Adaptive Group Coordination

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Abstract

Human groups exhibit poor performance in many social situations because task constraints promote either individual maximization behavior or diffusion of responsibility. We introduce a group task that tests human coordination when only a shared group goal exists. Without communication, group members submit numbers in an attempt to collectively sum to a randomly selected number. After receiving group feedback, members adjust their submitted numbers in the next round. Small groups generally outperform large groups, and for all groups, performance improves with task experience, and reactivity to feedback decreases over rounds. Our empirical results and computational modeling provide evidence for adaptive coordination in human groups despite minimal shared history and only indirect communication, and perhaps most interestingly, as the coordination costs increase with group size, large groups adapt through spontaneous role differentiation and self-consistency among members.

Keywords: Collective behavior; agent-based models; adaptive behavior; group coordination

Introduction

Groups often suffer from behavioral limitations, including impaired brainstorming performance (Kerr & Park, 2001), difficulty in utilizing shared and unshared pieces of information (Stasser & Titus, 1985), and inability to gauge the relevant contributions of individual members (Littlepage, Schmidt, Whisler, & Frost, 1995). Many group limitations worsen as group size increases, and because large groups confer anonymity, members increasingly fall prey to diffusion of responsibility (Darley & Latane, 1968; Freeman, Walker, Borden, & Latane, 1975). Even when shared resource tasks encourage implicit coordination (Ostrom, Gardner, & Walker, 1994), conflicts arise when members choose individual gains over group gains.

However, many situations require coordinated contributions in order to achieve a shared group goal. For example, a potluck dinner ideally coordinates participants' food contributions so there is enough to sate everyone, without excess left-overs that no one wants to take home. However, individuals often make unilateral decisions about how much food to bring to the potluck. The question then arises of how the group as a whole can coordinate the correct amount of food to bring, with some individuals volunteering to bring extra food to make up for other individuals who forget to bring any food. Research labs rely on the combined contributions of individuals to develop a research program and lab reputation that leads to grant funding, which may in turn benefit the individuals. Similarly, statistical analyses in baseball and basketball increasingly value players based on the team's performance while the player is in the game, rather than individual statistics such as points scored (Berri, Schmidt, & Brook, 2006). In these examples, a group member can undermine a team's performance by either taking on too little or too great a burden, and unlike intellective tasks in social psychology, where a correct solution can propagate from an individual to the rest of the group (Laughlin, 1980), these situations involve the coordination or summation of multiple individual contributions. Although some studies show that group members can adequately share pieces of information under the right circumstances (Stasser & Stewart, 1992; Stewart & Stasser, 1995), and some group learning can occur via indirect feedback (Maciejovsky & Budescu, 2007), there has been relatively little research on group coordination and adaptation to tasks with shared goals.

In order to isolate and test the coordination capacities of groups, we developed a simple round-based group game called "Group Binary Search" (GBS) that creates a test bed for pure coordination without competing individual goals. In the GBS game, a computer server randomly chooses a number between 51 and 100, and without communication, each group member submits a guess between 0 and 50. The computer compares the sum of participants' numbers to its selected number, and broadcasts the same directional (e.g. "Too High") or numeric (e.g. "Too Low by 17") feedback to all members. Given the range of individual guesses, group members must coordinate to achieve the shared goal. During the next round, members can adjust their guesses and receive the new feedback, and the game continues until the group correctly sums to the computer's number. We coined the name Group Binary Search after the binary search algorithm in computer science (Knuth, 1997), which searches for a number in a sorted list by iteratively guessing the median number in the current range of possibilities. For numeric GBS games, a normative solution suggests that all players should change their guesses by $\frac{\text{Distance from Goal}}{\text{Number of Players}}$, plus a further increment by 1 with probability $\frac{\text{Remainder}}{\text{Number of Players}}$. but no group consistently showed this behavior in our experiments. Instead, even though each individual presumably knows what the group *should* do, individuals display a large variance in guess adjustments due to their uncertainty regarding others' actions. Stock market investors face a similar dilemma when they know a company's expected value but fear trading on that knowledge because of the unpredictable noise introduced by other traders (Camerer & Fehr, 2006).

