Title
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Memory Foraging in a Spatial Domain

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Abstract

Search is a ubiquitous behavior for a variety of species. Converging evidence from several domains suggests that there may be common principles that apply to search processes regardless of the species, or contexts, in which they are observed. Theories of cognitive or memory search have been motivated by findings in the animal foraging literature, and have recently been the subject of increased attention (see Hills et al., 2015; Hills, Jones, & Todd, 2012, for example). This approach has been quite successful in terms of applying the principles of spatial search to cognitive search, but here we add additional justification by grounding cognitive search in spatial measures. We asked subjects to perform a semantic fluency task, recalling items from the category of cities in California, so we could use physical, geographic coordinates to characterize cognitive search. Our findings support the notion that cognitive search is similar to spatial search.

Keywords: Spatial Cognition; Spatial Search; Cognitive Search; Memory; Memory Search; Categorical Recall; Collaborative Recall; Collaborative Dynamics

Introduction

A common metaphor for remembering is "a stroll down memory lane." This suggests that the cognitive act of remembering is like a traversal through some landscape, where the landscape is made of memories, knowledge, or information.

The nature of this landscape, of how information is organized and searched, is a fundamental question in the cognitive, psychological, and philosophical sciences. Implied by the "memory as landscape" metaphor is the idea that memory structure is semantic in nature, such that recalling the concept *birthday cake* may make you think of a semantically related concept such as *birthday candle*. Indeed, semantically related items have long been shown to prime one another (Meyer & Schvaneveldt, 1971). By this metaphor, then, as we stroll to the location in memory space that codes for birthday cakes, we are already close by, and might pop in on, the location for candles. There are, however, different accounts of what characterizes a "location" in memory space. Many of these accounts are from the domain of word learning (e.g. Osgood, 1952). These include representations of semantic meaning as networks of connected nodes (e.g. Collins & Loftus, 1975), as feature lists (e.g., Smith, Shoben, & Rips, 1974), and as high-dimensional spaces learned through, for example, statistical co-occurrences of words, such as in LSA and BEAGLE (see Deerwester, Dumais, Furnas, Landauer, & Harshman, 1990; Jones & Mewhort, 2007).

While lexical accounts of semantics may be intuitively appealing with respect to concepts such as birthday cakes and candles, a relatively small amount of research has investigated the organization of geographic and spatial information in cognitive space (but see Montello & Freundschuh, 1995). That is, spatial knowledge is often acquired through means such as experience (navigation and locomotion) and visualizations (maps and other images), which are less easily fit into existing linguistic accounts of semantic memory. Still, Louwerse and Zwaan (2009) showed that language encodes quite a bit of geographic and spatial information, suggesting that spatial knowledge may not be qualitatively different from other semantic knowledge.

Spatial and semantic information is only useful for an agent, of course, when it can be retrieved and used. Spatial search has long been a topic of investigation in fields such as ecology, where animal foraging behaviors are examined (Pyke, 1984; Charnov, 1976), but more recently it has been noted that investigations of search problems in diverse domains are increasingly converging on similar solutions (e.g. Hills et al., 2012). Although a review of the posited search strategies is beyond the scope of this paper, we refer the reader Hills et al. (2015) for a review of search in a number of domains. The point we wish to make here is that research on cognitive search is increasingly being motivated by spatial search. The focus of the present paper, then, is to explore the "memory as landscape" metaphor as it relates to spatial search, and add to the conversation on whether the dynamics of cognitive information foraging are similar to the dynamics of spatial geographic foraging.

Other work relating physical space with cognitive processes has found that similarity and time are often understood in terms of space and spatial metaphors (Winter & Matlock, 2013; Boroditsky, 2000). In visual search, Kosslyn, Ball, and Reiser (1978) found that distances between sequentially foveated objects was related to scanning time, even when the material between the objects was manipulated. In another study, participants were asked to spatially organize a set of items which were produced previously, by other participants, in a categorical recall task. The spatial distances were found to correlate with the temporal distances observed in the preceding recall task (Montez, Thompson, & Kello, in press).

Similar to Montez and colleagues' study, here we seek to construct a spatial representation of recall behaviors. Using an extended version of the semantic fluency task (Bousfield & Sedgewick, 1944), subjects are asked to spend twenty minutes recalling locations in their home state of California. This task gives us coordinates for objectively calculating distance and associating spatial locations with cognitive processes. We also show that this task can be used to explore more complex cognitive search processes, such as interactive, collaborative search.

