Emergent Collective Sensing in Human Groups

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Abstract

A variety of simple strategies have been proposed to explain collective intelligence in both humans and non-human animals, such as copying successful individuals or copying when uncertain. Yet the cognitive abilities supporting these strategies in collectives remain poorly understood. Here, we propose that social reasoning plays an important role, allowing latent properties like "success" to be flexibly inferred from outward behavior when there is no direct access to others' payoffs. Such inferences allow social learning to be balanced with exploration. In Experiment 1, we designed a collective search paradigm for human participants, inspired by the nonhuman animal literature, and found that performance quickly improves as a function of group size. In Experiment 2, we placed human participants in scenarios with artificial agents that were explicitly constructed to evaluate the role of two mechanisms: independent exploration and targeted copying based on social inferences about who is currently successful. Finally, in Experiment 3, we generalize these results to groups in a more complex and noisy environment. Taken together, we find that even the most rudimentary human social cognition abilities afford robust and flexible use of social learning strategies.

Keywords: collective intelligence; distributed cognition; social cognition; social computation; online experiments

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1 Introduction

Relying on others can be as risky as it is rewarding. Advice seekers must disentangle good advice from bad, and balance the potential benefits of shared wisdom against the cost of being pulled in different directions. A group where everyone is sensitive to "who knows what" can be quite effective at sharing information and solving problems together, but getting that meta-knowledge is not trivial. What cognitive abilities enable such achievements of collective intelligence?

The study of social learning examines how people and other animals make use of information from others around them. A large body of work in human and non-human animals has focused on what strategies, or heuristics, allow social learning to be effective (Laland, 2004; Hoppitt & Laland, 2013; Rendell et al., 2011; Laland, 2017). Indiscriminate copying, for example, is not an effective strategy. As more individuals rely on imitation, rather than independent asocial learning, it becomes increasingly likely that a random target of copying is using outdated or inaccurate information, decreasing the mean performance of the group (Rogers, 1988). For the group to benefit from social learning, imitation must be deployed selectively (Kameda & Nakanishi, 2003; Boyd & Richerson, 1995; Kendal, Coolen, van Bergen, & Laland, 2005), both in choosing the appropriate time to learn from others (*when* strategies) and choosing the appropriate individuals to learn from (*who* strategies). For example, a "copy-when-uncertain" heuristic allows an agent to deploy social learning only when independent exploration becomes challenging, or a "copy-successful-individuals" heuristic allows an agent to filter out low-quality social information and target other agents most likely to increase their own fitness.

Attention has increasingly turned from documenting evidence for individual heuristics to investigating the abilities underlying the flexible use of different strategies (Heyes, 2016a; Kendal et al., 2018). Agents often use hybrid strategies, combining multiple sources of *who* or *when* information, or deploy different strategies in different contexts (McElreath et al., 2008). Thus, it may be useful to view social learning behavior not as the application of an inventory of simple copying rules, but as arising from deeper cognitive abilities. Especially in the case of humans, and some non-human primates, there has been substantial interest in the extent to which social learning relies on abilities like meta-cognition (Heyes, 2016b) or theory of mind (Shafto, Goodman, & Frank, 2012) that go beyond pure associative learning (Behrens, Hunt, Woolrich, & Rushworth, 2008; Heyes, 2012b, 2012a). These proposed abilities allow agents to maintain explicit representations of "who knows" and thus concentrate social learning on particularly knowledgeable individuals. Similar cognitive abilities have been implicated in organization science as predictors of collective intelligence in small groups (Woolley, Chabris, Pentland, Hashmi, & Malone, 2010; Engel, Woolley, Jing, Chabris, & Malone, 2014).

We suggest that these social inference abilities may also help shed light on a puzzle raised by *who* heuristics like "copy-successful-individuals." Computational simulations (Schlag, 1998; Lazer & Friedman, 2007; Rendell et al., 2010) and human experiments (Mason, Jones, & Goldstone, 2008; Mesoudi, 2008; Mason & Watts, 2012) typically provide agents the ability to directly observe the underlying payoffs of different agents (sometimes at a cost). However, many real-world environments do not provide such direct access. Indeed, hiding payoffs can reverse the benefits of selective copying because the solutions of different agents cannot be compared (Wisdom, Song, & Goldstone, 2013). Accounts of selective copying that rely on information about who is successful or knowledgeable must also provide an account of how agents *come to know* this information. While it is possible that associative learning allows agents to adopt particular external cues as proxies (e.g. visible health or wealth), social inference abilities may provide a more flexible alternative. Humans continually move between different contexts where success manifests in different observable behaviors: a reliable cue of success in one environment may not be reliable in another. By inverting a generative model of behavior (e.g. Jara-Ettinger, Gweon, Schulz, & Tenenbaum, 2016; Baker, Jara-Ettinger, Saxe, & Tenenbaum, 2017), agents can make context-sensitive predictions and flexibly infer the hidden success or knowledge of others.

This ability has been extensively studied in cognitive science. Even young children are able to rapidly infer which partners are more trustworthy and knowledgeable than others, and prefer to learn from them (Wood, Kendal, & Flynn, 2013; Sobel & Kushnir, 2013; Gweon, Pelton, Konopka, & Schulz, 2014; Poulin-Dubois & Brosseau-Liard, 2016; Harris, Koenig, Corriveau, & Jaswal, 2018; Mills & Landrum, 2016), and adults can appropriately discount unreliable social information in their decision-making (Hawthorne-Madell & Goodman, 2019; Vélez & Gweon, 2019; Whalen, Griffiths, & Buchsbaum, 2017). However, this cognitive science literature has largely developed independently from work on social learning strategies in larger collectives. Previous work in animals has suggested that inferences about underlying cues may prevent costly and erroneous cascades of behavior (Bikhchandani, Hirshleifer, & Welch, 1998; Giraldeau, Valone, & Templeton, 2002), but the broader implications of social inference abilities for collective intelligence remain unclear.

In the present work we bridge these two literatures by examining the behavior of human groups in a collective sensing task[1] where others' payoffs are not directly observable. This task builds on a recent task designed to study the collective sensing of fish schools (A. Berdahl, Torney, Ioannou, Faria, & Couzin, 2013). In our experiments, human participants controlled avatars in a virtual world. Each location corresponded to a hidden score value that fluctuated over time. They could continually observe the movements of other agents but only had access to the score at their own current location. Across three experiments, we used this virtual environment to investigate how the performance of groups changed as a function of group size (Experiment 1), evaluate the individual social learning mechanisms driving collective success (Experiment 2), and measure the effect of noise on social learning (Experiment 3). Taken together, this work suggests that even in novel environments where the payoff information of other agents is not directly accessible, individual social cognition may nonetheless enable flexible collective intelligence.

[1]Collective sensing is related to collective foraging tasks (Dechaume-Moncharmont et al., 2005; Goldstone, Ashpole, & Roberts, 2005), but the 'resource' is not consumable so there are no competitive dynamic.

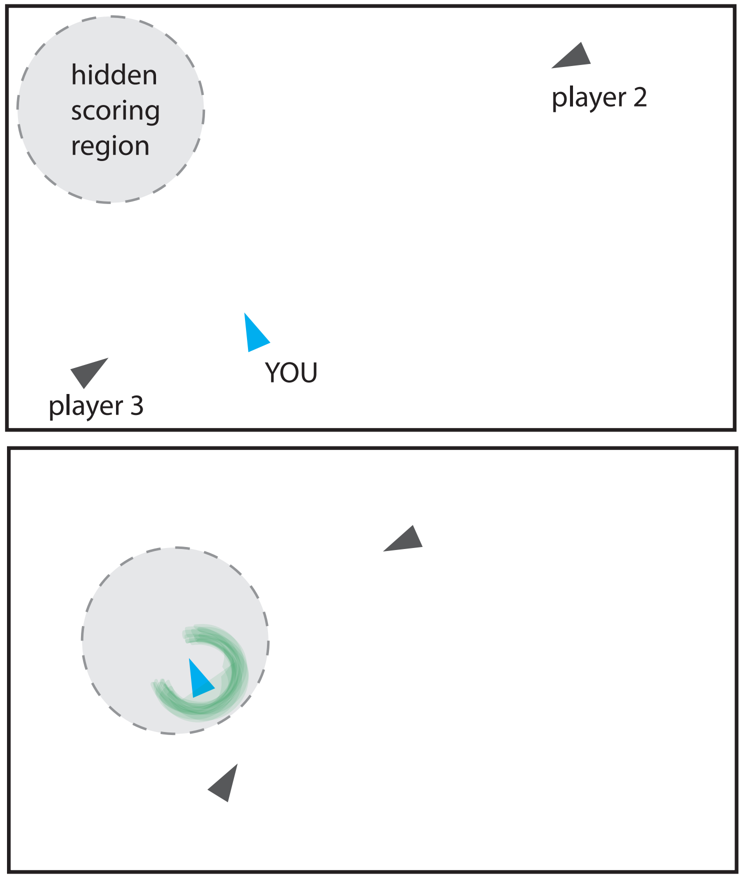

Figure 1: Example states of the multi-agent tracking task used in Exp. 1. Hidden scoring region is shown in grey, slowly drifting over time. Bottom frame shows participant receiving a bonus reward upon entering the region. The halo indicating this bonus was only visible to the participant inside the region, and not to the other participants.

