Social Sampling in Decision Making for Online and Offline Activities

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Abstract

When making decisions, humans often rely on information from their social networks through a process termed *social sampling*. Prior work suggests that when drawing social samples, people search through their contacts in a sequential manner based on structured social categories (e.g., family vs. friends; online vs. offline contacts). We examined whether the problem domain impacts how one categorizes their social contacts and which social categories they sample from. In our study, participants answered questions about the relative popularity of either national parks or social media platforms, respectively associated with offline activities (e.g., visit a national park) and online activities (e.g., use an online social media platform). Participants then provided frequency information about the number of their contacts who have visited the parks or used the social media platforms in different social groups. Adopting a hierarchical Bayesian modeling approach, we compared two social sampling models: one defining social groups based on closeness of social relations (i.e., family, friends, acquaintances), and one defining social groups based on contact mode (i.e., online vs. offline contacts). Results indicate that when making comparison judgments related to online activities, participants are more likely to sample from social circles of online contacts, and when judgments are related to offline activities, they are more likely to sample from social circles of offline contacts. These findings suggest that people sample from different members of their social network depending on the type of decision they are making.

Keywords: decision making; inference; sampling; online networks; heuristics

Introduction

The internet has revolutionized the ways we access information and communicate with others. It not only facilitates access to an ever-growing trove of information, but allows people to use social media platforms to produce information content. New phenomena have emerged, such as mass collaboration based on crowdsourcing, polarization, and echo chambers that can amplify misinformation. Information plays a fundamental role in human decisions, which in turn determine important outcomes for individuals and societies. Hence, understanding the psychological processes that guide human decision making for online and offline activities is an important area of research.

In making judgments and decisions, people often rely on information in their social networks. When asked about the infection rate of the most recent Covid-19 variant, we might think of how many of our co-workers have missed work after catching the illness, or the number of our Twitter friends discussing the spread of a new variant in the area. This example illustrates *social sampling* – the act of drawing a sample from one's social network to inform an inference (e.g., Schulze, Hertwig & Pachur, 2021).

Social sampling is related to the availability heuristic in judgment and decision making, whereby a person assesses the frequency of an event by the ease with which instances can be brought to mind. Tversky and Kahneman (1973) showed that the availability heuristic leads to systematic biases in human judgments. Multiple factors contribute to assessments of availability (Pachur, Hertwig & Rieskamp, 2013; Schwarz et al., 1991; Sherman, Mackie & Driscoll, 1990). Hertwig, Pachur and Kurzenhauser (2005) presented participants with pairs of risks (e.g., colon cancer and lung cancer) and asked them to estimate which one causes more deaths per year. They compared evidence for four cognitive mechanisms and found strongest support for a heuristic they termed "availability-by-recall" in which people recall the total instances of each event among their social network and choose the option for which more instances can be recalled.

Rather than considering one's entire social network as one space to assess frequency, subsequent research has investigated how one's social environment can be decomposed into different social categories to provide sets of sampling spaces for estimating frequency data. This hypothesis is intuitive, as our decisions are likely to be influenced more strongly by close family members or friends than by strangers. Schulze et al. (2021) developed a computational model, the social-circle model (SCM), to account for how people search contacts in different social categories when using sampling to judge the relative frequency of two events. The social-circle model assumes that people's social categories are organized by default into four circles based on closeness of social relations (self, family, friends, acquaintances). People then sequentially inspect instances in each social circle to estimate relative frequency in order to make a decision. The order of social-circle inspection is probabilistic, based on circle weights which are estimated as individual-level parameters. For example, a participant may trust information from family members more than from strangers, so a decision is more likely to be consistent with frequency data based on their family members rather than strangers. When sufficient evidence is accumulated to make a judgment, search is terminated. Schulze et al. (2021) showed that the social-circle model based on sequential sampling among social categories provides a good account of relative frequency judgments in different domains and across age groups. Their findings

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suggest that the search process underlying social sampling is not exhaustive, but sequential and limited.

