The gold miner's dilemma: use of information scent in cooperative and competitive information foraging

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Abstract

When searching for new information, do people focus their search on places not-yet discovered by others, or on places that others also focus on? Through a controlled experiment, we investigated heuristic rules that people adopt in social information search, a growing characteristic of how people find information in this hyperconnected world. Three people were connected online to simultaneously search for specific objects in multiple images, under either a cooperative or a competitive setting. They were provided with information about the current number of objects collected and the cumulative time spent on each image. People used such information to decide when to stop the current search and which image to explore next. Further, people paid more attention to others and distribute search efforts when cooperating, compared to when competing against others. Our findings highlight the heuristic rules that people adopt when searching in groups for new information.

Keywords: collaboration, competition, crowdsourcing, information foraging, information scent

1. Introduction

Rapid advances in information technologies have facilitated growing exposure to an overwhelming amount of information (Eppler & Mengis, 2004), making it difficult for people to find the information they need quickly. To address this challenge, considerable effort has been placed toward optimizing information systems through which people search and retrieve information (Hevner, March, Park, & Ram, 2004). Traditionally, information systems regard information search to be an individual activity (Hansen & Järvelin, 2005). However, a growing body of literature has demonstrated the feasibility of collectively searching information in a group (Amershi & Morris, 2008; Maekawa, Hara, & Nishio, 2006; Morris & Horvitz, 2007; Morris, Paepcke, & Winograd, 2006; Smeaton, Lee, Foley, McGivney, & Gurrin, 2006). Collaborative information seeking (CIS) aims to introduce algorithms that could enhance group performance in information search within information systems. In contrast to our rich knowledge about collective information search from conceptual and qualitative perspectives (Evans & Chi, 2008; Hansen & Järvelin, 2005; O'Day & Jeffries, 1993), a paucity of quantitative studies hampers our ability to establish information systems that could fully capitalize on collective activities in information search.

Compared to individual information search, groups with shared goals can benefit from collective information search through faster gathering of more complex information (Hansen, Shah, & Klas, 2015). For example, small groups of students working on projects show qualitative improvement using a web-based collaborative search tool that allows them to see other users' bookmarks and edit texts as a group (Leeder & Shah, 2016). In medical care, for example, collaborative information systems are employed to effectively distribute human resources among patients (Paul & Reddy, 2010). With the ubiquity of computers and mobile devices, collectively searching information as a group could become more and more common in this hyperconnected world.

One of the fundamental components in CIS is social awareness (Morris & Horvitz, 2007). By knowing what others have done and are currently doing, groups can reduce effort in duplicating searches through spontaneous division of labor. Following the same logic, such an awareness should also be favorable when people compete against one another for information discovery. Presently, it is unclear how people use information about others' activities when collaboratively searching for unique information or competing against one another to appropriate that information. For example, if you see someone exiting a gold mine with an armful of gold, will you go there assuming that there is gold to be found there, or will you avoid that location assuming that the mine is already empty? Alternatively, if you see someone spending a very long time in a gold mine, what does it tell you about the remaining resources in the mine?

Social awareness in information search activities has exclusively been investigated in a collaborative context, but it might also be important under competitive settings. Competition for information search can be found, for example, when researchers seek for the discovery of valuable information that might lead to patents or scientific publications, and when stock traders hunt for the latest information about the business before the markets respond to the news. However, we know little about how social awareness is exercised in competitive settings. Revisiting the analogy of gold mining, do people respond differently to information about others' activities when they get to share the gold found with team members, compared to when they keep the gold they dug?

Here, we investigated how people use knowledge about the levels of exploitation and exploration of information patches when searching for new information in groups. We conducted an online experiment on social information search in the context of environmental monitoring. In the experiment, groups composed of three participants searched environmentally relevant objects across multiple virtual locations, under either a cooperative or a competitive setting. Participants were provided with information about the total number of objects collected and the total time spent by all participants in the group at each location, along with the current positions of others. We analyzed participants' actions to identify which information about others' activities influence their decisions regarding when to leave their location and where to move next.

2. Literature review

2.1. Information foraging

When a foraging animal searches patchily distributed food, it needs to decide when to abandon the current food patch and move to the next. In animal ecology, optimal foraging theory provides mathematical underpinnings of foraging behavior, where the decision is modelled as a function of key variables, including current food density, search efficiency, food handling time, and travel time, toward maximizing payoffs (Stephens & Krebs, 1986).