2 Experiment 1: Collective sensing across group sizes

2.1 Participants

We recruited 781 unique participants from Amazon Mechanical Turk to participate in this experiment. All participants were from the United States. After excluding 52 participants due to inactivity or latency, and 9 others for disconnecting in the first half of the game, we were left with usable data from 720 participants in 312 groups. These groups ranged in size from one to six individuals.

2.2 Stimuli and Interface

The virtual game environment measured 480 pixels in width and 285 pixels in height. Avatars were represented by triangles that were 10 pixels in length and 5 pixels in width, rotated to the direction the avatar is facing. Participants controlled their avatars by clicking and using two keyboard keys. Clicking within the playing area instantly oriented the direction of the avatar to be facing the location clicked. Participants could hold the "a" key to accelerate or hold down the "s" key to stop. The avatars automatically moved forward at a constant velocity of 17 pixels per second if no buttons were pressed, but instantaneously increased to a constant velocity of 57 pixels per second for the duration of time that the "a" key was held down and decreased to 0 pixels per second for the duration of time the "s" key was held down.

We designed the environment as a multi-agent tracking task (Fig. 1). The score that agents obtained at each location at each point in time was determined by an underlying "score field." This field was hidden from participants, who only had access to the score at their current location. We generated score fields by first initializing a circular region with a diameter of 50 pixels at a random location on the playing area. Inside this region, the score was set to 1. Outside this region, the score was set to 0. We then moved this region along a straight line to a randomly chosen target location within the playing area at a speed of 17 pixels per second. Once it reached this location, we selected another target location, and repeated the process for the duration of the experiment. We pre-generated 5 such score fields, so multiple groups were randomly assigned to the same underlying field.

Because these simple score fields were binary (i.e. either inside or outside the circular scoring region), we showed participants binary feedback about their current score. When an avatar entered the circular region, it was surrounded by a salient sparkling halo and the border of the playing area turned green (see supplementary Fig. 7 for screenshots). Critically, this feedback was only visible to the participant controlling that avatar; participants did *not* directly observe whether other participants were in the scoring region. They could only see the spatial location and orientation of other participants.

Each participant played in a single continuous game lasting for 5 minutes, and locations were updated every 125 milliseconds; participants thus saw all other participants moving in real time. To discourage inactivity, participants also received 2/3 of a point for each second they were actively participating in the game. For any moment when an avatar was touching a wall, we displayed a large warning message and set the participant's current score to zero so that they stopped accumulating points.

2.3 Procedure

After agreeing to participate in our experiment, participants were presented with a set of instructions describing the mechanics of the game, using a cover story framing the game as a search for the "magical bonus region". The participants were informed about the dynamics of the underlying score field and also explicitly informed that "There is no competition between players; the magical region is not consumed by players. It simply changes location over time." Participants were not explicitly instructed or suggested to cooperate or coordinate with each other.

After successfully completing a comprehension test, participants were then redirected to a waiting room. For each waiting room we started, we randomly sampled a target group size between 1 and 6. Participants would wait for up to 5 minutes or until the pre-assigned number of other participants joined. While in the waiting room, participants

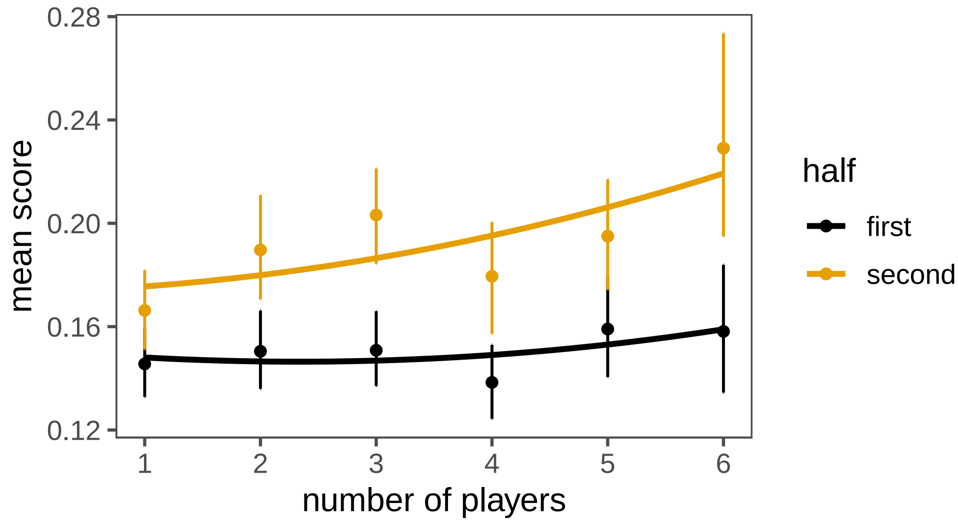

Figure 2: Mean performance of human participants in each half of Experiment 1 as a function of group size. Larger groups saw significant gains in performance. Error bars are 95% bootstrap confidence intervals using the group as the primary bootstrap unit.

could familiarize themselves with the controls of the game. Participants were not shown any score in the waiting room unless the participant was against a wall, in which case the border of the playing region would turn red and a warning appeared on screen. All participants spent at least one minute in the waiting room to help ensure familiarity with the controls before starting the game.

Both in the waiting room and the actual game, participants were removed for inactivity if we detected that they had switched to another browser tab for more than 30 seconds total throughout the game or if the participant's avatar was moving into a wall for 30 consecutive seconds. We also removed participants if their ping response latencies were greater than 125ms for more than 75 seconds in total throughout the game. To minimize disruption of large groups, we allowed multi-participant games to continue after a participant disconnected or was removed, as long as at one or more participants remained.

We paid participants 75 cents for completing our instructions and comprehension checks, and the participants could receive a bonus of up to $1.25 during the five minutes of gameplay. Each point in the game corresponded to $0.01 of bonus. Each participant was also paid 15 cents per minute for any time spent in the waiting room, minus any time that participant spent moving into a wall. These numbers were chosen so that the participants were expected to receive at least a wage of $9 per hour for the totality of their time active in the experiment.

We implemented this experiment using the MWERT framework (Hawkins, 2014), which uses a stack of recent web technologies capable of handling the challenges of real-time, multi-participant web experiments, including Node.js, the Socket.io module, and HTML5 canvases.

2.4 Results

We hypothesized that individuals in larger groups would be able to achieve higher scores on average than individuals in smaller groups. We also hypothesized that the advantages of larger groups would accrue later in the game, when participants had adjusted to the mechanics of the environment and the behavior of the other participants. To test these hypothesis, we examined performance during each half of the 5-minute session. In cases where one or more participants were disconnected or removed, we measured the size of the group at the end of the session. We constructed a mixed-effects regression predicting each individual participant's average score over the time period, including fixed effects of period (first vs. second half), the continuous number of participants in their environment (one through six), and their interaction. We also included random intercepts for each group and each of the five underlying score fields. First, we found a main effect of practice: scores were significantly higher on the second half of the session ($b = 2.1, t = -10.8, p < 0.001$). However, we also found a significant interaction with group size: while performance on the first half was similar across group sizes, the performance of each individual on the second half significantly increased in larger group sizes from a score of 0.16 in groups of 1 to 0.24 in groups of 6 ($b = 0.33$, $t = 2.8$, $p = 0.004$; see Fig. 2).

3 Experiment 2: Evaluating copying strategies

What cognitive abilities allowed humans in Experiment 1 to benefit from collective intelligence even when the payoff information of other agents is not directly accessible? We hypothesized that human behavior in this environment is driven by two underlying strategies: (1) independent exploration and (2) precise, targeted copying based on social inferences about success. These hypothesized strategies rely on cognitive abilities allowing humans to infer "who knows" about high-scoring locations based on outward behavioral traces (e.g. slowing down or stopping in a region) and also to inhibit social influence to act independently when appropriate.

The design of Experiment 1 made it challenging to disentangle these strategies. For example, we were interested in analyzing participant clicks to detect signatures of selective copying, but because there was a unique 'spotlight' at each point in time, different copying strategies were confounded: participants who were already obtaining reward and trying to stay inside the spotlight were, by necessity, clicking close to other participants who were obtaining reward, even if they were not intentionally copying them.

For our second set of experiments, then, we designed a sequence of controlled scenarios that are more diagnostic for testing the use of these different strategies. We placed participants into an environment with artificial agents that we designed, rather than other humans, and we manipulated the location of the score field to estimate the probability of copying different agents under different conditions.