Social categories can be defined in different ways (Bond Jr., Jones & Weintraub, 1985; Hills & Pachur, 2012). A common basis is closeness of social relations, as used in the social-circle model. However, in the modern internet age, social categories can also be defined based on *mode of contact*, such as offline friends vs. online friends. Hecht, Pachur and Schulze (2022) compared the SCM to a variant of it in which the social circles are defined according to contact mode – whether one usually has online vs in-person contact with a person. They presented subjects with pairs of countries (e.g., Spain and Italy) and asked them to estimate which country receives more visitors. Participants provided frequency information for different social circles by listing the number of their contacts who had visited each country, along with information about each contact's social category and mode of contact. They found that 36% of subjects were best described by the social sampling model based on contact mode (SCM-C), 30% by the original SCM based on social categories, and 27% by the availability-by-recall model. These findings suggest that the search process underlying social sampling is flexible depending on what social categories a person brings to mind.

Several theories posit that concepts in memory are associated with related concepts, with each concept represented as a node connected to other nodes in a network (e.g., Collins & Loftus, 1975; McKoon & Ratcliff, 1992). When a word or image is presented, it can serve as a prime, activating associated concepts in memory, temporarily making those concepts more accessible. This assumption is supported by empirical work; for example, when a word is presented, people can identify associated words faster than non-associated words (e.g., McKoon & Ratcliff, 1992). This line of work suggests that social contacts may be organized in memory such that each contact is associated with related contacts. These associations may be based on social category (e.g., family members associated with family members), or contact mode (e.g., online contacts associated with online contacts).

Just as networks of related concepts can be activated by associated cues, it follows that networks of social contacts can be activated in different contexts. In the case of social sampling, we expect that the specific question being asked may serve as a cue that activates certain types of social categories in sampling process involved in decision making. Specifically, when asked about online activities, the context of the question may activate social categories defined by contact mode (online contacts vs. offline contacts). In contrast, when asked about offline activities, social circles based on closeness of social relations may have a higher likelihood of being evoked. Hence, the characteristics of the activity in question may influence what social categories are involved in social sampling.

We conducted two behavioral experiments to investigate whether the grouping of social circles, and the weight given to each circle, depend on the question being asked. We predicted that when making decisions about an online activity, people will be more likely to employ social categories based on contact mode and place more weight on online contacts. Conversely, when answering a question about an offline activity, people will be more likely to use social categories based on closeness relations and rely more on offline contacts.

Social-Circle Model

We adopt the social-circle model (SCM) developed by Schulze et al. (2021; see also Pachur & Schulze, 2023). The SCM provides a sampling-based model to account for how people infer which of two events is more frequent in a population. The SCM assumes that people make the inference by sequentially inspecting circles of contacts defined by social categories: self (circle 1), family members (circle 2), friends (circle 3), and acquaintances (circle 4). The order in which circles are inspected is probabilistic, and defined by weight parameters for each circle $w_i, i \in \{w_{self}, w_{family}, w_{friends}, w_{acquaintances}\}$. Greater weight value for a social circle indicates the frequency data in that circle is more likely to be sampled first. In a given circle, instances of each event (e.g., friends who have travelled to Yosemite or the Grand Canyon) are tallied. The difference between the proportional tallies is contrasted against a threshold *d* which represents how much evidence is required to make a comparative decision.

If the evidence meets or surpasses the threshold, search is terminated; otherwise, the next circle is inspected. The model

Table 1: Parks and social media platforms presented in the comparison task. Objective rank is based on the number of visitors (users) in databases. Subjective rank is based on participants' selection frequency for each park (social media platform), with highest rankings indicating the most selected items in the comparison task.