Our GBS game shares qualities of several other tasks from game theory and behavioral economics, but GBS uniquely tests participants' adaptive coordination strategies when only a shared group goal exists. Many 2 x 2 symmetric games such as Prisoner's Dilemma display coordination in order to achieve higher individual payoffs, and in fact, simulations support the evolution of mutual reciprocity in Prisoner's Dilemma (Browning & Colman, 2004), and coordinated alternating reciprocity in games with related payoff structures such as Battle of the Sexes, Leader, and the route choice game (Helbing, Schonhof, Stark, & Holyst, 2005). Each of these games emphasizes individual maximization with clear payoff structures, while the GBS game emphasizes group maximization without a clear trial-based payoff structure. Group members have a wide range of possible guesses, and they do not receive rewards unless the group goal is reached, so the task encourages group members to continually make complementary guess refinements until the goal is reached. Even pure coordination games in game theory focus on clear payoff structures with pure – and sometimes mixed – strategies leading to Nash equilibria (Colman, 2003).

Some more naturalistic framings of coordination allow a wide range of responses, but still emphasize individual payoffs in tasks such as group foraging (Roberts & Goldstone, 2006), group path formation (Goldstone, Jones, & Roberts, 2006), spontaneous traffic lane formation (Helbing, Molnar, Farkas, & Bolay, 2001), and commons dilemmas (Ostrom et al., 1994). In commons dilemmas, group resources are typically over-harvested unless the group communicates (Bouas & Komorita, 1996) or enacts rules (Ostrom, Walker, & Gardner, 1992). However, given that our later empirical and modeling results show adaptive group behavior, it is intriguing that sequential sampling versions of commons dilemmas demonstrate position effects in which early samplers take large shares, and later samplers request diminishing shares without even knowing how many resources are left (Budescu & Au, 2002).

The GBS game also complements coordination tasks geared towards larger populations, such as minority, majority, and business entry games. The minority game assumes that individuals want to avoid crowds, and it examines how effectively individuals differentiate and distribute themselves to two options, given that only members of the resulting minority are rewarded (Arthur, 1994). Experimental and simulated minority games often show oscillating group choice behavior, typically approaching a 50/50 split between options, but the group can deviate towards extreme proportions (e.g. 0% or 100% select option A) if the members fail to differentiate (Botazzi & Devetag, 2003). In contrast to simulation results (Savit, Manuca, & Riolo, 1999), humans coordinate with minimal information in minority games, and increased information from longer reinforcement time windows does not improve group performance. Majority games actually encourage conformity and attempt to model situations where individuals benefit from acting in crowds, such as momentum trading and aggregating to form cities (Kozlowski & Marsili, 2003). Self-fulfilling prophecies naturally emerge in these situations, as momentum traders flock to the majority stock (Marsili, 2001). Business entry games occupy a gray area between minority and majority games. In these tasks, individuals (businesses) receive a small reward for staying out of a market and a large reward for entering a market, but no one in the market receives a reward if too many people join (Camerer & Fehr, 2006). Each of these games differs from the GBS game by encouraging conformity or differentiation in attempts to maximize individual payoffs. The GBS game is agnostic to strategies, allowing both coordination and differentiation of strategies (substitutable or complementary strategies, as per Camerer and Fehr (2006)) in pursuit of global coordination.

Methods

Participants

Participants were 106 undergraduate students at Indiana University who received course credit for approximately 1 hour of participation. Participants were run in 18 GBS experimental sessions with the following group sizes: 2, 2, 2, 2, 2, 2, 3, 3, 3, 4, 4, 4, 6, 7, 10, 16, 17, 17. Each group participated in 10 games, alternating between directional feedback games and numeric feedback games. Participants were instructed not to talk to each other, and they were informed that there were a total of 10 games and they would finish the experiment more quickly if their group quickly coordinated to the solutions. We did not highlight the number of participants in a group, but that information was available, given that all group members were simultaneously present and visible in the computer laboratory.