Inspired by the optimal foraging theory in animal ecology, human behavior of computer-mediated information search can be analyzed from the perspective of payoff maximization. Just as a bee collects nectar by hopping between patches of flowers, a human gathers information by navigating through hyperlinked websites. At each visit, one needs to make decisions about when to stop searching information in the current website and move to the next, by trading off between the expected information gain in the current and next information patches (Pirolli & Card, 1999).

Aside from the absence of predation risk, information search behavior can be fundamentally different from animal foraging behavior with respect to the nature of resource. Whereas food is depletable upon consumption, information is typically not

(Moody & Walsh, 1999). Such a trait underlies online recommendation systems, where users can reuse information collected by other users, either intentionally or inadvertently (Farzan & Brusilovsky, 2018). Under certain circumstances, however, information can be depletable upon consumption: these circumstances include when a group of users collaboratively gathers information while avoiding duplicated effort (Shah, 2010) and competes against one another for information discovery.

2.2. Information scent

When a foraging animal travels between food patches, decisions on patch selection and residence time are largely influenced by patch profitability, which is inferred from observing behavior of other animals (Valone & Templeton, 2002). Likewise, humans are known to use additional information to make better decisions in information search. For example, people are more likely to rely on ranks in search engines (Pirolli & Card, 1999), follow hyperlinks whose sources are more credible (Sundar, Knobloch-Westerwick, & Hastall, 2007), and revisit previously rewarded locations (Chukoskie, Snider, Mozer, Krauzlis, & Sejnowski, 2013). These cues serve as 'information scent' that signals the value of the action; models incorporating information scent successfully describe human behavior in online information search (Fu & Pirolli, 2007; Pirolli, 2005).

2.3. Social information search

Collaboratively searching information in a group could augment search efficiency when information is complex or difficult to find alone (Shah, 2010). From a couple planning for a vacation trip to a group of researchers reviewing literature, social information search offers several advantages, like faster problem solving and lower redundancy of efforts (Clearwater, Huberman, & Hogg, 1991). Many algorithms have been implemented in information systems toward reducing search redundancy by heightening awareness of others' actions (Amershi & Morris, 2008; Maekawa et al., 2006; Morris & Horvitz, 2007; Morris et al., 2006; Smeaton et al., 2006). These algorithms can increase effectiveness of group search by dynamically coordinating information behavior of users (Pickens, Golovchinsky, Shah, Qvarfordt, & Back, 2008).

As in solitary search, decisions in social information search could be influenced by information scent, but our knowledge of this potential link is currently limited. One study demonstrated that humans imitate actions of others in search of non-depletable resources, even when they do not know the payoff of others (Tomlin, Nedic, Prentice, Holmes, & Cohen, 2017). But, what would they do if information depleted upon discovery? This is the case of searching for new information, where you can only discover information once before it loses its value. In such a case, individual decision on patch selection and residence time could be influenced by others' actions, such as how much information has been collected by others (that is, a level of exploitation) and how much search effort has been paid by others (that is, a level of exploration) in each information patch. Thus, we hypothesized that:

H1. Without knowing the quality of each information patch, people would select the patch that was less exploited and explored by others.

Further, the use of information scent in social information search may depend on social environments. Goal interdependence theory posits that reward schemes should modify the way people interact with one another (Deutsch, 1949). However, little is known about the differential effect of cooperative and competitive environments on the use of information scent in social information search. Considering that cooperation is facilitated by spontaneous division of labor, we hypothesized that:

H2. Cooperating people would pay more attention to others and distribute search efforts across a search space, compared to people in a competitive setting.

3. Materials and methods

3.1. Experimental platform

The experiment was designed to investigate social information foraging under uncertain resource levels, framed in a citizen science project aimed at monitoring the environment of the Gowanus Canal (Brooklyn, New York, USA). Three users ("foragers") were connected online and saw a map of the Canal, which contained equidistantly spaced six locations ("patches"). Foragers could individually move their boat icons, starting from the same end of the Canal, to one of the patches at a constant speed, requiring 5 seconds to move to the adjacent patch.