For conceptual clarity about our design and analysis, it is helpful to define three broad 'states': exploring, exploiting, and copying (e.g. Rendell et al., 2010). We define *exploiting* as selecting an action that maximizes the expected score given the agent's current knowledge of the environment, i.e. staying close to a known location of the spotlight. We define

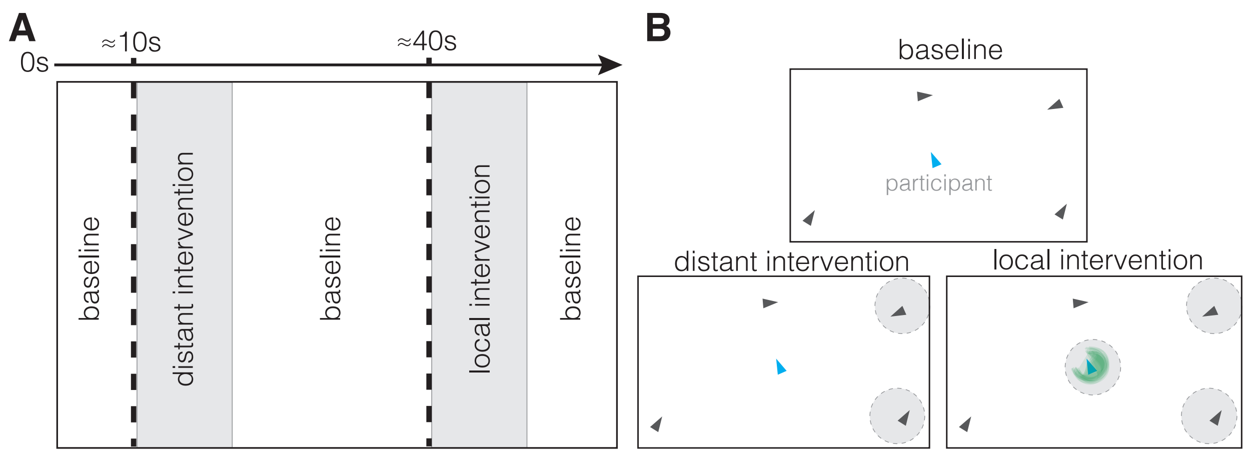

Figure 3: Design of Experiment 2. (A) The timeline of the test round involves a baseline condition with no score field, and two causal interventions on the score field beginning at approximately 10 seconds and 40 seconds. (B) These interventions manipulate the location of the score field to ensure the participant is receiving high reward or not, respectively, while a subset of other agents are receiving high reward.

copying as forward motion, sometimes accelerated, toward the location of another agent. We define *exploring* as selecting an action that has an unknown outcome, often moving to a region without other agents. In this environment, exploiting, exploring, and copying behavior were associated with distinct and recognizable movements. Our hypothesized strategies can be operationalized as selective deployment of these three states: exploiting rather than copying or exploring when one is in a high-scoring region, and copying rather than exploring in low-scoring regions only when it can be inferred that another agent is receiving a high score, based on outward behavioral signatures.

3.1 Methods

3.1.1 Participants

We recruited 28 unique participants from Amazon Mechanical Turk. All participants were from the United States.

3.1.2 Stimuli & procedure.

As in our first experiment, participants were given control of an avatar to explore a virtual environment and were rewarded based on their location according to a hidden "score field." The interface and controls were the same as in Experiment 1, but the procedure differed in several ways. Instead of a single 5-minute session, we designed a sequence of shorter scenarios that were informative for distinguishing between several different potential mechanisms that could be used in the game. These scenarios carefully controlled score field dynamics and bot behaviors.

Practice phase To acclimate participants to the task environment, each game began with four one-minute long practice rounds. In the first and third practice rounds, the score field was *visible* to the participant so they could observe its dynamics. In the second and fourth practice rounds, the score field was invisible to the participants, as in Experiment 1. Additionally, we randomized participants into two different groups, who practiced with different score field dynamics. In a "wall-following" pattern, the high scoring region moved contiguously along the walls of the playing area. In a "random-walk" pattern, the high scoring region slowly drifted, as in Experiment 1, from one random location to another within the playing region. Because we did not observe substantial differences in participant behavior depending on the score field dynamics observed during the practice phase, we collapsed over this factor in our analyses.

Test phase After the four initial practice rounds, participants played two one-minute test rounds that were the focus of our analyses. In one of the two test rounds, no other agents were present (non-social condition), and in the other there were four bots in the environment (social condition). We randomized the order of social and non-social conditions across participants. Each of these rounds was further divided into three conditions, where we causally intervened on the score fields to better test our hypotheses about exploring, copying, and exploiting behavior.

For the *baseline* condition, there was no score field. During these times, all the bots were randomly exploring, with two randomly exploring along walls (in association with the wall score field dynamic) and two exploring the center region (associated with the random walk score field dynamic). Around the ten second mark and the forty second mark in each round, we introduced the two high scoring regions into the game (see Fig. 3A). In the *distant intervention* condition, we superimposed the wall-following and random-walk score field patterns to create a bi-modal dynamic score field. We centered one high scoring region on a wall-following bot and one high scoring region on a bot in the center region. In the *local intervention* condition, however, we also placed a high scoring region on the *participant*, wherever they were. In this condition, they automatically received a high score for roughly the ten second duration that the high scoring regions were present (see Fig. 3B). We randomized the order in which these two interventions appeared.

Bots followed a simple selective copying algorithm. They were programmed to immediately stop upon entering a high-scoring area. If other bots in the environment were stopped, they copied them, and explored non-socially when no other bots were stopped. The wall-following bots only copied other wall-following bots, and the bots in the center region similarly only copied each other. Bots were not responsive to the participant's behavior, only to each other. In the non-social round, we simulated the same bots, so that the distribution of score field positions was the same across the two conditions. The score field manipulation was triggered for the bots approximately two seconds after it was triggered for the participant in the local intervention condition. We offset the onset in order to ensure that participants were already aware of their own score before observing any reward-related bot behavior.

3.2 Results

To analyze our data from this experiment we use a mixed methods analysis involving both a qualitative coding approach and a quantitative analysis of behavioral traces and click data.

3.2.1 Qualitative Coding Results

For our qualitative analysis, two authors manually coded videos of our 28 participants. We coded for three behavioral signatures — *selectivity* in copying exploiting bots, *eagerness* in copying other agents, and *independence* in exploration — on a scale from 0 to 1. *Selectivity* was defined by examining behavior during the distant condition, when the participant was not themselves receiving a reward but another agent was: selectivity was coded as a preference for moving towards agents who were exploiting, as opposed to moving toward agents who were exploring or copying. This behavioral signature marks participants as selectively copying agents who are exploiting the high scoring regions. *Eagerness* was defined by the same preference for moving toward exploiting agents during the local condition when the participants were themselves receiving a high score, such that their copying behavior was not contingent on their own state. Eager agents copy even when they could be exploiting the high scoring region they have already identified. Finally, *independence* was defined by reverse-coding a preference for moving towards agents who were *not* stopped, at any point in the task—i.e., indiscriminately copying other agents. This signature primarily captures whether participants were preferentially moving toward other agents during the periods when there was no score field active, thus we interpret low prevalence of this signature as high independence. The endpoints of the scale roughly represented the proportion of time the participant spent displaying the behavior in question compared to the potentially available opportunities to do so.

The two coders achieved a correlation of $r = 0.75$ for selectivity, $r = 0.55$ for eagerness, and $r = 0.60$ for independence. The coders resolved disagreements in our codes by averaging. First, we found that a substantial fraction of participants display selective copying behavior and independence (Supplemental Fig. 8). We found that 71% of participants had an average selectivity rating of at least 0.5, and 86% had an average independence rating above that level. These proportions were significantly greater than 50% using a two-sided binomial test, $p = 0.036$ and $p = 0.001$, respectively. In comparison, only 1 participant (4%) was coded as eager at that level, which was significantly less than 50%, $p < 0.001$. These qualitative results show that participants appeared to selectively copy stopped agents when they themselves were not receiving reward, but otherwise mostly inhibited social influence.

