participant's solution and then slightly tweaking this solution. Once tweaked, the improved solution was then available to other participants, including the individual who was originally imitated. The association of high individual scores with high imitation rates by others in the group (regardless of the individual's behavior) reinforces the idea of a systemic benefit for imitation rather than a view of imitation as a purely self-benefiting act. It may be that, regardless of the intentions of individuals, imitation benefits the

group by acting as a filter for propagating and preserving the better solutions available in a group at a given time, as was found in a recent competition of social learning strategies in a simulated environment (Rendell et al., 2010).

s0060



4. COLLECTIVE SEARCH IN A PROBLEM SPACE WITH INTERACTIONS AMONG SOLUTION ELEMENTS

p0255

This third experiment was an effort to replicate and extend the surprising result from the experiment described in Section 3, namely, the group advantage for individual imitation. Members of a group obtained higher scores when their peers had higher, not lower, rates of imitation. A good animal behavior analog for this effect is the cliff swallows studied by Brown and Brown. These birds feed off of airborne insects that travel in large, amorphous clouds that are buffeted by winds. The swallows produce a loud, vocal signal when they have found a region with many insects, even though it is energetically costly to produce this signal, and nearby swallows may compete with the calling bird for insects. One of the reasons why a cliff swallow engages in costly signaling of insect food sources is that it benefits by having other cliff swallows foraging nearby. The swallows recruited by the signal track the subsequent movements of the insects more effectively than the original swallow could if foraging by itself. Likewise, when participants are surrounded by peers who engage in strategic imitation, then the participants may benefit even when their own solutions are being imitated. The imitators will tend to modify what they have imitated, and some of these modifications will produce even better outcomes than the original solution. In these cases, imitated participants can then benefit by reciprocally imitating the peer who originally imitated them.

p0260

This experiment (Wisdom, Song, & Goldstone, 2008; in press) was designed to offer two methodological improvements over the previous experiment. This previous experiment has the desirable feature that the construction of solutions is relatively open ended, and the final productions look like coherent artistic objects, albeit extremely simple ones. An offsetting disadvantage of these drawings is that it is hard to definitively assess whether a participant is imitating another drawing or simply independently creating similar drawings on their own. Furthermore, the scoring scheme for evaluating the drawings does not permit interactions between solution parts. Interactions between solution parts are particularly interesting because they allow for “rocky” fitness landscapes for a problem space.

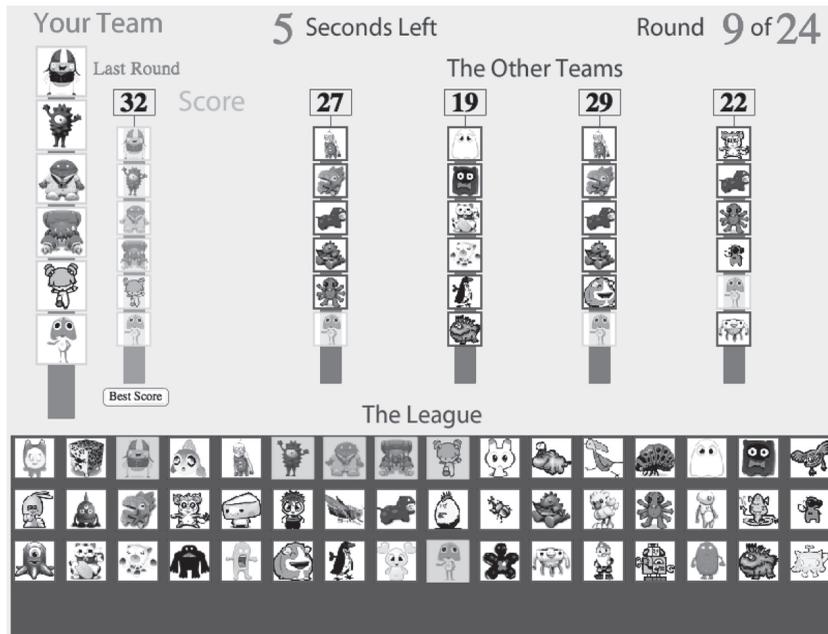
Pixel overlap with a hidden “mystery” picture determined fitness, meaning that the quality of a solution was linearly and equally influenced by each pixel. Many real-world problems have a nonlinear characteristic that makes finding good solutions difficult. For evading predators, claws for climbing trees and heavy armor are each good, but the combination is poor because the heavy armor makes climbing difficult. Tea may be improved by either milk or lemon, but not both combined.