Once a boat reached a selected patch, a computer screen displayed a 360° image taken by our aquatic robot vehicle (Laut, Henry, Nov, & Porfiri, 2014), and foragers performed image tagging (Fig. 1). To create an image tag, foragers dragged one of the tags listed on the left (Boat, Construction machine, Floating object, Land vehicle, and Tree) onto an object in the image and adjusted the size of the selected area by dragging corners of a box to cover the object. When foragers pressed the "Submit" button, a selected area became black, and they were not allowed to create a new tag on the overlapping area. They could exit from the image by clicking the "Exit" button and move to a different patch by selecting the next destination on the map. In addition to the three foragers, one user was assigned as a validator to prevent malicious online behavior of foragers (see Supplementary Information for details).

During the activity, foragers saw two bars next to each patch on the map. The bars corresponded to the total number of tags created and total time spent by all foragers in each patch, and the heights of the bars dynamically changed in real time during the activity. In addition, foragers saw location of others, remaining time, and the number of points earned in real time.

3.2. Data collection

We recruited online crowdworkers located in the U.S. through Amazon Mechanical Turk. We did not screen participants or collect personal information, such as age and gender, as the platform does not provide such information.

Before undertaking the task, workers were navigated through background information, including pollution problems in the Gowanus Canal and our aquatic robot vehicle for environmental monitoring, and were presented an overview of the group activity, including boat navigation, tagging, and validation. Then, a point system and a monetary reward scheme were explained to workers, who were randomly assigned into one of two groups at this stage. Workers in one group were notified that 1 point would be given to all three foragers for each tag, regardless of who submitted it, and that the points would be converted to a bonus reward of $0.10 per point, with a maximum of $3.50, in addition to a participation fee of $1.50 upon completion of the task. Workers in the other group were notified that 1 point would be given to only a forager who submitted the tag, with each point cashed in a bonus reward of $0.30, with a maximum of $3.50, in addition to a participation fee of $1.50. We explicitly presented to the workers in both groups that the objective of the task was to collect as many points as possible. The difference in the point system was designed to create cooperative and competitive environments, without explicitly instructing them to cooperate or compete.

Next, participants took a practice session, following a tutorial on how to pan and zoom an image, select a portion of an image, and submit. In the practice session, they were instructed to collect five tags in an image similar to those used in the main task. When participants completed the practice session, they were transferred to an online waiting room until other team members finished the practice session.

The experiment lasted for 10 minutes. The same set of six images were utilized for all groups, but the order was randomized for each group. Upon completion, each user was provided with a unique token that encrypted individual points. When one of the team members quit during the experiment, the remaining users were provided with a token and the experiment was stopped (see Supplementary Information for details).

We recorded data of 43 groups (172 participants) in the cooperative condition and 45 groups (180 participants) in the competitive condition. In the following analysis, we used the data of the groups in which all performed the activity for at least 6 minutes and each forager created at least 1 tag. Consequently, we analyzed 36 groups (144 participants) in the cooperative condition and 34 groups (136 participants) the competitive competition.

3.3. Patch selection

We investigated how the patch trait influenced decisions on the selection of a next patch. To that end, we ranked the available patches in an ascending order with respect to the levels of exploitation and exploration when foragers exited the current patch. The levels of exploration and exploitation were assessed by the cumulative time spent and the cumulative number of tags created at each patch, respectively. These levels were further partitioned into the amounts attributed to their own activities and those to the others, respectively, by acknowledging that foragers could remember their own activities. In the same way, we ranked the cost of moving, measured as a distance from the current location, from the shortest to the longest. Although foragers were allowed to change the destination during the movement between the patches, we excluded such a case from the analysis (1.2% of the total selections). For each patch trait in each reward condition, we compared total counts of the ranks against the expected proportions that were obtained by simulating the case where the foragers would randomly select the next patch for 10,000 times. Differences from the expected proportion was tested using a χ^2 goodness-of-fit test.

In a similar way, we investigated whether people avoided moving to patches that were occupied by others. For each condition, we counted the cases where foragers selected the next patch that was occupied by at least one other forager and compared against the expected proportions that were obtained in the same way.

Next, we investigated whether patch traits influenced decision-making differently. The observed ranks were fitted into a proportional odds model with a logit link, considering the ordinal nature of the dependent variable. In the model, we specified the ranks of selected patches as a dependent variable, the patch traits (5 levels: cost of moving, exploitation by themselves, exploitation by others, exploration by themselves, and exploration by others), condition (cooperation or competition), and their interaction as explanatory variables, and individual identity as a random effect. When the significant effect of the interaction term was found, we performed pairwise comparisons across the traits within each condition and each trait between the conditions, with *p*-value adjustments using the Benjamini–Hochberg procedure (Benjamini & Hochberg, 1995). A proportional odds model was performed in R package 'ordinal' (Christensen, 2019), and a post-hoc test was run in R package 'emmeans' (Lenth, Singmann, Love, Buerkner, & Herve, 2019).