National parks	Number of visitors	Objective rank	Subjective rank (Exp 1)	Subjective rank (Exp 2)
Golden Gate N.R.A.	15,638,911	1	5	7
Great Smoky Mt. N.P.	12,937,633	2	9	5
Gateway N.R.A.	8,728,291	3	8	9
Lincoln Memorial	7,825,397	4	3	10
Lake Mead N.R.A.	5,578,226	5	10	4
Grand Canyon N.P.	4,732,101	6	1	2
Rocky Mountain N.P.	4,300,424	7	7	1
Yosemite N.P.	3,667,550	8	2	6
Yellowstone N.P.	3,290,242	9	4	3
Sequoia N.P.	1,153,198	10	6	8
Social media platforms	Number of users	Objective rank	Subjective rank (Exp 1)	Subjective rank (Exp 2)
Facebook	3,030,000,000	1	3	3
Instagram	2,000,000,000	2	1	1
TiktTok	1,090,000,000	3	2	2
LinkedIn	930,000,000	4	7	7
Snapchat	750,000,000	5	5	5
Reddit	500,000,000	6	6	6
Pinterest	450,000,000	7	9	10
X (Twitter)	393,000,000	8	4	4
Twitch	180,000,000	9	10	9
Discord	150,000,000	10	8	8

assumes noise (σ) in the comparison of instance knowledge against the difference threshold. The SCM includes six parameters that are estimated from the data of individual participants: weights for each of the four circles (w_i), a difference threshold (d), and response noise (σ).

We also adopted the approach taken by Hecht et al. (2022) in using the SCM based on contact mode (SCM-C). The SCM-C is identical to the SCM except that instead of being defined by social categories based on social closeness, the social circles are defined by mode of contact: self (circle 1), offline contacts (circle 2; people contacted mostly in person), mixed (circle 3: people contacted equally often online and offline), and online contacts (circle 4; people contacted mostly through online social media).

Experiment 1

Method

Participants A total of 192 undergraduate students (M_{age} = 20.30, SD_{age} = 1.78, 152 female, 35 male, 2 non-binary or other, 3 prefer not to say) were recruited from the subject pool for the UCLA Psychology department, and participated for course credit. Of these, 23 failed at least one of two attention check questions and were excluded from analyses, resulting in a sample of 169. Experiments were approved by the UCLA Office of the Human Research Protection Program.

Materials and Procedure Each subject was randomly assigned to either the offline activity (park) condition or the online activity (social media platform) condition. The experiment included two blocks. In the first block, after reading instructions, participants completed the comparison task. In the offline activity condition, they were presented with pairs of national parks and asked to judge which park receives more visitors. In the online activity condition, they were presented with pairs of social media platforms and asked to judge which platform has more users (see Figure 1).

A total of 10 national parks and 10 social media platforms were used to include targets spanning a large range of popularity. Each participant judged all possible pairs of parks (social media platforms) across 45 trials. We randomized the order in which the pairs were presented, and the left-right display ordering of pairs, across participants. Table 1 lists the parks and social media platforms that were used and the actual number of visitors (users) for each. Park data was obtained from the National Park Service database (National Park Service, 2024), and social media platform data was obtained from Wikipedia ("List of social platforms with at least 100 million active users", 2024).

In the second block, participants completed a recall task. For each park (social media platform), participants were asked if they personally had visited the park in the last ten years (or uses the social media platform), and the total number of people they know who have done these offline (online) activities. They were then asked to report how many of those contacts are (1) family members, (2) friends, and (3) acquaintances. They then reported the contact mode with which they communicate with those contacts by reporting how many of the total contacts belong to each of the following categories: (1) communicate mostly face-to-face, (2) mixed communication: half face-to-face and half through social media, and (3) communicate mostly through social media. For the contact mode question, participants were asked to consider only the 24 months prior to the study, and to exclude phone calls and direct messages.

The order of the parks (social media platforms) in the recall task was randomized between participants, as was the order of the social category and contact mode recall questions. There was one attention check question during the inference task and one at the end of the experiment.

Parameter Estimation and Model Evaluation Procedure To examine which model best accounted for human judgments in both conditions, we compared four models: the SCM, SCM-C, availability-by-recall (based on one's total number of contacts), and a guessing strategy (where either option is selected with a 50% probability). We used a Bayesian sampling approach for parameter estimation and