Specifically, we explore three main questions as they relate to the category of locations in California. The questions, and their associated hypotheses, are as follows:

Q_1 : Are items retrieved in an order consistent with their geographic coordinates? H_1 : Yes, and if so, randomizing the order of recall events in a dataset will cause the recall trajectory to span a significantly larger distance.

Q_2 : Do temporal dynamics reflect geographic distances? H_2 : Yes, and if so, there will be a correlation between the temporal and spatial distances for pairs of consecutive recall items.

Q_3 : Is the spatial coordination of a dyad related to that dyad's task success? H_3 : Yes, and if so, there will be a correlation between the quality of a dyad's interaction and the dyad's task performance. Since a precise quantification of coordination dynamics, both in search and in general, is beyond the scope of this paper, we adjust our hypothesis to touch on one small part of coordination that may reflect coordination dynamics: The distances, over time, between partners' recall items. Thus, our adjusted H_{3b} will be that distances between dyads' partners will be correlated with dyads' task successes.

Below we describe the experiment we used to address our research questions. Results significantly support H_1 and H_2, but are inconclusive (although show interesting patterns) with respect to H_{3b}. We conclude by discussing how these results contribute to the "memory as landscape" metaphor and the cognitive search literature.

Methods

Participants were recruited from a subject pool of University of California, Merced undergraduate students who participated for course credit (5 male, 26 female; mean age $= 19.77$ years, $SD = 1.56$ years). All participants reported having lived in California for the majority of their lives (mean time of residency in California $= 19.16$ years, $SD = 2.41$ years), and reported being native or proficient English speakers. Twenty subjects were randomly assigned to collaborating dyads, for a total of ten dyads, and eleven subjects worked individually. None of the dyads reported knowing each other before the experiment, so the dyads were given five minutes to introduce themselves to each other before the task began. The brief familiarization period was intended to enhance comfort and performance on the task [1]. Subjects were comfortably seated across the table from each other in a small experiment room, and wore Shure microphone headsets. Speech was collected using an M-Audio MobilePre recording interface and Audacity software.

Procedure

Dyads completed two sets of recall tasks, each of which lasted for twenty minutes (adapted from Rhodes & Turvey, 2007). The recall tasks included recalling from the category of animals, or the category of cities and towns in California. The order of the recall task categories was counterbalanced across dyads. Before receiving information about the category, subjects were given the following instructions: "In a moment, I'll give you the name of a category for the first session. Your goal will be to work together to think of as many items from that category as you can. When you think of an item, just say it out loud. You can be as specific or as general as you wish. For example, if the category were Food you could say 'Fruit', and you could also say 'Orange' or 'Mandarin Orange'. But keep in mind that your goal is to recall as many different items as possible. If you are unsure if an item does or does not belong to the category, just say it anyhow, don't spend time worrying about whether something counts or not," (adapted from Rhodes & Turvey, 2007). In order to minimize task constraints and make the task feel slightly more natural, we indicated to participants that extraneous conversation was allowed during the task, but that they should stay focused on the category, and keep attempting to recall additional items throughout the twenty minutes. After taking any questions, the category was assigned and the experimenter left the room for the duration of the task. Between recall rounds, subjects were given a 2-3 minute break. At the start of the second round, they were again reminded to keep trying to recall new items for the duration of the task.

Data Analysis

For the purposes of the present paper, we discuss only results from the category of cities and towns in California.

Audio Transcription The speech recordings were loaded into Praat audio analysis software for annotation. Subjects were recorded onto unique channels, so their utterances could be considered individually. Onsets of recalled item utterances were marked, excluding any extraneous conversation. That is, "Oh, we can't forget 'Merced'," would be marked at the onset of the recalled item 'Merced'. All submitted items were transcribed, but consecutive repeats were removed. Incorrect items ("Reno", which is in Nevada, not California), geographic landmarks ("Monterey Bay" bay, "Sierra Nevadas" mountains), and non-specific areas ("Bay Area", which refers to several locations around the San Francisco Bay) were removed. Pronunciation errors ("Rancho Cucamongo" instead of the correct "Rancho Cucamonga") and common abbreviations ("L.A." instead of the official "Los Angeles") were corrected. Districts, neighborhoods, planned communities and census-designated areas with names recognized by the U.S. Geological Survey (e.g. "Hollywood", "Downieville"; *http://geonames.usgs.gov*, 2014) were retained.