3.4. Patch residence time

To understand how people use social cues to decide when to leave the current patch, we investigated the influence of the number of tags collected and time spent by others on the patch residence time. At each exit instance, we ranked the exited patch from the least to the most exploited or explored among all patches.

For each patch trait, we fitted the patch residence time into a generalized linear mixed-effects model with gamma errors and a log link. In the model, we specified ranks at the exit, condition, and their interaction as explanatory variables, and individual identity as a random effect. In addition, we specified in the model the patch residence time in the marginal value theorem (Charnov, 1976) as an offset (that is, a dependent variable with a fixed slope of 1), thereby controlling for variations in individual search efficiency and remaining resource levels (see Supplementary Information for details).

The model was fitted using R package 'lme4' (Bates, Maechler, Bolker, & Walker, 2019), with the bound optimization by quadratic approximation (BOBYQA) in R package 'optimx' (Nash, Varadhan, & Grothendieck, 2018). The statistical significance was obtained through a Type II Wald χ^2 test using R package 'car' (Fox et al., 2019). In the case of significance, we performed a pairwise post-hoc test with the Benjamini–Hochberg procedure (Benjamini & Hochberg, 1995) using R package 'emmeans' (Lenth et al., 2019).

4. Results

4.1. Patch selection

Foragers used knowledge about each patch to select the next patch (Fig. 2). In the cooperative condition, foragers' decisions on selecting the next patch were influenced by all patch traits investigated (χ^2 goodness-of-fit test, $p < 0.001$ for all). By contrast, in the competitive condition, foragers did not use the knowledge about the number of tags collected by others $\chi^2_4 = 8.923, p = 0.063$) and time spent by others $\chi^2_4 = 9.311, p = 0.054$). Under competition, decisions on selecting the next patch were influenced by the number of tags collected on their own ($\chi^2_4 = 199.600, p < 0.001$), time spent on their own ($\chi^2_4 = 193.330, p < 0.001$), and distance ($\chi^2_4 = 58.073, p < 0.001$). In all significant cases, foragers were more likely to select higher ranked patches.

The location of others influenced foragers' decision in selecting the next patch differently depending on the social conditions (Fig. 2). In the cooperative condition, foragers were more likely to avoid others and select an unoccupied patch ($\chi^2_1 = 27.973, p$

< 0.001), whereas in the competitive condition, their decision was not influenced by the presence of others ($\chi^2_1 = 0.858, p = 0.354$).

A log-odds test revealed the importance of the patch traits on selecting the next patch (Fig. 3). Their ranks were explained by a significant interaction between patch traits and conditions ($\chi^2_4 = 19.559, p < 0.001$). Post-hoc pairwise comparisons showed that, in the cooperative condition, foragers selected patches with the highest ranks in the number of tags collected on their own, followed by the number of tags collected by others, time spent on their own, time spent by others, and distance ($p \leq 0.018$ for all except between time spent by others and distance, $z = 0.414, p = 0.707$). Similarly, in the competitive condition, foragers relied the most on the knowledge about the number of tags collected on their own, followed by the number of tags created by others, distance, time spent on their own, and time spent by others ($p \leq 0.029$ for all). Foragers in the competitive condition were more likely to select the closer patches ($z = 3.343, p = 0.002$), whereas those in the cooperative condition were more likely to select the patches where others spent less time ($z = 2.090, p = 0.044$).

4.2. Patch residence time

Foragers stayed in each patch for 120.0 ± 73.4 s in the cooperative condition and 104.7 ± 51.0 s in the competitive condition. The patch residence time was not significantly different between the conditions ($\chi^2_1 = 1.864, p = 0.172$).

We found significant effects of social cues (that is, the knowledge about others' activities in the patch) on the patch residence time (Table 1). Variation in patch residence time was explained by the rank of time spent by others ($\chi^2_5 = 21.613, p < 0.001$). By contrast, the rank of the number of tags collected by others did not explain the variation in the patch residence time $\chi^2_5 = 9.311, p = 0.097$). Further, there was no significant difference between the conditions in any patch trait ($\chi^2_1 \leq 0.968, p \geq 0.325$), or interactions between rank and condition ($\chi^2_5 \leq 9.227, p \geq 0.100$). Post-hoc analysis revealed that foragers were more likely to spend less time in the patch that was explored by others for a longer time (Fig. 4).