p0265 The third experiment was designed as a conceptual replication of the second, permitting greater clarity in interpreting participants’ strategies, and greater flexibility and complexity in the design of the search space. We were again interested in documenting the strategies participants used to determine whether to imitate or innovate, and how these strategies affected group-level measures of performance.

s0065 **4.1. The “Creature League” Task**

p0270 One hundred and fifty-three participants were distributed across 39 sessions in groups ranging from 1 to 9 participants. Each participant’s task was to score the most points possible over 24 10-s rounds, by assembling together teams of Pokemon-like creatures. Figure 1.16 shows the interface for the experiment. Score feedback was generated according to a stable (within each game) but hidden payoff function, featuring a linear term and pairwise interactions among the icons. In each round, participants could observe each of their fellow players’ solutions and associated scores, and imitate them in whole or in part. The size and the complexity of the problem space (and thus the task difficulty) were manipulated in two different conditions via the sizes of the overall set of icons and the subset that could be evaluated in one solution, as well as the number of pairwise interactions between icons.

p0275 All participants’ actions were recorded and synchronized by a game server at the end of each round. The display included an area for the participant’s own current solution (“team” in Figure 1.16), an area that could be toggled to show the participant’s team on the previous round or their best-scoring team so far in the game (along with its associated score), an area which showed all of the solution elements (the “league” of potential team members) that were available for selection, and indications of the current round in the game and the amount of time remaining in the current round. In sessions with more than one participant, the display also showed the solution and associated payoff of each other participant from the previous round. The ordering of peers’ solutions in each participant’s display was



f0085

Figure 1.16 Example of experiment interface for experiment 3. Participants assemble their teams on the left. Teams assembled by other peers are shown on the right. The entire league of possible players is shown in the bottom section labeled “the league.” For color version of this figure, the reader is referred to the online version of this book.

kept constant within each condition but not across conditions, to avoid imitation based on past behavior.

p0280 Any individual element could be copied from any part of the display to a participant’s current solution by dragging and dropping it with the mouse, except for those already in the participant’s current solution, which were faded in the display and nondraggable. The current solution could be replaced entirely by another solution by selecting the score box above the latter as a “handle” and dragging it to the current solution area. A short video demonstrating all available actions in the game can be viewed at <http://cognitrn.psych.indiana.edu/CreatureGameClip.mov>.

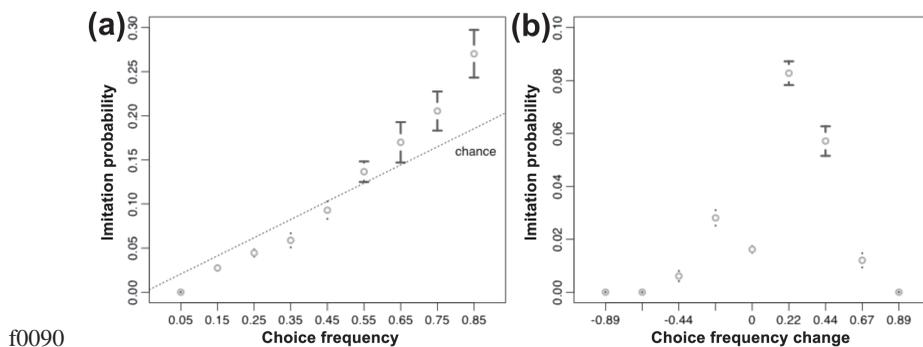
p0285 In each game, each creature icon was associated with a certain positive number of points (its own “abilities”), and several unidentified pairs of icons were associated with separate positive point bonuses or negative point penalties (reflecting “how well they got along”) when they were both on the same team in the same round. These latter bonuses

and penalties can be understood as “interaction effects” on top of the “main effects” of each icon’s value, and is how the complexity of the search space was manipulated. Simply adding the influences of each individual icon does not predict a team’s score because of these interaction terms. The icons’ display positions and associations with the payoff function were shuffled randomly for each game, so that their appearance and placement in the display did not give clues as to their point values. Score feedback (the sum of the individual and pairwise terms described above) was given after each round.