3.2.2 Quantitative Behavioral Results

Next, we tested these same hypotheses quantitatively using data we recorded of participants' locations and the state of the environment at each time step of the experiment. We operationalized copying using participant clicks. Because clicking near another agent moved them closer to their target's location, and success is based on spatial location, we

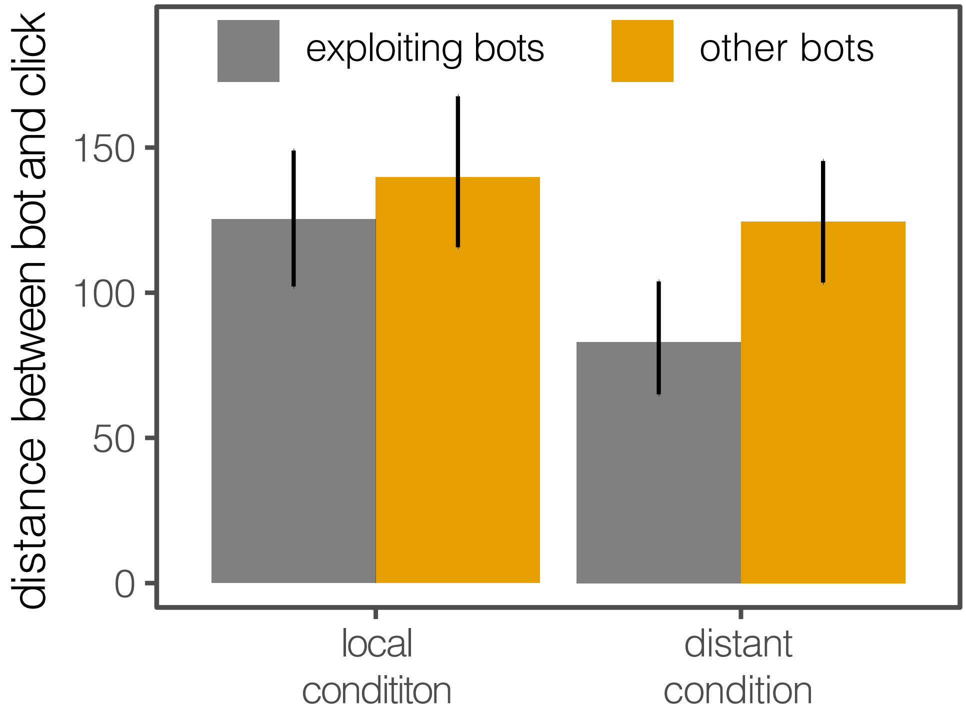

Figure 4: Participants selectively copy other agents who appear to be exploiting, but only when they themselves are not receiving reward (i.e. the distant intervention condition). We operationalized copying in terms of the spatial distance from the click to the bot's location, so lower distance is evidence of copying. Error bars are bootstrapped 95% CIs.

examined the proximity of each click to other agents. To test whether participants selectively copy agents who appear to be exploiting, we computed both the distance to the nearest agent who is stopped, and the nearest agent who is not stopped. We then compared copying rates across the two score field conditions: we predicted that participants would inhibit selective copying in the *local* condition, when they automatically received a score in their current location, relative to the *distant* condition, where the score field was only placed on top of artificial agents. To test this prediction, we constructed a mixed-effects regression model predicting the proximity of each click to the nearest agent as a function of experimental condition (local vs. distant), visible behavior (exploiting vs. not exploiting), and their interaction. We included the maximal random effects supported by our within-participant design, allowing random intercepts, main effects, and interactions at the participant-level. We found a significant interaction, $b = 47.6, t = 2.5, p = 0.02$, indicating a selective preference for copying other exploiting agents, but only in the condition when the participant was not themselves receiving a reward (see Fig. 4). To control for the possibility that this result is a product of generic biases in the spatial pattern of clicks, rather than the use of social information, we conducted the same analysis on clicks in the *non-social* condition, where no artificial agents were visible but the underlying score field dynamics were the same. In other words, this condition allows us to examine the proximity of clicks to where other agents would have been. We found no significant interaction in this condition, $b = 30.1,\ t = 1.4,\ p = 0.18$. A stronger test of this comparison would be the three-way interaction in a single model testing whether the interaction estimated in the social condition differed significantly from the one in the non-social condition. This three-way interaction was not significant, $b = 20.1,\ t = 1.2,\ p = 0.19$. Exploring the baseline variability of clicks in non-social environments is likely to be a fruitful target for future work using a more highly-powered sample.

4 Experiment 3: Generalizing to more complex environments

To generalize our understanding of these findings to more complex environments, and to more explicitly compare our findings to the nonhuman animal literature, we conducted a final experiment using the materials designed by A. Berdahl et al. (2013) to examine collective sensing in fish. These environments are significantly more complex than the binary spotlight and border environments we used in Experiments 1 and 2. They require agents to use continuous gradients to navigate noisy and fluctuating score fields. We manipulated the level of noise across different groups, predicting that the cognitive abilities discussed in the previous sections may be less reliable under noisier conditions. To test that the social learning strategies identified in the previous experiments also generalize to different external behavioral signatures, we also modified several other aspects of the experiment interface, including the movement controls. This small change created a different behavioral cue of success (spinning in place rather than stopping or slowing), which agents equipped with social inference mechanisms should be able to use for selective copying just as effectively as participants in the previous experiments.

4.1 Methods

4.1.1 Participants

We recruited 563 unique participants from Amazon Mechanical Turk to participate in our experiment. All participants were from the United States. After excluding 72 participants due to inactivity or latency, and 6 others for disconnecting in the first half of the game, we were left with usable data from 437 participants in 224 groups. 113 individuals (63 groups) were in the low noise condition and 324 individuals (161 groups) were in the high noise condition. These groups ranged in size from one to six individuals. Since only one group of size six completed the task without disconnections, we ignored this group in our analysis.

4.1.2 Stimuli and Procedure

Our primary change from Experiments 1 and 2 was switching from a binary score field to a more complex, gradient score landscape. These more complex fields were generated using the method reported by A. Berdahl et al. (2013). We began with the same randomly moving "spotlight" of high value as before. However, we then combined the spotlight with a field of spatially correlated, temporally varying noise. By manipulating the proportional weighting of the noise field and the spotlight, we generated two different conditions, corresponding to two of the noise levels used by A. Berdahl et al.. In the *low noise* condition, the spotlight was weighted strongly compared to the noise field (10% noise), with the noise field providing minor background variation (see Supplemental Fig. 9, left). In the *high noise* condition, the weighting of the noise field was increased (25% noise), providing more extreme fluctuation outside of the spotlight (see Supplemental Fig. 9, right). To decrease variability and increase statistical power, we generated only four distinct score fields per noise level, so multiple groups experienced the same fields.

In addition to these more complex score fields, we made several adjustments to the interface. First, rather than showing their current score as binary—a glowing halo around the participant when inside the spotlight—their score was presented as a percentage at the top of the playing area (see Supplemental Fig. 11 for a screenshot). Second, rather than clicking to change direction, participants controlled their avatars using their keyboard. The left and right arrow keys were used to turn (at a rate of 40° per second) and the spacebar was used to accelerate. Unlike before, we did not provide a mechanism to stop completely. Given the closer relation to A. Berdahl et al. (2013) in this experiment, it is also relevant that the speeds of the avatars and the playing area dimensions (480×285) throughout all of our experiments were matched to those reported by Berdahl et al.; in this experiment, we additionally used the same total task length of six minutes.

The procedure was similar to Experiment 1: after successfully completing a comprehension test, participants were redirected to a waiting room where they could get used to the controls. Participants were not given any practice rounds, or any information about the nature of the underlying score fields. The conditions for removal due to inactivity or latency, and the bonusing scheme, were also similar to Experiment 1 with slightly different parameters.

4.2 Results

Our analyses focus on two primary questions: (1) how does the introduction of a noisier environment affect collective performance, and (2) how do the selective social learning strategies identified in Experiment 2 play out in such an environment, when inferences about the success of other agents may be less reliable?

4.2.1 Effects of noise on collective performance

We begin by analyzing patterns of collective performance across groups of different sizes and across the different noise conditions. As our measure of performance, we computed the average score obtained by participants over each half of the experiment. To test effects of performance, we constructed a linear regression model with main effects of group size (1 through 5), half ('first' vs. 'last') and noise condition ('low' or 'high'), as well as their interactions. All three main effects were significant: all else being equal, scores tended to increase with group size, $b = 1.4,\ t = 3.9,\ p < 0.001$, were higher in the second half compared to the first half, $b = 2.7,\ t = 5.2,\ p < 0.001$, and were higher in the low-noise condition than the high-noise condition, $b = 4.1,\ t = -7.8,\ p < 0.001$. The only significant interaction was between noise condition and group size, $b = 0.89,\ t = 2.4,\ p = 0.018$, indicating a stronger