5. Discussion

This study presents empirical evidence on heuristics of social decision-making in groups whose objective is the discovery of information. Our results demonstrate that people use their own activities and knowledge about others' activities as information scent to decide when to stop and where to go next during their information search. Further, people use such knowledge differently depending on the reward scheme, whereby people paid more attention to others' activities in a cooperative setting than a competitive one. These findings contribute to a better understanding of the use of information scent and heuristics in social information search, while offering insight into real-world system designs for information gain and discovery through group activities.

It is likely that people used knowledge about the levels of exploitation and exploration in social information foraging as a proxy for the patch quality in the absence of a complete assessment of the environment (Wu, Schulz, Speekenbrink, Nelson, & Meder, 2018). Similar results are reported in online information search, where people are more likely to select links that have higher ranks in relevant attributes, such as credibility, published dates, and the number of related articles (Sundar et al., 2007). In our experiment, people were more likely to move to less exploited and less explored patches, which may reflect people's perception of the reliability of such information as a proxy for the patch quality. However, the levels of exploitation and exploration do not necessarily indicate patch quality, and the use of such information can lead to suboptimal decisions (Giraldeau, Valone, & Templeton, 2002). For example, patches where people collected fewer tags or spent less time should signal poor, rather than rich, patch quality if people perform exhaustive search at each visit. Thus, our results indicate that people are likely to behave under the presumption that others do not search thoroughly, or patch quality is equal among patches.

Although people used both the levels of exploitation and exploration at each patch to decide where to go next, they were more likely to select the location where people collected fewer tags than the location where people spent less time. This indicates that the level of exploitation served as a stronger information scent than the level of exploration. At an individual level, exploitation–exploration trade-off is modulated by various factors, such as available information, environmental uncertainty, and individual differences (Mehlhorn et al., 2015). For instance, people are more likely to exploit currently available resources when the uncertainty is within expectation, whereas they shift to explore for new resources under environmental changes (Cohen, McClure, & Yu, 2007). In our experimental setting, it is possible that people relied more on the level of exploitation in selecting the next location because the resources were predictably depleted over time. Interestingly, knowledge about the activity of others was used only in cooperative information search. It is possible that people took into account such knowledge to distribute their effort toward a shared goal. Avoidance of others was also found only in the cooperative information search, supporting this possibility.

In general, people stayed less in the patch where others spent a longer time, but the number of tags collected by others in the patch did not influence their decisions to leave. This indicates that the level of exploration, but not exploitation, by others influences a forager's decision to leave the information patch in social information foraging. Our results are consistent with a similar study on solitary information foraging, where patch residence time was influenced by the total time spent at the current patch, but not the total number of resources consumed (Hutchinson, Wilke, & Todd, 2008). The use of such knowledge contrasts with decision-making in selecting the next patch, where people opt for a patch where other people have collected fewer tags, over a patch where other people have spent less time. This could indicate that knowledge about the levels of exploitation and exploration has different social utilities; the level of exploitation served as information scent for patch selection, whereas the level of exploration served as information scent for the activity upon patch selection.

We adopted ranks, instead of absolute or relative differences, of the patch traits to investigate the influence of patch traits on decision-making in social information search. It is well known that our perception of absolute difference diminishes when a positive constant is added to all choices, whereas the perception of ratio enlarges when all choices are proportionally increased (Prelec & Loewenstein, 1991). We used ranks to mitigate the uncertainty about how people would compare among choices. However, ranks are not able to capture a change of the perception over time, where the same absolute or relative difference at the beginning of the experiment may be perceived differently toward the end. Further, ranks may not be suitable to investigate individual differences on decision-making, considering that perception of relative and absolute values in decision-making differs among individuals (Malenka, Baron, Johansen, Wahrenberger, & Ross, 1993).