After transcription, location names were matched with latitude and longitude coordinates in decimal degrees using databases retrieved from GeoNames and Wikimedia's GeoHack tool (*http://www.geonames.org*, 2014; *https://wmflabs.org*, 2015).

[1] Previous work, from ourselves and others, has shown that more familiar groups tend to perform better on memory tasks (Barnier, Sutton, Harris, & Wilson, 2008; Szary & Dale, 2014).

Table 1: Datasets used in the analysis. Notations, given in parentheses, indicate condition with I (independent) or C (collaborative), with a subscript 1 or 2 to indicate the number of participants included in each level of analysis (individual or group, respectively). See text for details.

Condition:	*Levels of Analysis:*	
	Individual	Group
Independent	Solo (I_1)	Nominal (I_2)
Collaborative	Extraction (C_1)	Dyad (C_2)

Scoring We use a two-by-two scheme where we consider two participation conditions (independent or collaborative) on two levels of analysis (individual or group). See Table 1 for a depiction of this scheme, and a description of the notations (I_1, I_2, C_1, and C_2) used herein. We refer to individuals participating alone as simply *solos*, or I_1. Datasets from multiple individuals who participated independently were later combined and analyzed at the group level, which is an approximation of a *nominal* comparison[2], noted as I_2. For participants in the collaborative condition, we can extract from the group level each individual's datasets, which we refer to as *extractions*, or C_1. Finally, group level datasets from individuals who were performing the task collaboratively are *dyads*, noted as C_2.

For group level datasets (I_2 and C_2), the instantaneous onset times for each participant's recalled items and their corresponding location coordinates are merged into one dataset. For each dataset, scores are computed as the unique number of locations recalled (that is, repeats are excluded). Inter-retrieval intervals (*IRIs*) are measured as the amount of time (in milliseconds) between consecutive recall events. Geographic distances (*GDs*) are measured as the number of miles between consecutive recalled locations. GDs are calculated using the Haversine formula, which gives the great-circle distance between two points on an sphere (Sinnott, 1984). Finally, the distance between partners in the group-level datasets (inter-partner distance, *IPD*) is calculated using the Haversine formula, where points are each partner's most recently recalled locations over time.

Results

Scores

Outliers were defined as data points falling outside $+/-1$ standard deviation from the mean of each condition and removed. Mean remaining scores are shown in Figure 1. Dyads outperformed solos, recalling 86.7 ($N = 7$, $SE = 3.25$) and 65.7 ($N = 9$, $SE = 5.10$) locations, respectively, $t(14) = 3.25$, $p < 0.001$. Unsurprisingly, nominal pairs recalled 110.8 ($N = 38$, $SE = 2.27$), which is significantly more than dyads, $t(43) = 4.40$, $p < 0.0005$, and is consistent with the literature on collaborative inhibition (Basden, Basden, Bryner, & III, 1997). Extracted datasets were significantly worse than the next best (solo), recalling only 47.9 ($N = 13$, $SE = 2.58$), $t(20) = -3.39$, $p < 0.005$.

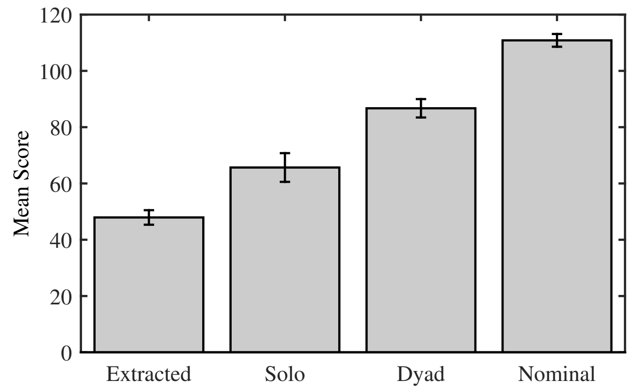

Figure 1: Mean number of locations recalled for each condition and level of analysis. Error bars show $+/-$ *SE* for the remaining data.