s0070 **4.2. Major Results and Implications**

p0290 Over the course of the 24 rounds, people’s scores improved substantially, and improved more in the larger group sizes. Imitation of other players’ teams was common, and the score of the imitated participant was greater than that of the imitator in 89.6% of cases, equal to it in 2.6% of cases, and less than that of the imitator in 7.8% of cases, consistent with a “copy better-performing individuals” strategy.

p0295 One apparent heuristic that participants use to choose an icon to imitate is to select an icon that is popular among peers. If one were to randomly select an icon to imitate, then an icon that appears on more peers’ teams would be more likely to be selected. The expected probability of an icon being selected by this random imitation strategy is shown by the straight dashed line in Figure 1.17a. In fact, the empirically observed probability of imitation increases more precipitously with an icon’s frequency



f0090

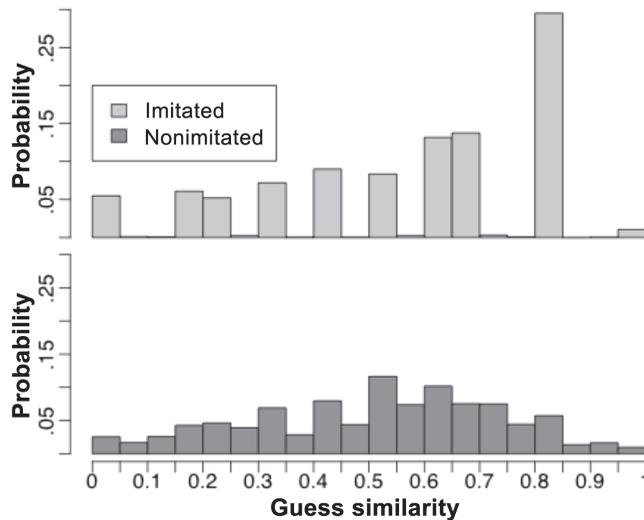
Figure 1.17 (a) Experiment 3 shows a bias toward choosing solution elements that were more frequently represented on other teams. This bias exceeds what would be expected by chance. (b) There was a positive momentum bias toward choosing elements whose representation on other teams was increasing over rounds. For color version of this figure, the reader is referred to the online version of this book.

than the dashed line, indicating that people have an even greater probability of selecting popular icons than would be predicted by chance.

p0300 Another kind of heuristic is to use the momentum of an icon's popularity as a cue to the usefulness of an icon. An icon has positive momentum on Round t if it increased in frequency on peers' teams from Round $t-1$ to t . An icon has negative momentum if it decreased in frequency from Round $t-1$ to t . One plausible assumption is that an icon has positive momentum because it has conferred an improvement on these teams. Accordingly, participants may not only be using the base popularity of an icon to select an icon to imitate but also the round-to-round change in popularity, choosing on Round $t+1$ an icon that has positive momentum on Round t . The X-axis of Figure 1.17b is the change in frequency of an icon from one round to the next. The strong deviation from symmetry around the $x=0$ axis indicates a sizeable positive momentum bias. For example, participants are much more likely to choose an icon that has increased its frequency on peers' teams by 0.22 rather than decreased its frequency by 0.22, even equating for the current frequency of the icon.

p0305 The second experiment revealed a bias (Figure 1.15) for participants to selectively imitate teams that represented solutions similar to their own solutions. The third experiment replicates this effect, as shown in Figure 1.18. The horizontal axis of Figure 1.18 represents the similarity of two teams of icons. For example, if two teams share 4 out of 6 of their icons, then their similarity is 67%. The vertical axis shows the probability of an event occurring. As the similarity of two teams increases, the probability that the creator of one of these teams will imitate (top panel) rather than ignore (bottom panel) the other team also increases.