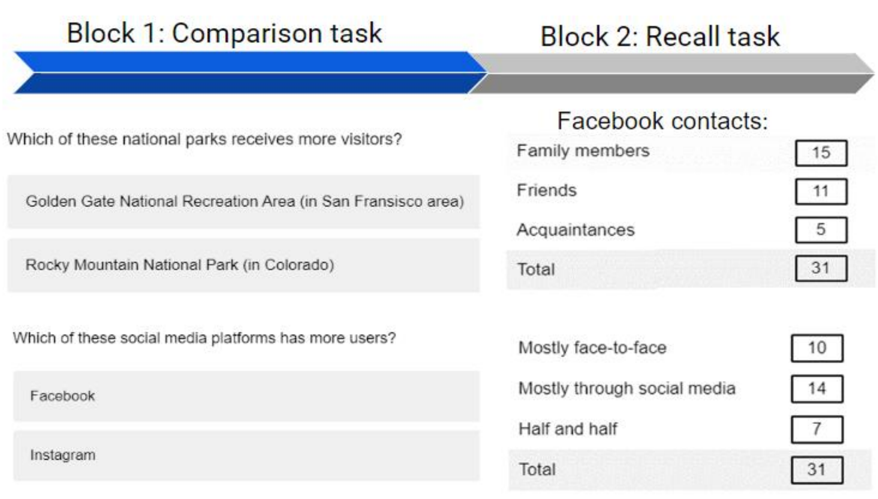

Figure 1: Illustration of comparison and recall tasks.

model comparison. To estimate parameters for each subject for the two social circle models, we did a coarse grid search using 5,000 parameter sets sampled from a prior distribution, computed likelihoods for each to compute the initial estimates, and then used a Markov-Chain Monte Carlo (MCMC) sampling method with a chain length of 1,000, taking every 10th estimate and skipping the first 30%. We used the median of the resulting sample as the parameter estimate. To compare how well each model accounted for each participant's judgments in the comparative task using the frequency data reported in the recall task, we computed the evidence for each model. As a measure of model prediction accuracy, we assessed the number of model decisions (out of 45) that matched those of the human participants in the comparative judgments**.**

Results

Human Data

We computed the subjective rank of each park (social media platform) based on the frequency with which each item was selected in the comparison task, averaged across participants (see Table 1). Spearman's rank correlation was computed between the objective rank based on the databases of visitor (user) records and subjective rank based on human responses for both conditions; in the park condition, the correlation was negative, $r(8) = -.32$, $p = .37$. This suggests that participants' knowledge about parks were generally inaccurate according to objective data. On the contrary, in the social media platform condition, the correlation of objective and subjective ranks was positive, $r(8) = .76$, $p = 01$, suggesting that participants have a good sense of popularity of different social media platforms in daily life. The median of the total recalled contacts was 30 in the park condition, and 396.5 in the social media platform condition.

Model Comparison

We computed model prediction accuracy by using reported frequency data in the second block (recall task) to predict comparative judgments in the first block. Higher prediction accuracy indicates that the model provides a better account of each participant's comparative inferences. Figure 2 depicts the proportion of participants whose inferences were best accounted for by each of the four models. In the offline activity (park) condition, 29% of participants were best accounted for by the SCM based on closeness of relation, 18% by the SCM-C based on contact mode, 52% by the SCM and SCM-C equally, none by availability-by-recall, and 1% by guessing. In the online activity (social media platform) condition, 49% were best accounted for by the SCM, 26% by the SCM-C, 25% by the SCM and SCM-C equally, and none by availability-by-recall or guessing.

As another measure of model accuracy, we took the number of trials (out of 45) in which the model prediction matched the human decision. Figure 3 depicts model accuracy for each model, for both conditions. For the park condition, the guessing model achieved approximately

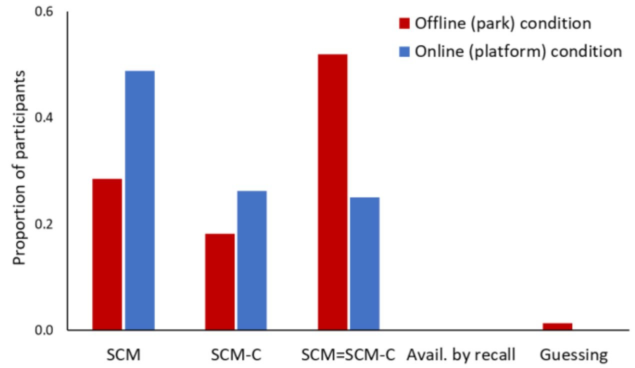

Figure 2: Proportion of participants best accounted for by each model in Experiment 1. "SCM=SCM-C" refers to participants who are accounted for equally well by both models.

chance accuracy at .49, availability-by-recall achieved .71, and the SCM and SCM-C models tied for the highest performance at .78. For the online activity condition, the guessing model achieved .50, availability-by-recall achieved .70, SCM-C achieved .74, and SCM performed best at .76.