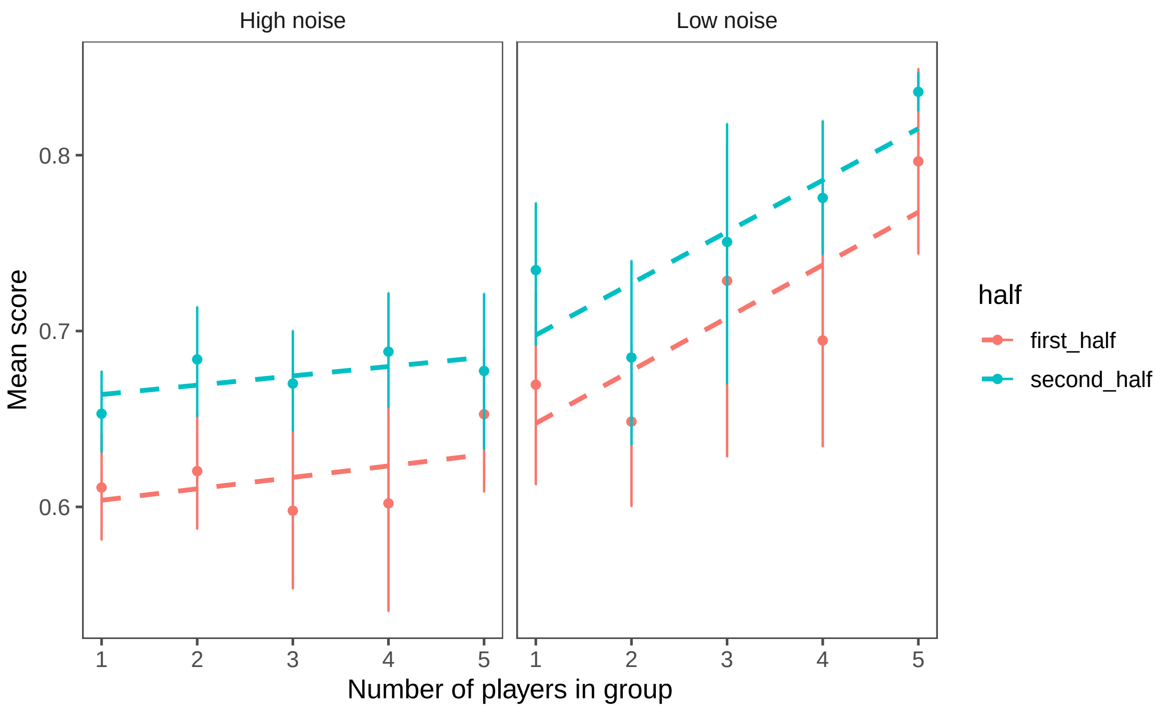

Figure 5: Mean performance as a function of group size under different noise conditions. Error bars are 95% bootstrap confidence intervals using the group as the primary bootstrap unit.

effect of group size in the low-noise condition than the high-noise condition (see Fig. 5). We also conducted a mixed-effects regression including random intercepts for each group (i.e. controlling for possible correlations between participants in the same group) and for each score field (i.e. controlling for the possibility that some randomly generated score fields were more difficult than others). We found that the main effects of group size, game half, and noise condition were robust ($p = 0.037, p = 0.001, p < 0.001$, respectively) but the interaction was no longer significant, $p = 0.23$, with the group-level random intercept accounting for the bulk of the additional variance. We suspect this discrepancy is due to dramatic loss in power to detect an interaction after shifting from the participant-level unit of analysis to the group-level unit of analysis, especially given imbalances in sample sizes across noise conditions. Thus, we believe this effect merits further investigation. Overall these results indicate an important role of the environment in group success: under low noise, larger groups perform systemically better than smaller groups, similar to the effect found in Experiment 1, yet this advantage appears to be weaker under high noise.

4.2.2 Analysis of social learning strategies

In order to understand the mechanisms that may have contributed to effects of noise on collective performance, we more closely analyzed the underlying behavior of the participants in our games. While we relied on click data as a useful measure of copying in Experiment 2, here used a simple *state-based* representation of participant behavior based on their keyboard actions. We empirically determined the state of each participant at each point in time — exploring, exploiting, or copying — using a simple set of hand-specified criteria. All of these criteria depended only on information that was observable to participants in the game (i.e., the filters do not depend directly on the hidden scores of other individuals), and hence we can use these states as proxies for what participants might be able to infer. Additionally, because the states are not defined in terms of score values, we can meaningfully quantify the relationship between state and performance.

Our criteria for classifying the three states are as follows.

- *Exploiting* behavior was not trivial for participants since the avatars always move at least at a slow constant velocity. Unlike in the previous experiments, where the "s" could could be pressed to stop in place, a participant in Experiment 3 could either meander around a particular location or persistently hold down one of the arrow keys while moving at a slow speed, which creates a relatively tight circular motion around a particular location. We call this second activity "spinning" because of its distinctive appearance. We then classify a participant as exploiting if the participant is spinning for 1 second, or if the participant moves at a slow speed for 3 seconds and has not traveled more than two thirds of the possible distance that the participant could have traveled in that time. The second condition is captures the meandering behavior of individuals who have not discovered how to spin.

- *Copying* behavior is more difficult to identify, but is likely characterized by directed movements towards other participants. We thus classify a participant as copying if they move at the fast speed in a straight line towards any particular other participant for a 500ms window. We consider a participant to be moving towards another participant if the second participant is within a 60° on either side of the first participant's straight-line trajectory.

- We classify behavior as *exploring* if the participant is neither exploiting nor copying. Thus, a participant will be classified as exploring if that participant is either moving slowly but not staying in the same general location, if the participant is moving quickly but not towards any particular person, or if the participant is moving quickly and turning.

We now proceed to use this classification scheme to analyze the behavioral strategies used by participants in our game. First, in line with our finding in Experiment 2 that participants inhibit copying when they find themselves in high-scoring regions, we predicted that the probability of the exploiting state would increase as participants receive higher scores. To test this prediction, we constructed a logistic mixed-effects regression model predicting the probability that each individual is in the 'exploiting' state at each time step. We included fixed effects of their current background score and noise condition, as well as their interaction. We also included random intercepts for each group and score field. First, we found a strong main effect of the current score: regardless of noise condition, participants are significantly more likely to exploit in higher scoring locations than in

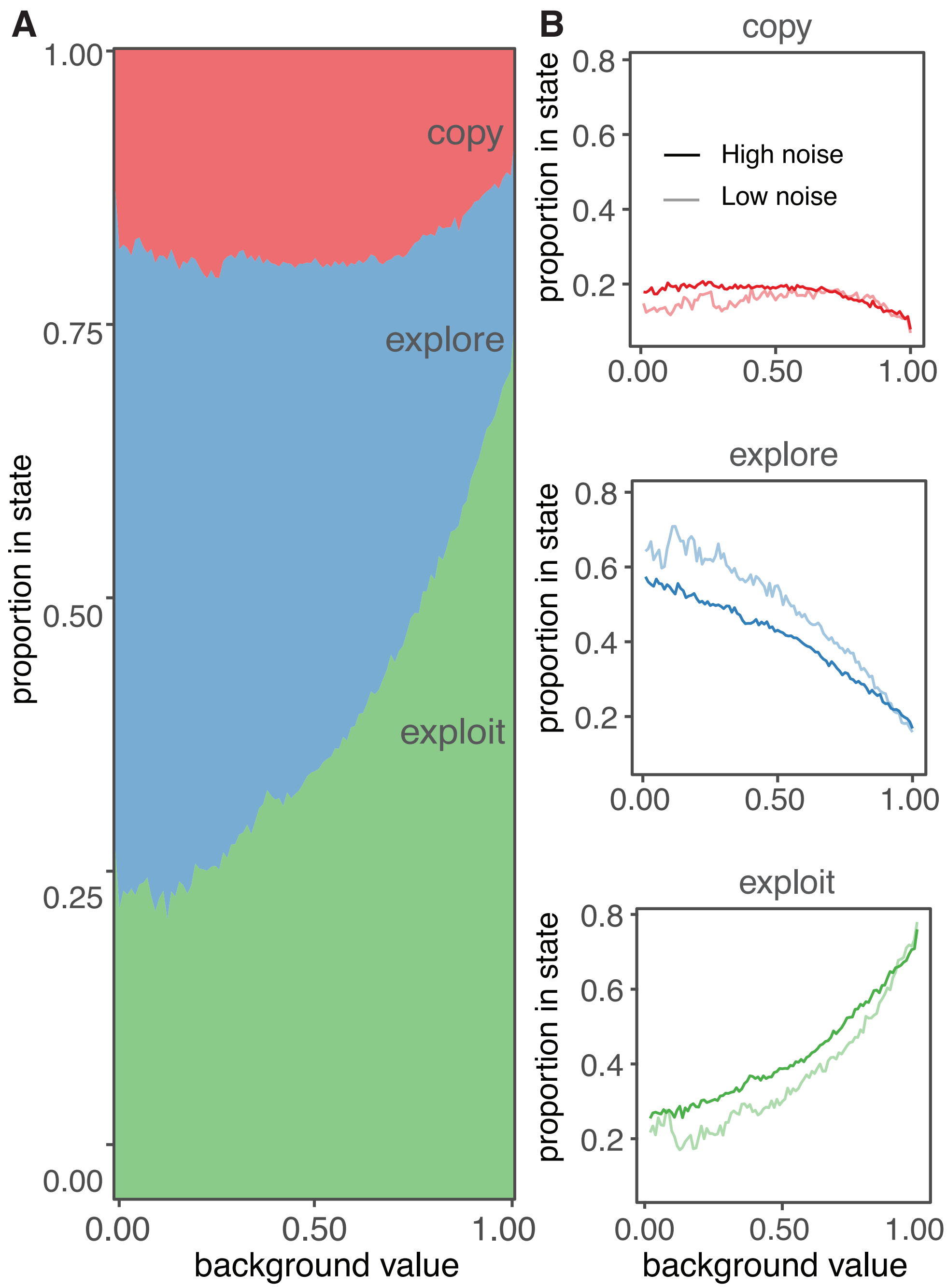

Figure 6: (A) The probability of an individual being in a particular behavioral state as a function of the individual's score, combined across both conditions. (B) Participants tended to begin exploiting at lower background values in the high-noise condition, leading to less copying and exploration.