Material and Procedure

Participants sat in a university computer lab at personal computers running the game via client Java applets connected to a computer server. Before each game, the server randomly chose a number between 51 and 100. During each round, each participant entered a guess between 0 and 50. After a 15 second guessing period elapsed, the server compared the sum of participants' guesses to its number, broadcast the same feedback to all participants' screens, and began the next round. Participants only knew the group sum's relation to the server's number (e.g. "Too high" for directional feedback games, or "Too high by 17" for numeric feedback games), without knowing the server's actual number or the current group sum. If the participants' guesses correctly summed to the server's number, or if 15

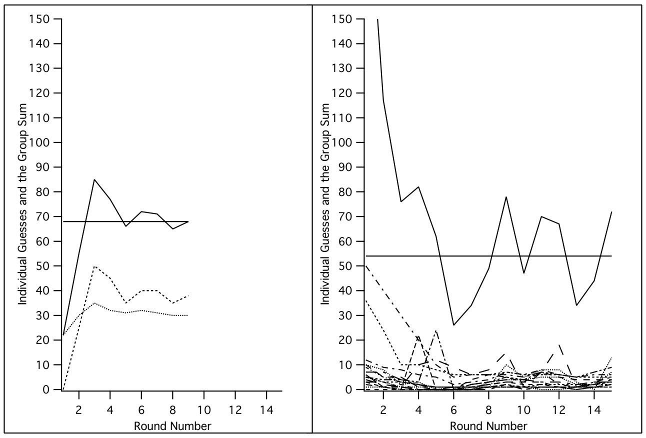

Figure 1: GBS games with 3 and 17 participants

rounds passed unsuccessfully, then the game ended, and the next game began after a short delay.

Results and Discussion

Figure 1 shows directional feedback games from a 2- and 17-participant group, and all graphs for the 18 groups are at: http://cognitrn.psych.indiana.edu/GBS_graphs.zip. In general, groups coordinated very well, with 7.03 average rounds to solution for numeric feedback games, and 10.51 for directional feedback games, a significant difference under a two-tailed t test, $t(17) = 5.47$, $p < .001$. For many of the analyses, we defined "small groups" as groups with 2 or 3 participants, and "large groups" as groups with 10 or more participants. These group sizes showed strongly contrasting behavior that will be discussed later, while the medium-size groups displayed a mixture of behaviors from the two group types. Small groups solved the games in an average of 6.80 rounds (numeric=4.31, directional=9.34), compared to 11.95 rounds for large groups (numeric=11.05, directional=12.85), $t(11) = 6.46$, $p < .001$. These results suggest that participants successfully modulate their reactions based on the feedback magnitude, and small groups, with their fewer degrees of freedom and decreased uncertainty, coordinate more quickly. One can imagine large groups allowing reactions to offset each other, thus averaging and coordinating to the solution more rapidly, but instead the larger groups exhibited larger oscillations. All group sizes showed similar improvement across games, with a -.264 correlation between game number and average rounds to solution, $p < .001$, and both large and small groups showed approximately the same learning correlations, -.270 and -.273, respectively (the medium size groups slightly lower the average). Figure 2 shows similar learning in numeric and directional feedback games.