Parameter Estimates

We then examined the mean parameter estimates across participants to compare them between the offline (park) and online (platform) activity conditions. Figure 4 shows the mean weight estimates of participants for whom the SCM and SCM-C provided the best account. For the SCM model, there are not large differences in the circle weights between the offline and online activity condition, suggesting that the type of question being asked (park visits vs. social media usage) has little impact on the relative importance of social categories in sampling. The largest differences between conditions are seen in the SCM-C model which defines social circles based on contact mode (online vs. offline contacts), for which the mean weight estimates in the offline activity (park) condition are .16 (self), .21 (online contacts), .33 (offline contacts), and .29 (mixed), and in the online activity (platform) condition are .15 (self), .35 (online contacts), .24 (offline contacts), and .25 (mixed). It is noteworthy that in the

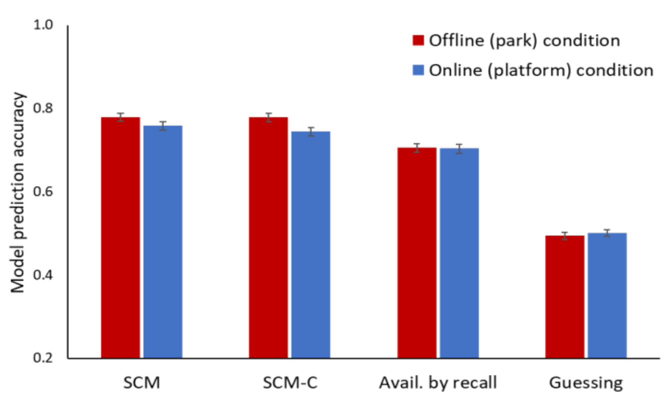

Figure 3: Model prediction accuracy of four models for each condition in Experiment 1. Error bars reflect + 1 SEM.

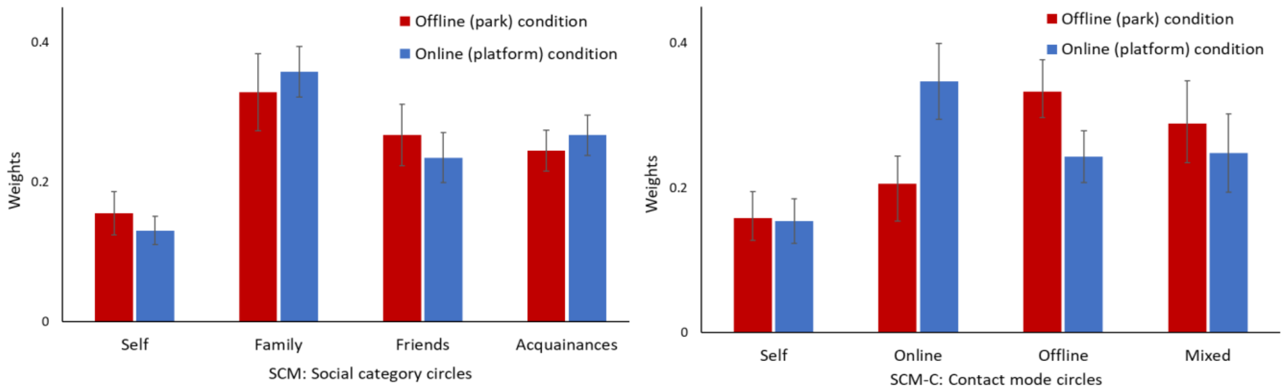

Figure 4: Mean parameter estimates for circle weights in the SCM (left) and SCM-C (right) models for Experiment 1. Error bars reflect $\pm$ 1 SEM.

offline activity condition, the mean weight of the offline contacts (.31) is significantly higher than for the online contacts (.21), while the reverse is seen in the online activity condition, where the mean weight of the online circle (.35) is significantly higher than for the offline circle (.24).