lower scoring locations, $b = 3.2,\ z = 310, p < 0.001$ (see Fig. 6A). Selective exploiting is clearly adaptive, as participants will tend to remain in high scoring regions but quickly move away from low scoring regions either by exploring independently or by copying other individuals. At the same time, strategies differed dramatically across noise conditions: we find a significant main effect of noise, $b = 0.3,\ z = 3.7,\ p < 0.001$, indicating that participants are significantly more likely to engage in exploitation in the high noise condition at all background values. We also found a significant interaction between condition and background value, $b = -0.3,\ z = -33,\ p < 0.001$, indicating that the increased likelihood of exploitation is especially pronounced at lower background values (see Fig. 6B). Similar regressions predicting the probability of 'copying' and 'exploring' states found that participants were also *less* likely to be exploring, $b = 0.26,\ z = 27,\ p < 0.001$, and *more* likely to be copying, $b = 0.08,\ z = 6.2,\ p < 0.001$, at lower point values.

A lower threshold for exploitation may also help explain gaps in collective performance across noise conditions. First, a willingness to exploit at lower point values may, by definition, lead to lower overall performance. Second, it may make copying less effective, preventing social learning mechanisms from improving performance in larger groups. That is, if participants are willing to exploit at lower background values, then external cues of exploiting (i.e. "spinning" behavior) will provide statistically weaker evidence of underlying success. To test this hypothesis, we identified all of the events in our dataset where one participant copied another and measured the current score of the target of copying. We found that targets of copying tend to be in lower scoring regions in the high-noise condition, $d = 0.08,\ t = 4.02,\ p < 0.001$. These results clarify the interaction between human social learning strategies and environmental conditions, and raise interesting questions about the robustness of social inference based copying. We discuss these questions in more detail below.

5 Discussion

Our experiments established that human groups display collective intelligence – in the form of emergent sensing – during a dynamic spatial search task. Individuals in larger groups were better able to sense and respond to their environment. Further, we were able to uncover the mechanisms driving the emergent sensing: individuals, who only had access to extremely local (scalar) information about the spatial resource field, were able to use information inferred from the behaviors of other individuals to develop a non-local measure of the hidden underlying resource field. We confirmed that selective social learning relying on simple agent-reasoning, rather than indiscriminate copying, was employed to enable this intelligent collective behavior. We also confirmed that these abilities and behaviors were sustained in a more complex experimental environment. The inference drawn appeared to be rapidly learned during the experimental trials and may be unique to humans, suggesting that human's meta-cognitive reasoning and agent reasoning abilities, such as theory of mind, may allow collective intelligence to rapidly emerge in novel settings.

Comparison to Prior Work. Our study design was inspired by a collective sensing task used in the animal behavior literature, particularly the one proposed for groups of fish by A. Berdahl et al. (2013). We found similar improvements in performance as a function of group size in humans, suggesting that the general phenomenon of collective sensing persists across different species (A. M. Berdahl et al., 2018). However, the mechanisms driving the collective sensing appear to be very different between the fish and humans. In fish schools, resource-level-dependant speed modulation induced group-level turning toward high-resource areas, while humans were led to these high-resource areas via strategic copying based on the inferred performance of others. These differences support recent work in social learning (Wisdom et al., 2013; McElreath et al., 2008), which find flexibility in the strategic deployment of imitation in humans. Appendix A provides one plausible model that could describe the form of selective copying we observe.

Differences in the group performance versus group size between fish and humans reveals a potential trade-off between the underlying mechanisms. First, we found that humans were able to achieve increases in performance at much smaller group sizes than fish. Humans had substantial improvements in performance at just five participants, while schools of fish only showed really significant improvements at groups of 64 and 128. Second, while there was no difference in the effect of group size across different environmental noise levels for fish, we found that in the small-group regime we considered, the benefits of larger group sizes only accrued in low-noise conditions for humans. Taken together, these two differences show that the emergent sensing in humans may be more powerful than that found in fish, but the mechanism used by the fish is more robust to noisy environments. However, we note that it is difficult to make quantitative comparisons between human performance to the performance of fish given the differences between the perceptual and motor abilities of fish in a tank and those available to participants in our simulated environment. Yet our study nonetheless raises interesting questions about the potential trade-offs between differences between mechanisms for collective intelligence.

Social Learning in Non-human Animal Groups. Our work demonstrates consequences of fast social inferences in human groups. In contrast, the status of similar abilities in non-human animals remains more controversial. The use of fast social inferences in human groups may be widespread, but the status of similar abilities in non-human animals remains more controversial. Across a broad diversity of taxa, both gregarious and non-group-living species use social information when locating resources (Danchin, Giraldeau, Valone, & Wagner, 2004) and many examples are consistent with inferential behaviour. Just as our human participants moved toward others 'spinning' within a reward patch, vultures are attracted to the circling flight of other carrion eaters (Kane, Jackson, Ogada, Monadjem, & McNally, 2014). Bats use odors from the breath and fur of conspecific when deciding where to forage (O'Mara, Dechmann, & Page, 2014) and seem to prefer novel conspecifics, perhaps to inject new information (Ramakers, Dechmann, Page, & O'Mara, 2016). Cliff-dwelling swallows, appear to engage in signalling behavior at food sites (Brown, 1988; Brown, Brown, & Shaffer, 1991), which effectively externalizes success and draws conspecifics to enhance the efficiency of foraging (Torney, Berdahl, & Couzin, 2011). Uninformed fish and rats leave protection to follow trained conspecifics to feeding sites, presumably by responding to the behaviors trained individuals display when anticipating food (Reebs, 2000; Bennett G Galef & White, 1997). Despite the prevalence of social information use in foraging animals, and the superficial consistency with inference, it remains unclear whether these cases reflect social reasoning abilities beyond standard operant and respondent conditioning that associates social information with foraging success (Galef Jr & Giraldeau, 2001).

Organizational behavior. In addition to the recent literature on collective intelligence in nonhuman animal groups, there has been a long line of work studying the factors that predict the performance of human groups in various scenarios (Kerr & Tindale, 2004; Lazer & Friedman, 2007; Mason & Watts, 2012; Malone & Bernstein, 2015; Shore, Bernstein, & Lazer, 2015). Our findings are consistent with previous work suggesting that having a larger group is beneficial in complex, uncertain environments (Stewart, 2006). Unlike much of this previous work, however, we focus here on the possibility in larger groups of new emergent group abilities and behaviors, and on the mechanisms leading to these emergent properties.

Contextual Factors. The picture of collective intelligence in humans and across specifies that is emerging from the scientific literature is that different mechanisms likely give rise to collective intelligence in different species, and that the same can be said even of different types of human collective intelligence displayed in different contexts. Human collective intelligence on Wikipedia operates in a way that is very different from human collective behavior on social media platforms like Twitter, and both are quite different from the mechanisms of collective intelligence through which bees find new homes or ants scavenge for food. The mechanisms we identify in our experiment are yet another context. Still, the quest continues for what general abilities and principles underlie the range of intricate and sophisticated forms of human collective intelligence (Krafft, 2019), and what distinguish those as a group from the apparently simpler, more swarm-like forms of collective intelligence found in species such as social insects or fish. Focusing on cognitive abilities rather than behavioral strategies may provide a more domain-general way to understand collective intelligence.

6 Ethics

The research was reviewed and approved by the MIT Committee on the Use of Humans as Experimental Subjects (COUHES), Protocol 1509172301, as well as the Oxford Internet Institute Departmental Research Ethics Committee (DREC), CUREC 1A Research Ethics Approval Ref Number SSH_OII_CIA_20_002.

7 Acknowledgments

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship under Grant No. 1122374 to PK and Grant No. DGE-114747 to RXDH. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors(s) and do not necessarily reflect the views of the National Science Foundation. This material is based upon work supported by the Center for Minds, Brains and Machines (CBMM), funded by NSF STC award CCF-1231216. We are grateful to Colin Torney for providing the code to make the score field gradients.