Recall Dynamics

Inter-Retrieval Intervals The distribution of IRIs was fit to several different candidate models using the multi-model inference method and Akaike's Information Criterion, as described in Rhodes (2013). Candidate models included normal, exponential, lognormal, Pareto, and gamma distributions. The best fitting model for 1/11 solos was the lognormal distribution, and for 10/11 it was the Pareto distribution. For dyads, 6/10 were best fit by the lognormal distribution, and 4/10 were best fit by the Pareto distribution. For extracted datasets, 12/20 were best fit by the lognormal distribution, 1/20 was best fit by the exponential distribution, and 7/10 were best fit by the Pareto distribution. For nominal datasets, 49/55 were best fit by the lognormal distribution, 3/55 were best fit by the exponential distribution, and 3/55 were best fit by the gamma distribution. The finding that most IRIs (and, in fact *all* actual datasets, including I_1 and C_2) were fit by either Pareto or lognormal distributions is consistent with the IRI distributions exhibited in other categorical recall tasks (e.g., Rhodes, 2013; Szary, Dale, Kello, & Rhodes, in preparation)[3].

Geographic Distances Figure 2 illustrates the series of recalled items as travel trajectories on a map of California for each of the ten collaborating dyads. Across consecutive recall events in each condition, we tested for correlations be-

[2]These nominal pairings, which included all possible (unique) combinations of individual participants, allow us to (roughly) address whether any observed group-level differences are truly related to the interaction between two participants, or simply because there are two participants instead of one.

[3]Best fitting distributions are noted here simply to relate our findings to those using the more familiar category of animals, but we will not go any further into the analysis or discussion of these distributions. For further information on these distributions and ideas about their relevance, see Rhodes, 2013; Szary et al., in preparation).

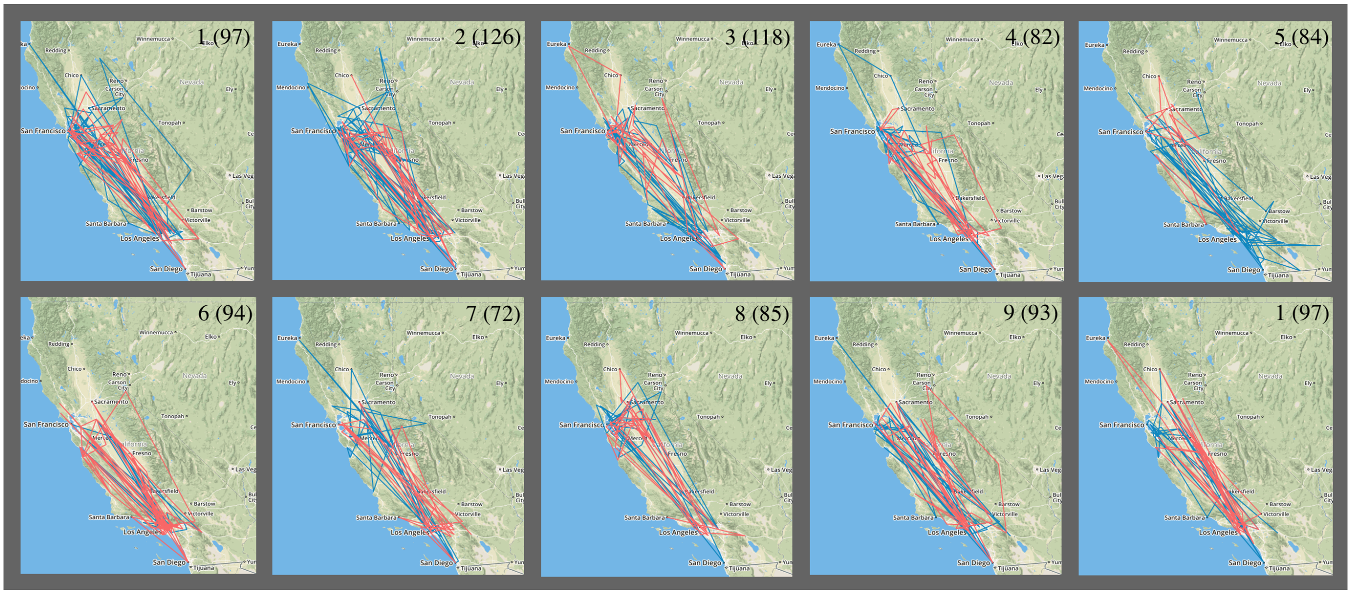

Figure 2: Each panel illustrates the recall trajectory of a collaborating dyad transposed on a map of California. For each dyad, one participant's recall events and paths are shown in blue, and the other in red. The overall score for each dyad is shown in the top right of each panel in parentheses. Maps were generated using *https://www.mapbox.com*, 2015.

tween GD and the log of IRIs[4]. The correlation was subtle but significantly positive for dyads, $r(1106) = .16$, solos, $r(955) = .26$, and extracted datasets, $r(1119) = .28$, (all with $p < 0.0001$). For nominal datasets there was no significant relationship between GD and IRI. Figure 3 plots GD against IRI for each condition and level of analysis.