Experiment 2

Method

In Experiment 2, we tested a modified version of the comparison task in which subjects rank the 10 parks (or social media platforms) simultaneously rather than judging each pair separately. Our goal for Experiment 2 was thus to test whether we whether we can obtain results consistent with those of Experiment 1 using a more efficient version of the task.

Participants A total of 191 participants (M_{age} = 29.79, SD_{age} = 7.72, 149 female, 42 male) were recruited for the experiment. Of these, 98 were undergraduate students recruited from the same subject pool used in Experiment 1. The remaining 93 participants were recruited through Prolific, were at least 18 years old and were located throughout the United States. Of these, 9 failed the attention check question and were excluded from analyses, resulting in a final sample of 182.

Materials and Procedure Participants recruited from Prolific were assigned to the offline activity (park) condition, and the undergraduate student participants were assigned to the online activity (social media platform) condition. The materials and procedure were the same as in Experiment 1 except for the following changes. For the comparison task, all 10 parks (or social media platforms) were presented on the same page in a random order, and subjects were asked to rank the parks (platforms) based on the number of visitors (users) they think each one has. To rank the parks (platforms), subjects clicked and dragged each option to rearrange them such that the one with the most visitors/users was on top. Subjects then completed the recall task as in Experiment 1.

Results

Human Data

We computed the average subjective rank of each national park and social media platform. For the offline activity (park) condition, the Spearman's rank correlation between the objective and subjective ranks was negative, $r(8) = -.30$, $p = .41$. For the online activity (social media platform) condition, the correlation was positive, $r(8) = .73$, $p = .02$. Both results replicated those in Experiment 1.

Model Comparison and Parameter Estimates

We employed the same parameter estimation and model evaluation procedures as used in Experiment 1. We converted the reported rankings from the first block to judgments for 45 pairwise comparisons (e.g., if a subject ranked Instagram first, we assumed they would select Instagram over all other options if judging pairs separately). Comparing the evidence for the four models in the park condition, 20% of participants were best accounted for by the SCM, 22% by the SCM-C, 52% by the SCM and SCM-C equally, 1% by availability-by-recall, and 5% by guessing. In the social media platform condition, 41% of subjects were best accounted for by the

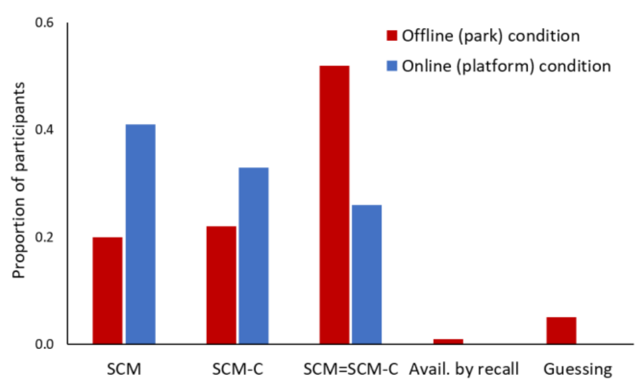

Figure 5: Proportion of participants best accounted for by each model in Experiment 2.

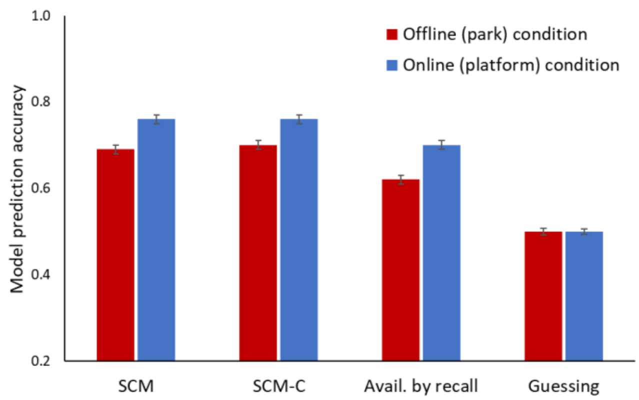

Figure 6: Model prediction accuracy of four models for each condition in Experiment 2.