8 Competing Interests

The authors declare no competing interests.

9 Data Accessibility

Data, experiment code, and analysis code are available at `https://github.com/hawkrobe/fish`.

10 Author Contributions

RH, PK, AP, NG, and JT formulated the study. RH and PK designed the experiments, implemented the experiments, and analyzed the data. HF assisted with data analysis. RH, PK, and AB wrote the manuscript. PK is the acknowledged head of the writing team. All authors gave final approval for publication and agree to be held accountable for the work performed therein.

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Appendix A: Behavioral Model

The trends we observe suggest a potential set of behavioral mechanisms that participants may be using in our task. We propose that each participant chooses an exploring, exploiting, or copying state based on the following rules:

1. If the participant is in a high scoring area, the participant will remain in that area exploiting.
2. If the participant is in a low scoring area and the participant perceives another person as possibly having a higher score, the participant may choose to copy that person.
3. Otherwise the participant will explore independently.

This model displays intriguing collective behavior in the score fields that have a smoothly moving high scoring region. When any individual finds a high scoring area, that participant will attract the other participants to that location by exploiting. Then such slowly evolving environments, when all the participants are together in a group exploiting a particular area, one of the participants will receive a lower score as the score field shifts. This participant will then either move closer to the others who are still exploiting or will shift to an exploring state. If that participant starts exploring but doesn't find any high scoring locations, the participant will return to the group if the group is still exploiting. If that participant does find a new high scoring area, though, the participant will start exploiting that area. The rest of the group will then follow after the highest scoring region shifts to where the exploiting participant is. This mechanism creates a kind of gradual crawling that effectively tracks the moving score field. Thus, by using this mechanism participants are improving both their own performances directly and also that of the entire group by participating in this process of emergent collective sensing. An example of this process occurring in participant gameplay is shown in Figure 10, and in our Supplementary Videos.

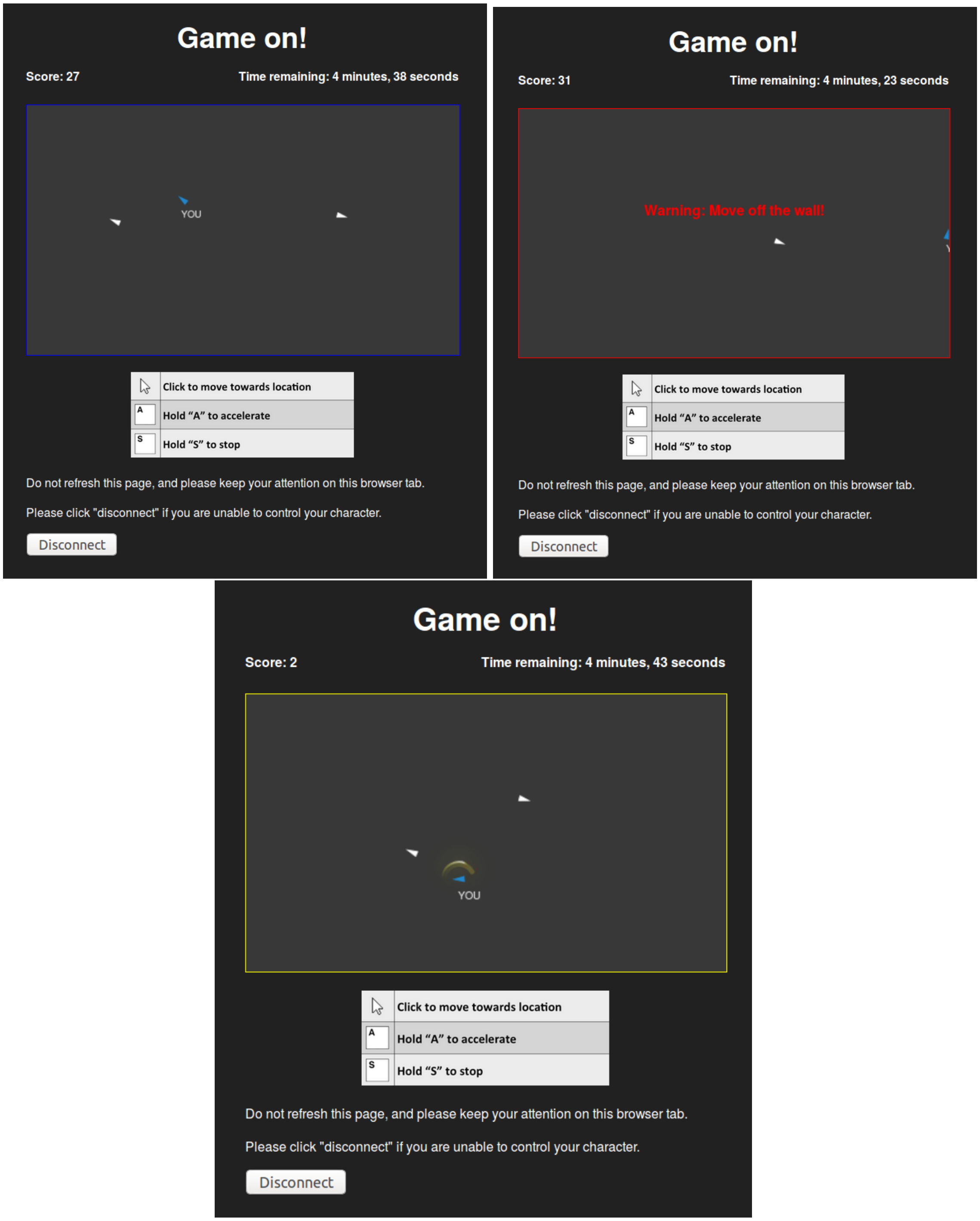

Figure 7: Examples of Experiment 1 interface.

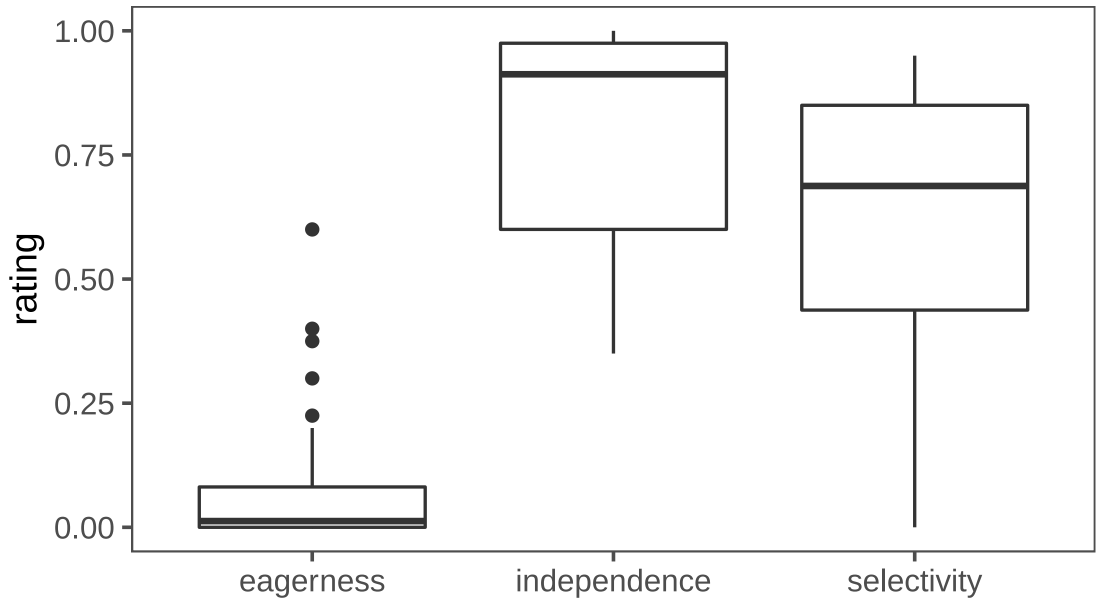

Figure 8: Distribution of ratings for three qualitative behavioral properties that were coded from videos in Experiment 2. Participants displayed relatively high levels of selective copying behavior and independent exploration, while eager copying is less common.