The sequence of locations recalled by dyads and solos was shuffled (within each dataset), and new GDs were calculated. As illustrated in Figure 4, the mean of all GDs for each of the two conditions was significantly higher when sequences were in a random order compared to their original order. For dyads, mean GD in the original order was 135.12 ($SE = 4.03$), and in the shuffled order was 174.79 ($SE = 4.00$), $t(2214) = 6.99$, $p < 0.0001$. For solos, mean GD for the original order was 11.27 ($SE = 4.07$), while in the shuffled order it was 169.35 ($SE = 4.30$), $t(1912) = 9.82$, $p < 0.0001$.

Inter-Partner Distances For group level datasets we computed IPD as described above. Although nominal pairs (I_2) did not actually work together, IPDs were computed using the simulated pairings of individuals' time series. Thus, I_2 IPDs do not actually measure any kind of interaction or collaboration dynamics. Instead, these IPDs might reflect differences in the composition of dyads with different hometowns and areas of expertise. For C_2, further research will need to tease apart whether different IPDs reflect this type of composition difference, or whether they capture collaboration dynamics.

Mean IPDs did not differ significantly by condition (for dyads, mean IPD = 189.63, $SE = 12.38$; for nominal pairs,

[4] To accommodate different scales of magnitude in the timeseries, IRIs were logged to show the effect, as in (Montez et al., in press).

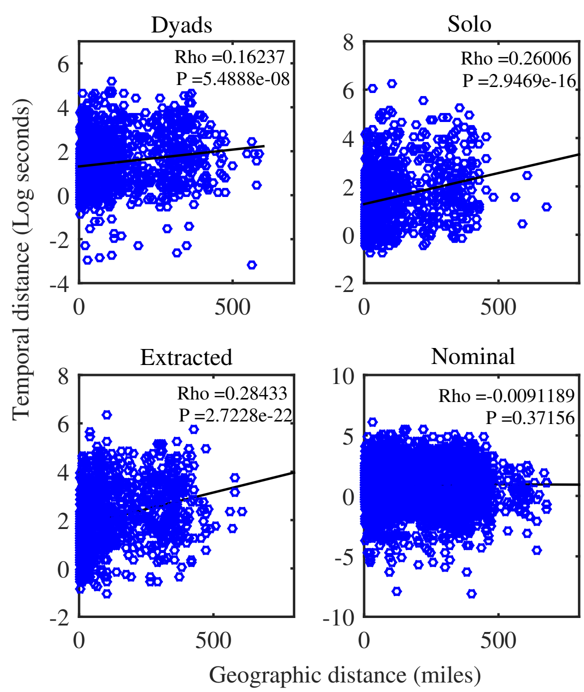

Figure 3: Each panel shows a scatter plot of geographic distance, in miles, plotted against the log of IRI times (in log seconds) for each pair of consecutive recall events in each of the four conditions. *Rho*, in the top left corner of each panel, shows Pearson's linear correlation coefficient and its significance, *p*.

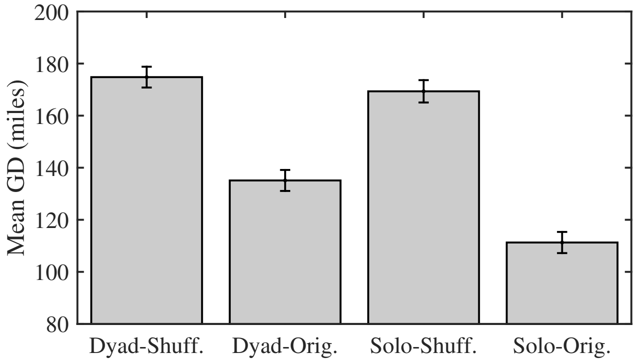

Figure 4: Mean geographic distance (GD) in miles for shuffled and original datasets in the dyad and solo conditions. Error bars show $+/-$ SE.