In order to examine consistent behaviors among participants, we calculated each participant's "reactivity" according to the formula ($G_r - G_{r-1}$) if the group was too low on the previous round, and ($G_{r-1} - G_r$) if the group was too high, where G_r is the participant's guess on round r. Groups generally under-react, as shown in Figure 3, though only small groups significantly under-react. These results are particularly revealing for directional feedback games, because groups react surprisingly close to the best-fit line despite only receiving directional information. In these cases, groups may follow a conservative strategy of gradually decreasing reactivities over rounds. In numeric feedback games, large magnitude feedback tempts individuals in large groups to over-react and form outliers, but overall, the analyses support a nuanced strategy of decreasing reactivity over time in both feedback conditions. The average reactivity of group members per round significantly decreases over the last six rounds prior to solution (This method of aligning rounds maintains some equivalence between numeric and directional games, and small and large groups, given their different solution times), ß = -.326, $p = .001$. However, a paired samples t test for all games of all groups reveals that participants significantly decrease their reactivities when the feedback direction (even for numeric feedback games) changes from one round to the next (mean decrease of 1.55), but maintain approximately the same reactivity (mean decrease of .11) when the feedback direction remains the same, $t(148) = 4.75$, $p < .001$.

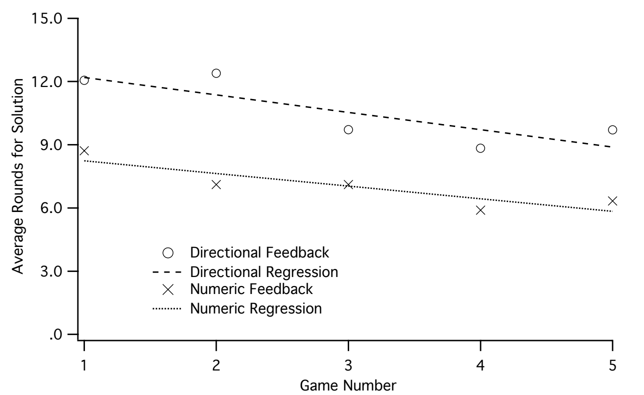

Figure 2: Average rounds to solution for numeric and directional feedback games

Models

Using agent-based models, we tested several reactivity strategies. For each model, we ran 18 groups in 10 directional feedback games, and we matched group sizes to our empirical groups. Each agent first sampled from an empirically derived initial guess distribution that took into account group size, such that there were three derived distributions, for large, small, and medium group sizes. On the second round, agents chose a reactivity from a uniform random distribution with a range of 0 to (50–current guess) if the group was too low on the previous round, and from a range of (-1*current guess) to 0 if the group was too high on the previous round. In order to maintain more realistic reactivities, we further constrained agents to sample until they chose a reactivity within the range -20 to +20. Model 1