p0310 Overall, the most common strategy is simply to retain icons on one's team, accounting for 74% of the icons on teams, followed by exploring by selecting icons from the league (15%), followed by imitating icons from other participants' teams (9%). Imitation became increasingly prevalent as the size of a group increased, and decreased with passing rounds. When participants imitated, they were much more likely to copy icons from teams that scored better than their own teams, very often the best available team. Exploring icons from the league also decreased with rounds, and the more conservative strategies of retaining icons and returning to one's own previous teams increased with rounds. Diversity of solutions decreased over rounds, and scores increased. Scores also increased as a function of group size, as larger groups brought in additional innovations for each participant to potentially incorporate in their own solutions.



f0095

Figure 1.18 Imitators' previous teams showed greater similarity to the teams they imitated than to those they did not imitate. The gaps in histogram distributions are artifacts of the coarse binning of team dyads into similarity values and the fact that not all similarity values are achievable with only six team members. For color version of this figure, the reader is referred to the online version of this book.

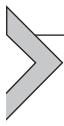
p0315 From a pragmatic perspective, one might be interested in which strategies lead to the best scores for an individual. Retaining icons previously on one's team produced the best overall score for individuals, followed by imitation, then retrieving previous teams, and lastly exploring. Exploring by sampling unknown icons from the league is a risky strategy, particularly after one has found a team with a score that is substantially better than a random team. However, it is also true that exploratory choices were more prevalent in teams that produced improved scores within the entire group (18% of icons) rather than those that did not offer improvements (13% of icons). A relatively small amount of exploration is collectively useful for bringing in new possibilities. As individuals imitated more, regressions indicated that their scores were likely to increase, and a similar positive relation was found for the retention strategy.

p0320 Very similar and significant patterns of results were shown in analyses of mean group score versus mean group guess proportion for each choice source, even when each individual was excluded from their group's aggregate behavior. That is, an *individual's score* was higher when *the individual's fellow group members* imitated and retained more, and explored and retrieved less. This pattern replicates the second experiment's surprising pattern that

it is better for an individual to be surrounded by imitators. A complete lack of exploration will of course result in a lack of improvements, but this experiment suggests that in a large and complex problem space, productive exploration may be readily incentivized by the potential for generating small improvements based on peers' solutions. This is analogous to the mixed equilibrium for individual contributions to group efforts found by Kameda and Tindale (2006).

p0325 The results regarding the group benefits of imitation and collective risks of exploration, taken together with the reductions in diversity over rounds, imply a view that is at odds with those predicted from a simple producer-scrounger dilemma interpretation of social learning (Kameda & Nakanishi, 2003). Much like "conformity," being a "scrounger" often carries a negative connotation or denotation, such as "social loafing" (Latané, Williams, & Harkins, 1979). However, such behavior may be appropriate when not all group members' full efforts are required to produce sufficient benefit. In a complex but relatively stable environment, the best outcome for the group may result from most group members converging on a "good enough" solution quickly to achieve high mean performance, and then introducing productive exploration when necessary. Given a baseline inclination to some amount of individual exploration, the limiting factor in improving search performance may be the amount of information sharing and coordination among searchers, which allow them to pool both the benefits and the risks of asocial learning (Hess & Ostrom, 2007).

s0075



5. LIMITATIONS, IMPLICATIONS, AND CONCLUSIONS

p0330

There are certainly limitations to the external validity of the reported experiments. The kinds of "innovations" that our participants were engaged in discovering were minor, simple, and highly constrained compared to the innovations created by artists, pharmaceutical companies, and even elementary school students during recess. Our participants only worked on revising their solutions for at most an hour, and each solution could be expressed in only 10–20 s. Given these limitations, it would be foolhardy to draw major implications from our studies for cultural improvement at a societal scale.

p0335

Perhaps the strongest general conclusion that can be drawn from our work is simply that social learning is a major factor in people's performance and problem-solving capacity. In this respect, the limited nature of our experimental paradigms is a rhetorical strength. Even when broader cultural contexts are kept to a minimum with our laboratory-based experiments,

participants often imitate one another and do so in predictable ways. Furthermore, even when the groups to which participants belong are ad hoc and temporary, and have only rudimentary communication possibilities, there are still sufficiently rich interactions between group members for unexpected group-level phenomena to arise. If these phenomena are robust enough to be found in our constrained, well-controlled laboratory conditions, then there is good reason to expect them to occur in other real-world contexts as well.