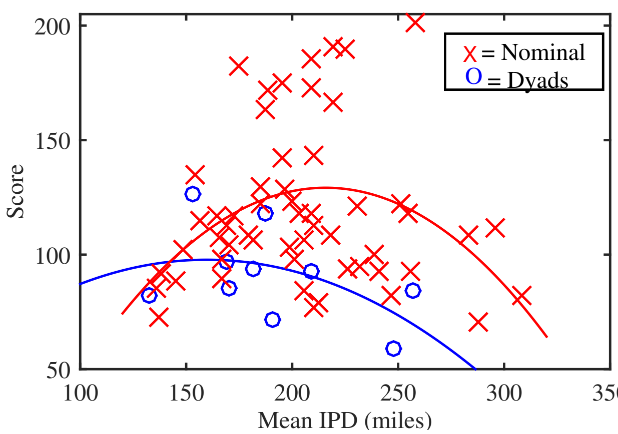

Figure 5: Data points represent average IPDs between partners for each dyad (blue) and nominal pair (red) across the entire task. Lines show quadratic fits to dyads (red; $y = -0.006x^2 + 2.6x - 150$) and nominal sets (blue; $y = -0.003x^2 + 0.95x + 22$).

mean IPD $= 204.25$, $SE = 5.45$). Figure 5 shows scores for each data set as a function of mean IPDs. Quadratic fits suggest a nonlinear relationship, where a certain IPD may be a somewhat "optimal" point for enhancing dyadic search. Interestingly, the optimal IPD may be smaller for collaborating dyads as compared to the simulated nominal groups. The effects are admittedly negligible, here, but we present them as a precursor to our computational modeling work on this same topic (in preparation).

General Discussion

Here, we discuss results only from the category of cities and towns in California. Future work will compare collaborative performance dynamics in the different (spatial versus semantic) task spaces, but here we simply note that the same general patterns are exhibited in the timeseries and score from the condition where participants recalled animals.

In the spatial domain, our results showed that simulated nominal pairs recalled significantly more items, on average, than interacting dyads, even though dyads recalled significantly more than individuals (or extracted dyad members; see Figure 1). This is unsurprising, as it is consistent with the existing literature on collaborative inhibition (Basden et al., 1997). However, we were more interested in investigating the dynamics of recall. Our next results showed that most inter-retrieval intervals were either power-law or lognormally distributed, which relates our categorical recall task using locations in California to the results of other recall tasks using animals (Rhodes, 2013; Szary et al., in preparation). Next, we correlated the sequence of inter-retrieval intervals to the sequence of inter-retrieval geographic distances and found subtle but reliably positive correlations. That is, cities that are closer together tended to be recalled closely in time, while cities farther from each other tended to be recalled with larger delays. This correlation held for all datasets *except* nominal pairs, in which two non-related datasets are merged into one (see Figure 3). It is interesting, although not altogether surprising, that the relationship between spatial and temporal dynamics is broken in this kind of artificial dyad. To further investigate the apparent spatial clustering in the sequence of recall events, we shuffled the order of recalled items within each dyad and nominal dataset. As further support of spatial clustering, shuffled datasets (in both conditions) had reliably larger average geographic distances (see Figure 4).

Finally, we used inter-partner distances (IPDs) as a coarse measure of collaboration. Overall, the mean distances were smaller for interacting dyads as compared to simulated nominal pairs, but this difference did not reach significance. This suggests that interacting dyads did not, on average, stay any closer to one another (in terms of their recall spaces) than would be predicted for noninteracting individuals foraging the same space, although we suspect that a more rigorous analysis with more data points might produce interesting results. As an example, quadratic fits suggest the possibility that a median IPD is related to better recall performance as compared to very small or very large IPDs. Median IPDs might reflect situations in which partners forage more-or-less in together (globally), but maintain a slight distance (locally) so as not to overlap with one another. This type of strategy has implications for research on coordination and alignment as well as optimal foraging theories, but further work is needed to explore it (and other) collaborative foraging strategies. As noted above, it is still unclear whether our IPD measure really taps into interaction dynamics, or whether it reflects something more basic, such as differences in group composition.

Conclusion

Overall, our results provide clear support for our H_1 and H_2: Items seem to be recorded in an order consistent with their geographic coordinates, and the temporal dynamics of their retrieval is reflected in geographic distances. Although H_3 could not be directly tested, H_{3b} was tested and gave mixed results: distances between partners during collaborative foraging are not linearly correlated with score, as hypothesized, but there may be an interesting nonlinear relationship for further research to explore.

These results add justification for the growing notion, popular in both intuitive and scientific accounts, that remembering can be likened to and investigated as a spatial search process. Rather than making any claims about the structure or nature of memory itself, we suggest that these results support the notion that search can be investigated as a general cognitive phenomenon, independent of the domain in which it is performed.

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