Supporting conceptual and qualitative studies (Morris & Horvitz, 2007; Reddy & Jansen, 2008; Shah & Marchionini, 2010), our findings quantitatively demonstrate the importance of knowledge about others' activities, which leads to spontaneous division of labor. Such a knowledge could also be applied to tools that assist competition for knowledge discovery in various scenarios, such as citizen scientists competing for solving scientific problems (for example, Foldit) and data scientists competing for finding efficient computer algorithms (for example, Kaggle). Capitalizing on heuristics in decision-making during social information search, designers could not only reduce cognitive overload by masking less relevant information, but also steer search efforts to desired directions. For example, selectively displaying how much others have already exploited the current site would accelerate people to move to other sites, leading to a large coverage of a search domain. By contrast, emphasizing how much time others have previously spent at a site would facilitate thorough search without a central control.

6. Conclusion and limitations

Information search is part of our everyday life, and our findings illuminate how humans perceive uncertain environments based on knowledge about others' activities. Revisiting the analogy of gold mining, when cooperating, people are more likely to go to the mine where others collected less gold or spent less time. On the other hand, when competing, people are not influenced by the observed behavior of others. Further, people spend less time in the mine where others spent a longer time. Understanding information scent in social settings may help design systems to enhance the efficiency of information search in groups.

Our experiment was conducted using paid crowdworkers through Amazon Mechanical Turk, which is common in studying human decision-making (Rand, 2012; Stewart et al., 2019). Although data on decision-making tasks from Amazon Mechanical Turk are considered as reliable as those using traditional methods (Buhrmester, Kwang, & Gosling, 2011), online experiments may decrease attentions of participants to follow instructions, compared to supervised experiments in a lab (Oppenheimer, Meyvis, & Davidenko, 2009).

This could potentially confound the results, especially in studying group behavior. On the other hand, the diverse demographics of online participants (Paolacci, Chandler, & Ipeirotis, 2010) could contribute to the generalizability of our findings on human decision-making.

Another limitation of using crowdworkers in behavioral experiments entails anonymity and lack of controlling individual variation in behavior. Further, awareness of participating in behavioral research may bias data quality by influencing motivations. In this study, we did not collect demographic information or screen participants. Although we designed the experiment to be robust with respect to motivational differences and we statistically controlled for individual variation in information search skills in the analysis, knowledge about individual attributes is needed to elucidate how group compositions could influence social information search.

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Figures and Tables

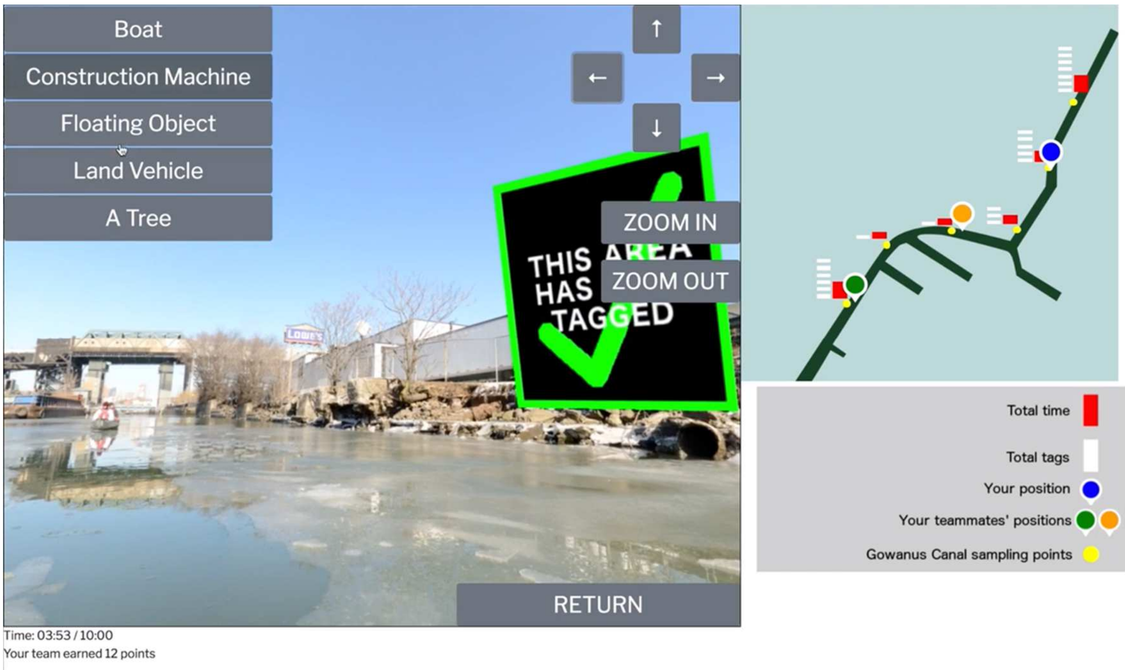

Fig. 1. Screen shot of the user interface. Users explore the 360° image of a polluted canal by panning and zooming the camera and tag objects listed on the top left. The mini map on the right shows locations of others, as well as a total number of tags collected and total time spent by all at each location.