s0080 **5.1. Imitation Heuristics**

p0340 Some of the heuristics for imitation that we observed have been previously documented in animal behavior and social psychology. Others are more novel. Across the three reported experiments, the heuristics for which we have solid, replicated evidence include the following:

s0085 **5.1.1. Frequency**

p0345 Imitate options that are relatively prevalent among one's peers. In our experiments, this frequency heuristic led to choices of frequently occurring options more than would be predicted by chance. For example, in the last experiment, icons that were the most prevalent, representing 17% of all icons across all teams, were copied by participants who did not already possess the icons 27% of the time.

s0090 **5.1.2. Upgrade**

p0350 Imitate options that produce results better than one's existing solution. In our experiments, this takes the form of imitators choosing options that offer higher scoring solutions than the imitator's previous solution. Very often, the imitators choose the highest scoring option available to them.

s0095 **5.1.3. Early Imitation**

p0355 Imitate others' options more during the early, compared to late, rounds of innovation search. Early imitation is advantageous because one's own solutions are less likely to be strong at first, and there will be considerable diversity among solutions. In addition, uncertainty about a problem space is the largest at the beginning of the search process (Kendal, Cooley, & Laland, 2009). With passing rounds, our participants became more committed to their own solutions and were less likely to take a radically different approach by imitating a dissimilar solution. In our experiments, both imitation and open-ended exploration decreased over rounds, and although

these strategies have been contrasted, both are strategies for increasing the diversity of one's own solutions. As more information is gained about what solutions work well in a domain, the more conservative strategies of retaining one's solution and returning to one's previously strong solutions become more prevalent.

s0100 **5.1.4. Similarity**

p0360 Imitate elements of solutions that are already similar to one's own solution. All three experiments provide evidence that participants tended to preferentially copy relatively similar solutions. One reason why this similarity heuristic may be adaptive is that it prevents incorporating solution elements that are incompatible with one's previous solution and knowledge of the problem space. A bias toward borrowing from similar rather than dissimilar solutions has also been incorporated into general machine learning algorithms featuring multiple agents simultaneously searching for solutions (Goldberg, 1989, chap 1, pp. 1–23; Goldstone & Janssen, 2005). There are two possible drawbacks when agents borrow solution elements from other agents pursuing substantially different solutions. First, they abandon the knowledge of the problem space accumulated in their previous solution. Second, there is a strong risk that the resulting blend of solutions will be a suboptimal hybrid not well adapted to the niche of either of the original solutions. Given the complex search landscapes used in the experiments, participants may have been biased to copy solution elements from similar rather than dissimilar solutions to ensure greater solution compatibility.

s0105 **5.1.5. Momentum**

p0365 Imitate options that are increasing in their prevalence. The last two experiments revealed that participants tended to select options not simply based on their frequencies in the population, but also based on their round-to-round change in frequency. Options that have an increasing "market share" tend to be selected, and options that have a decreasing market share tend to be avoided. Our participants may have been using positive momentum as cue to the beneficial consequences of having a particular solution element.

p0370 Of these heuristics, the last two are the most novel, but even these have some precedent. In a form of Similarity Heuristic, Rogers (2003) observed that people, companies, and institutions often adopt innovations that are compatible with the solutions that they already employ. Our experimental contribution here is to show that this Similarity Heuristic continues to be adopted even when there are no retooling costs. Our experimental

evidence for a Similarity Heuristic despite all solutions being equally easily adoptable suggests that at least part of the basis for this heuristic is cognitive inertia and the tendency for people to preferentially continue pursuing their own approaches.