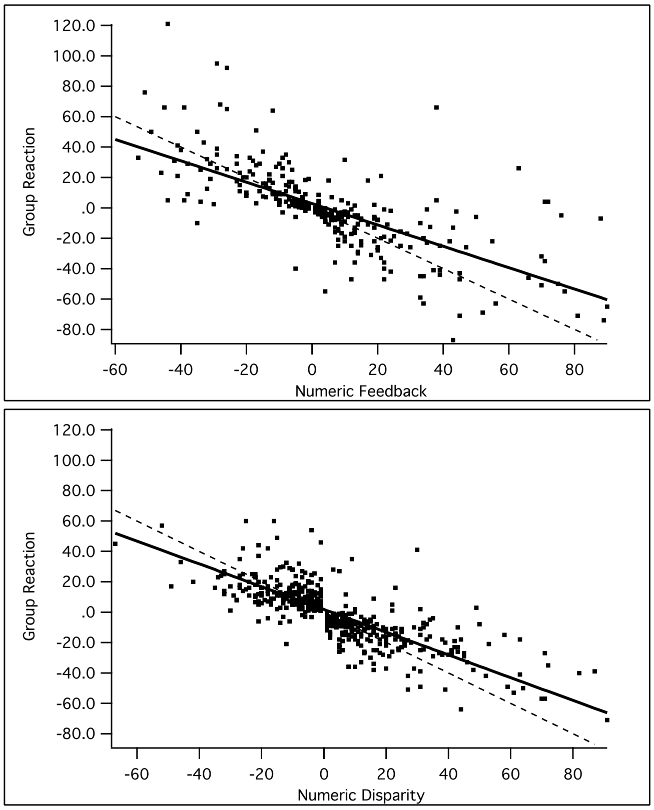

Figure 3: Average group reactivity for each distance from the correct solution

and Model 2 agents continued sampling reactivities in this fashion for every round of a game, but Model 2 agents probabilistically decreased their sampled reactivities across rounds. On each round, each possible reactivity number in the range -20 to +20 had a .5 probability of decreasing by an integer chosen from the uniform random range 0 to 5. For example, a Model 2 agent that would have chosen a +18 reactivity in round 6 may actually increase its guess by +12, because the chosen +18 reactivity was decreased across rounds. These random decreases were computed separately for each group game. Models 1 and 2 constitute groups that produce reaction in a feedback-consistent direction, and Model 2 adds the assumption that reactions decrease over time. Models 3 and 4 replace these random reactivity decreases with the notion of agent consistency, Each agent sampled a reactivity on the second round, and on each subsequent round, a Model 3 agent had a .5 probability of decreasing its reactivity by an integer chosen from the uniform random range 0 to 5, while a Model 4 agent only decreased its reactivity when the group feedback changed (e.g. from "Too High" to "Too Low"), and otherwise maintained the same reactivity from round to round. Thus, these models tested whether consistent agents should simply decrease their reactivities over time, or selectively decrease their reactivities when the feedback changed, as our empirical results support.

Model 4 coordinated significantly faster than the other models (means: Model 1=13.63, Model 2=12.84, Model 3=12.00, Model 4=10.29, Empirical=10.51), $p < .001$ for all pairwise model comparisons with Model 4, and was indistinguishable from our empirical results for directional feedback games, $p = .684$. The same model can solve numeric feedback games more quickly by modifying the range of initial agent reactivities according to the numeric feedback. Models 1, 2, and 3 were not significantly different from each other in pairwise comparisons, which illustrates the importance of flexible group coordination. Intuitively, Model 4 agents take large steps towards the goal when they are far away, then decrease their step sizes after passing the goal. In contrast, the approximate simulated annealing strategy (Kirkpatrick, Gelatt, & Vecchi, 1983) from Model 3 does not efficiently span large initial-to-goal distances unless it anneals slowly, but slow annealing results in inefficient oscillations around the goal. We further tested this intuition by comparing Models 3 and 4 on extended games that could go up to 30 rounds, and the influence of unsolved games especially hurt the average solution time for Model 3 (means: Model 3=18.99, Model 4=14.53, $p < .001$). When we tried to improve Model 3's performance with alternative values for the probability of reactivity decreases per round and the size of the uniform random range, Model 3 still converged on the target more slowly than Model 4 and our human participants because its agents failed to adjust their reactivities according to feedback. It is also noteworthy – but expected – that randomly choosing reactivities as in Models 1 and 2 cannot explain the empirical results, even when reactivities are constrained to a range and decreased over time.

Groups in numeric feedback games clearly do not pursue the expedient normative strategy. That strategy would quickly lead to a solution, and it should be an easy strategy for small groups to follow, but it requires *everyone* to simultaneously adjust their guesses by $\frac{\text{Distance from Goal}}{\text{Number of Players}}$, plus a further increment by 1 with probability $\frac{\text{Remainder}}{\text{Number of Players}}$. Our analyses indicate that 26% of numeric feedback rounds were evenly divisible for small groups, compared with 3.2% for large groups, $t(11) = 2.503$, $p < .05$. However, for these evenly divisible rounds, participants rarely employed the normative strategy, with an average of 14.9% of small group members and 0% of large group members employing the strategy on applicable rounds, $t(11) = 1.59$, $p = .14$. Instead, in conjunction with our empirical results that participants' reactivities decrease when the group feedback changes, our models suggest that human groups use a flexible, adaptive strategy for group coordination when members are uncertain about others' actions.