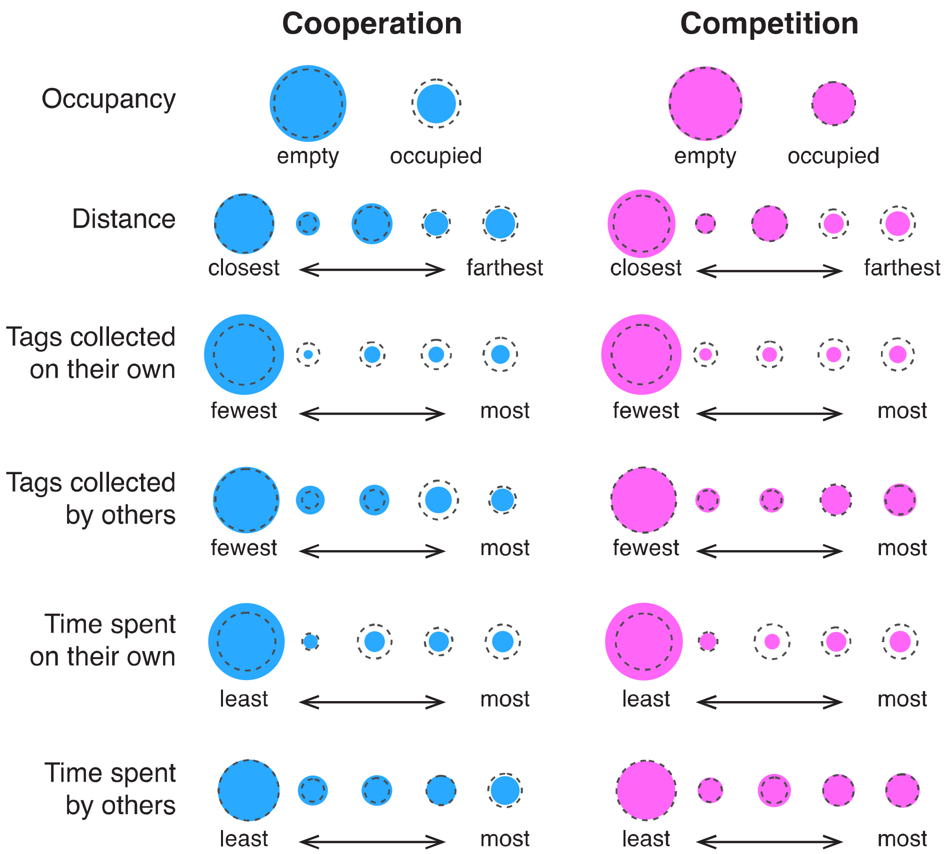

Fig. 2. Proportions of the next patch selected by patch traits. The patch traits investigated are occupancy (empty or occupied), distance from the current patch (ranked from the closest to the farthest), the number of tags collected on their own and by others (ranked from the fewest to the most), and time spent on their own and by others (ranked from the least to the most). Colored disks show the observed proportions (blue: cooperation, pink: competition), with the areas corresponding to the proportions. Dashed open circles indicate the expected proportion when a forager randomly selects the next patch (10,000 iterations). In each panel, the more the dashed circles are different from the solid ones, the more likely is for people to rely on that trait. For example, examining the tags collected on their own in cooperation, we note that people tend to select patches which they explored less before. Goodness-of-fit tests find significant deviations from the expected proportions for all except occupancy, number of tags collected by others, and time spent by others in competition.