p0375 A real-world precedent for the Momentum Heuristic is shown in baby-naming decisions by parents. An examination of 130 years of social security data on baby names reveals that, for the last 60 years, baby names that increase in popularity from 1 year to the next tend to increase in popularity still further in the following year (Gureckis & Goldstone, 2009). Likewise, a decrease in popularity tends to be followed by still further decreases. This stands in contrast to the years 1880–1940, when increases in popularity were more likely to be followed by decreases, and decreases by increases. The United States has gradually switched from a negative to positive momentum society, at least in terms of its baby names. It is tempting to suggest that this reflects an increasing “faddishness” in American society. Parents, wishing to avoid giving their child a name that will be unpopular in the future, use the increasing momentum of a name as a cue to its future popularity. An unintended consequence of employing a Momentum Heuristic is that the distribution of options in a group becomes increasingly well predicted by a Momentum Heuristic. As our participants or American parents increasingly rely on the Momentum Heuristic to make their choices, then the distribution of choices in the group becomes increasingly well predicted by positive momentum, further justifying the use of the Momentum Heuristic if one’s aim is to predict future popularity.

s0110 **5.2. Group-level Phenomena**

p0380 This unintended consequence of the Momentum Heuristic is a striking example of a group-level phenomenon that emerges from individual social learning heuristics. It is characteristic of the kind of collective phenomena that arise when decision makers affect the environment for subsequent decision makers because the environment is largely comprised of their decisions (Goldstone & Gureckis, 2009; Goldstone & Roberts, 2006; Roberts & Goldstone, 2006). One of our primary interests has been in bridging between individual- and group-level phenomena. Some of the major group-level phenomena that we have observed are as follows:

s0115 **5.2.1. Convergence**

p0385 Members of a group tend to converge on similar solution with time if they see each others’ solutions and measures of the success of these solutions.

s0120 **5.2.2. Inefficient Problem Space Coverage**

p0390 As a direct result of convergence, a group will often not efficiently cover a problem space. This was most striking in the first experiment, in which groups with members who could see every other member's solution performed less well than groups with members who had restricted access to others' solutions.

s0125 **5.2.3. Problem Space/Social Knowledge Match**

p0395 How well a group as a whole will solve a problem will depend on the match between the complexity of the problem space and its members' access to others' solutions. The specific nature of this interaction was revealed by human experiments, and broadly corroborated by computer simulations. In general, as the global maximum of a problem space becomes increasingly difficult to find via a simple hill-climbing search, then increasingly restricting the visibility of peer solutions will promote group performance. For easy problems, the critical determinant of group performance is how quickly word can be spread about good solutions, and hence, broadly interconnected social networks are superior. For hard problems, more sparsely interconnected social networks help the group explore different solution possibilities in parallel.

s0130 **5.2.4. Reciprocal Imitation**

p0400 Members of a group can benefit by being imitated because the imitators will subsequently modify the solution, and if the modification is favorable, the imitated members can copy the improved solution. One of the most surprising results from the last two experiments was that individuals benefited from being in groups with others who frequently imitated. Reciprocal imitation is a large part of the reason for this benefit. Imitation also has the collective benefit of keeping good solutions alive in the collective memory (Wegner, Erber, & Raymond, 1991).

p0405 Future work will be necessary to determine when different group-level patterns are observed. There is some tension between the benefits of having sparsely connected groups in the first experiment and the benefits of being surrounded by imitators observed in the last two experiments. Our tentative reconciliation is that being imitated is particularly advantageous when one is trying to search a region of a problem space that is too large for one to effectively survey by oneself. For the huge search spaces of the later experiments, it is to one's advantage to recruit others to one's region because these recruits can assist in the regional search for better solutions. In

the first experiment, one's chances for finding the global maxima are better if other people search in different areas rather than redundantly searching in the same region of the one-dimensional problem space.

p0410 While the external validity of our current experiments is undeniably limited, we take it as a sign that we are on a promising track that issues of external validity even arise. Humans are almost always social learners. We learn by being told, by being shown, and by watching others who are simply behaving and not trying to demonstrate anything. At a societal level, this social learning produces important and striking group-level consequences, including bandwagons, speculative bubbles, schisms and coalitions within a group, spontaneous formation of minority-opinion groups, opinion cycles, group polarization of opinion, and early market advantages. The kinds of solution copying processes that we observe in our experiments can hopefully provide a set of core patterns that combine in different ways to create these large-scale social patterns that intrinsically matter to us and shape our experiences and well-being. For this reason, the spread of solutions in a group is a process of consequence for the psychology of both learning and motivation.

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