Group Differentiation

The results so far have implied similar coordination mechanisms in small and large groups, but our final analyses show striking divergent behavior. We calculated the variance of reactivities within individuals (Did a participant exhibit consistent reactivities across rounds?) and between individuals (Did all group members have similar average reactivities?). For each of these analyses, we used groups – rather than individuals – as the unit of analysis by averaging over the individuals within a group. Individual variance significantly decreases over rounds (ß = -.519, $p < .001$) for large groups, but marginally increases for small groups (ß = .165, $p = .083$). The variance of reactivities among large group members marginally increases over games (ß = .291, $p = .068$), and greater variance among large group members significantly predicts faster coordination (ß = -.395, $p = .012$). In contrast, the variance among small group members significantly decreases over games (ß = -.370, $p < .001$), and does not predict solution time. The average reactivity of large group members also decreases across games (ß = -.313, $p = .049$), but there is no such relationship for small groups (ß = -.04, $p = .708$).

Taken together, these results suggest that it is beneficial for members of large groups to differentiate themselves from each other, and then maintain those roles in order to foster a predictable environment for subsequent adjustment and coordination. Human participants appear to adapt flexibly to the contingencies of group coordination, even when group members have minimal shared history and only indirect communication. The greater difficulty of the task for large groups may serve as a selective pressure that forces specialization. All of the group members are pursuing the solution, but some manifest this pursuit by adjusting their guesses, while others adopt small or zero reactivities in order to decrease the group uncertainty. Our analyses indicate that large groups coordinate more quickly when group members assume these complementary roles. Meanwhile, members of small groups can react in similar magnitudes, without even being self-consistent, and still coordinate rather quickly.

In post-task interviews, large groups invariably had many participants who stated that they stopped reacting once the group was close to the goal, because they assumed someone else would react, and having too many reactive people would risk overshooting the target solution. In this respect, the GBS game is a paradigmatic task where *orderly* diffusion of responsibility is a good thing. A simple strategy for dropping-out can lead to deadlock if too many people adopt it, so the group must coordinate its meta-strategy in order to coordinate to the goal. However, it is also possible to take meta-strategies too far. In each large group, at least one person mentioned attempting to compensate for an anticipated group over-reaction by reacting in the opposite direction when the group neared the goal. Analyses indicate that groups would have coordinated faster without this extra compensation.

Both large and small groups showed impressive learning trajectories, so it may prove worthwhile to examine groups that have played many more GBS games in order to test the limits of group differentiation and adaptation. Previous research indicates that diversity (Page, 2007) and transactive memory systems with divisions of cognitive labor (Wegner, 1987; Lewis, Lange, & Gillis, 2005) can improve group problem-solving. However, diversity only helps when group members recognize other members' roles (Polzer, Milton, & Swann, 2002), and group members sometimes fail to adapt their roles to changing group conditions (Lewis, Belliveau, Herndon, & Keller, 2007), which suggests that members of our large or small groups may require significant adjustment periods if we shift group sizes or memberships.

Conclusion

Our current research indicates that the GBS game is a useful framework for testing self-organized division of labor, role development in groups, and relations between individuals' strategies and group-level outcomes. This approach is distinct from previous studies that emphasize either competition among individuals while maximizing individual returns, or the propagation of individual solutions or information through a group. Many real world situations (scientific research teams, sports teams, multi-party business negotiations, committees, etc.) intrinsically involve actors adjusting their contributions in order to achieve a mutually satisfactory group goal, a win-win result. These tasks cannot be solved by lone individuals, and the participation of other individuals inevitably brings uncertainty. In these tasks, more activity is not necessarily better; rather, an individual's role must complement others' roles and actions to achieve the desired outcome. Our results suggest that teams of individuals with minimal shared history and minimal communication automatically adjust their effective sizes and member roles so that they coordinate appropriately for a task's complexity.

Although the GBS game is inherently a simple task, we view this as an advantage that allows us to control for nuisance variables and test groups with minimal shared histories and minimal communication. The task offers a simple experimental platform for studying the general problem of group coordination while maximizing group returns, much like Prisoner's Dilemma and the minority and majority games offer simple experimental platforms for studying the general problem of competition while maximizing individual returns.

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