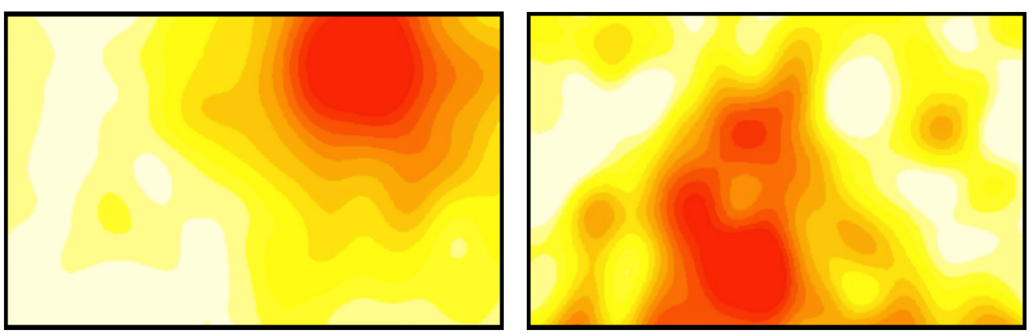

Figure 9: Example snapshots of score fields from the low noise (left) and high noise (right) conditions used in Experiment 3. Red areas indicate higher scoring areas.

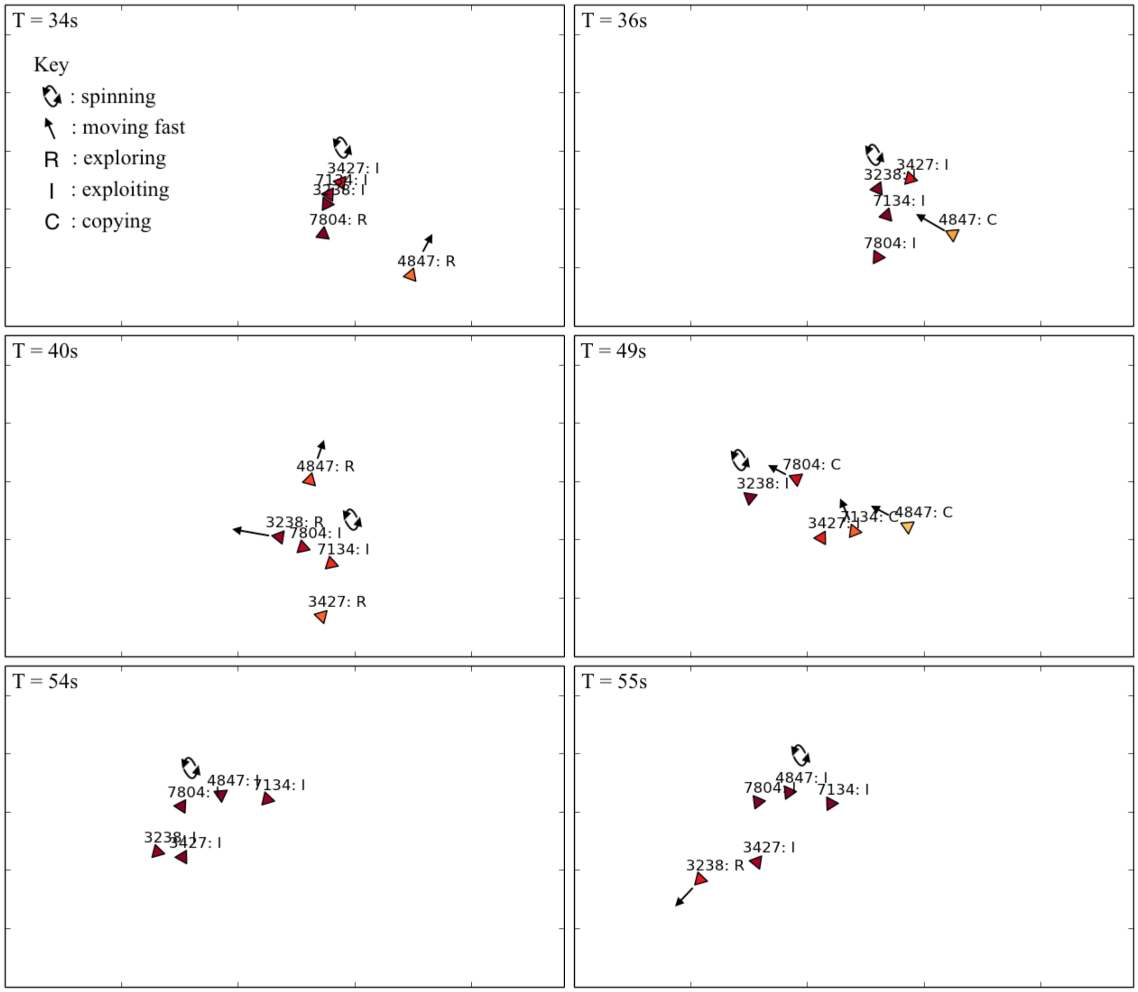

Figure 10: Reconstructions of actual gameplay in a five-person group illustrating both failed exploration leading to intelligent copying and successful exploration leading to collective movement. Colors indicate the individuals' scores, with red being higher and orange/yellow being lower. The participant labels indicate both participant IDs and also the participant states our feature extraction procedure inferred. Other annotations are provided to give a sense for the game dynamics. At 34 seconds, in the first panel, most of the group has converged on exploiting a particular area while one individual is exploring independently. To the right, at 36 seconds, the exploring individual appears to have failed to find a good location and ceases exploring by copying the group. At 40 seconds, the final panel in the first row, the score field has shifted and some of the group begins exploring while others continue to exploit. By 49 seconds, the first panel in the second row, one of the exploring individuals found a good location, and other participants have begun to move towards that individual. At 54 seconds, the entire group is exploiting the new area. In the final panel, at 55 seconds, the background has shifted enough again that one of the individuals begins to explore.

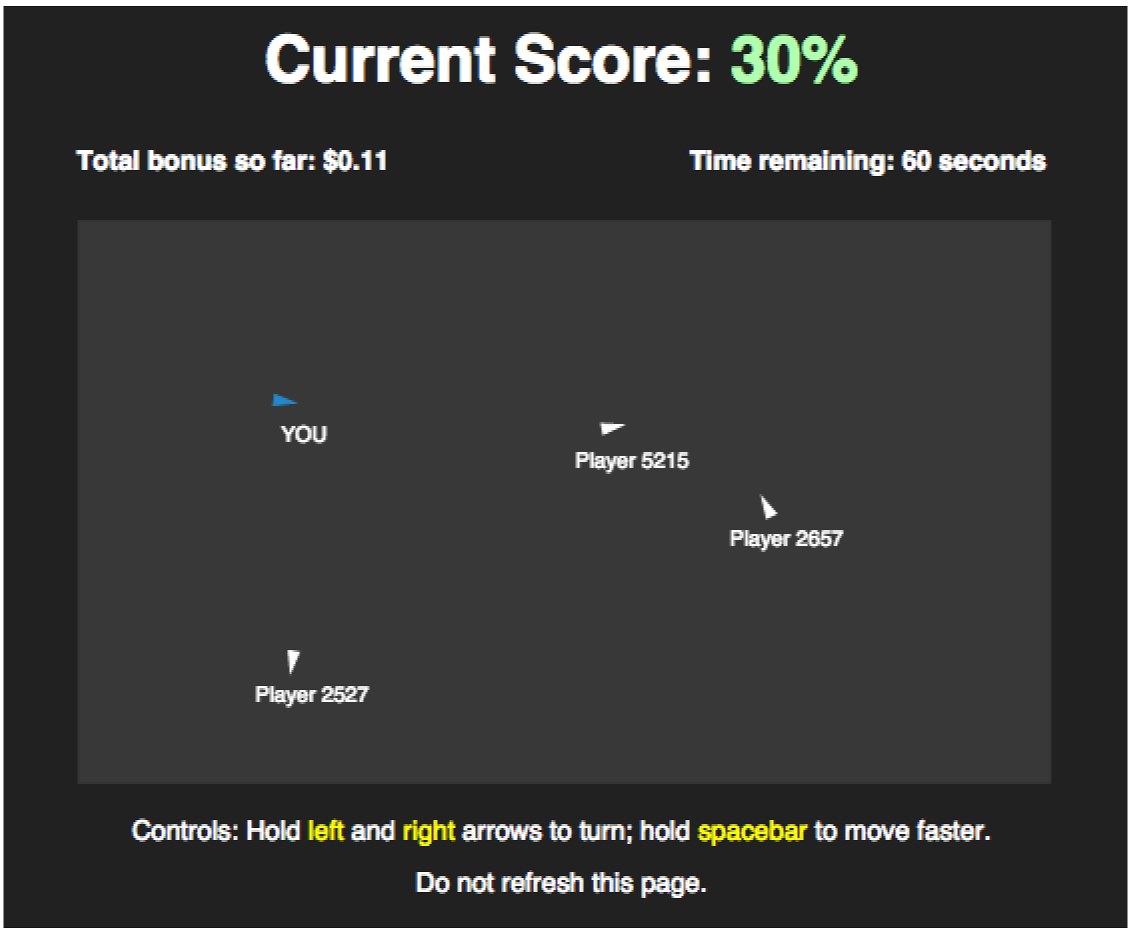

Figure 11: Screenshots of the Experiment 3 interface. The score displayed corresponds to the value of the score field at the location that the participant's avatar is occupying.