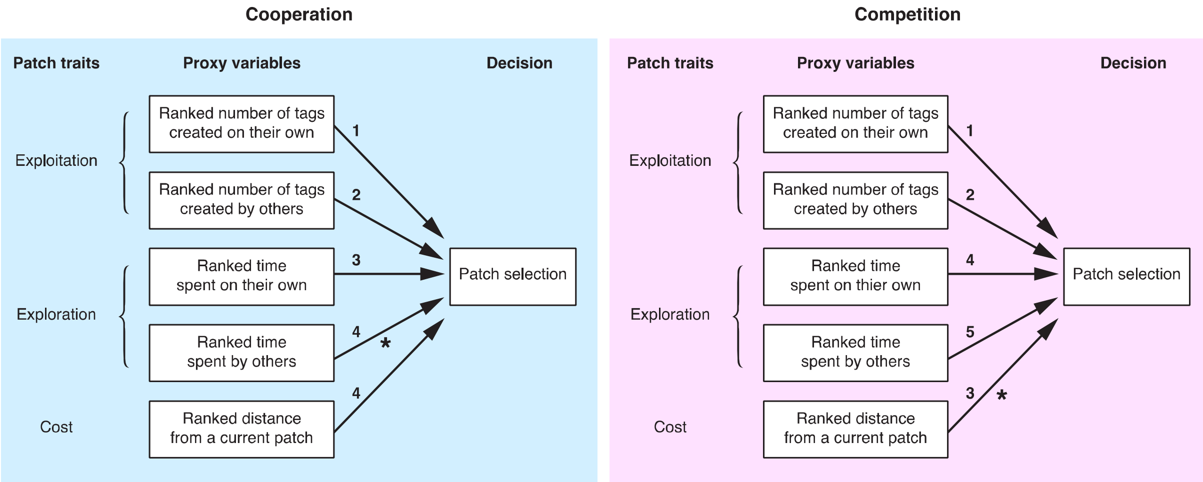

Fig. 3. Schematic representation of the importance of variables on patch selection. The selected patches are ranked by the number of tags collected on their own and by others (ranked from the fewest to the most), time spent on their own and by others (ranked from the least to the most), and distance (from the closest to the farthest). The numbers represent orders of importance of the variables, and the asterisks indicate greater influence than the corresponding ones in the other condition, based on a proportional odds model.

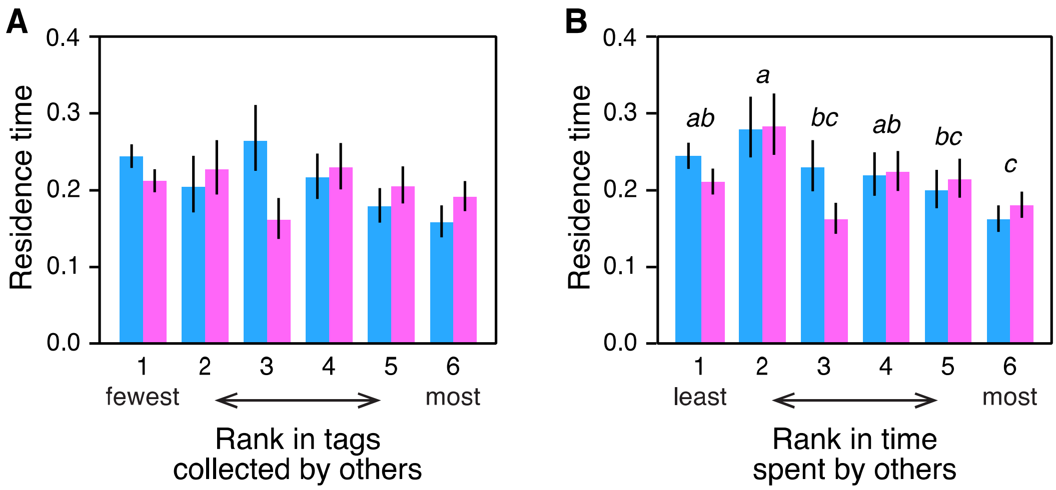

Fig. 4. Observed patch residence time (ratio to the prediction of the marginal value theorem) and the patch trait at exit. (A) Ranks in the number of tags collected by others (from the fewest to the most) and (B) ranks in time spent by others (from the least to the most). Blue and pink bars represent the cooperative and competitive conditions, respectively. Bars sharing the same letter(s) are not significantly different from each other based on a pairwise post-hoc test between ranks, aggregated over conditions.

Table 1. Summary of the generalized linear mixed-effects models for the effects of social cues on the patch residence time.

Variable	Chi-squared	*D.f.*	*P*-value
Tag collected by others			
Rank	9.311	5	0.097
Condition	0.717	1	0.397
Rank × Condition	9.227	5	0.100
Time spent by others			
Rank	21.613	5	< 0.001
Condition	0.968	1	0.325
Rank × Condition	5.560	5	0.351