SCM, 33% by the SCM-C, 26% by the SCM and SCM-C equally, and none by availability-by-recall or guessing (see Figure 5). These results replicated the general pattern found in Experiment 1.

Considering model prediction accuracy as measured in Experiment 1, in the park condition, the guessing model achieved .50, availability-by-recall achieved .62, SCM achieved .69, and SCM-C performed best at .70. In the social media platform condition, the guessing model achieved .50, availability-by-recall achieved .70, and SCM and SCM-C both achieved .76 (see Figure 6). These results are consistent with the findings in Experiment 1.

Discussion

The aim of this study was to investigate whether the domain of a problem influences how people group their social contacts, and which contacts they sample from, in social sampling. In both experiments, we found that the SCM based on social categories of closeness relations and SCM-C based on modes of contact accounted equally well for the performance of a large number of subjects, and hence, for those subjects we cannot draw conclusions about how the question domain affected how they grouped their social contacts. For the remaining subjects in Experiment 1, across both conditions, the SCM best accounted for a greater number of subjects than did the SCM-C; we thus did not find evidence that the problem domain systematically determined whether people grouped their contacts by social category or by contact mode in sampling (neither was such evidence provided by Experiment 2).

Interestingly, our finding in Experiment 1 that the SCM accounted for more subjects than the SCM-C differs from Hecht et al. (2022) who found that the SCM-C accounted for more subjects than the SCM (36% vs. 30%). This is perhaps due to the change of problem domain. We did however replicate their finding (in Experiment 1 and 2) that both the SCM and the SCM-C accounted for more subjects than either the availability-by-recall or guessing models. Furthermore, we did not find that the accuracy of each model differed substantially between conditions. However, we replicated the pattern reported by Hecht et al. (2021) that the SCM and SCM-C performed better than availability-by-recall, and availability-by-recall performed better than guessing.

Although we did not find evidence that the problem domain determined how people grouped their social network, we did find in Experiment 1 that for the SCM-C, the circle weights differed between activity conditions, suggesting that the question domain affects which contacts people first sample from. The weights for the online contact circle were greater than for the offline circle in the online activity (platform) condition, and the weights for the offline contact circle were higher than the online circle in the offline activity (park) condition. This result suggests that when asked about an online activity, people are more likely to sample first from online contacts, and when asked about an offline (in-person) activity, they are more likely to sample first from offline contacts. This is consistent with our prediction based on work on memory and semantic networks (e.g., Collins & Loftus, 1975; McKoon & Ratcliff, 1992) suggesting that one's social contacts may be associated with other social contacts who are contacted through the same mode (e.g., online or offline). A decision related to an online activity may serve as a retrieval cue activating that network of associations, leading one to sample frequency data from their online contacts. Similarly, people's offline contacts may be associated with each other in memory, and a question about an offline activity may activate those contacts, leading one to sample from this group first.

These findings contribute to the growing literature on how people use social sampling to make judgments and decisions. Hertwig et al. (2005) found that an exhaustive search strategy (availability-by-recall) performed better than alternative heuristic strategies, and Schulze et al. (2021) provided evidence that search in social sampling is limited, sequential, and structured, in contrast to the exhaustive recall strategy. Hecht et al. (2022) found that the contact mode (online vs. offline) by which someone communicates with their network members may be more important than more traditional social categories (e.g., family, friends). Our results are consistent with the previous findings that models that assume a serial search process that is sequential, limited, and structured provide a better account than exhaustive search (although an exhaustive recall model is a better account than guessing) in comparative judgment.

We extended previous work by providing evidence that people do not sample their contacts the same way for all types of inferences; rather, the question being asked may activate certain groups of social contacts, leading them to be prioritized in search. By using the problem domain as an additional retrieval cue, people can achieve greater efficiency and accuracy by sampling from those contacts who are most relevant to the decision at hand.

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