

Path Following in Social Web Search

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Abstract. Many organisms, human and otherwise, engage in path following in physical environments across a wide variety of contexts. Inspired by evidence that spatial search and information search share cognitive underpinnings, we explored whether path information could also be useful in a Web search context. We developed a prototype interface for presenting a user with the “search path” (sequence of clicks and queries) of another user, and ran a user study in which participants performed a series of search tasks while having access to search path information. Results suggest that path information can be a useful search aid, but that better path representations are needed. This application highlights the benefits of a cognitive science-based search perspective for the design of Web search systems and the need for further work on aggregating and presenting search trajectories in a Web search context.

Keywords: Search Paths, User Study, Path Following, Social Search.

1 Introduction

Path following is ubiquitous among social species in natural environments, be it mediated by stigmergic pheromone trails of ants and termites [1], emerging from crowd dynamics [2], or evidenced by the the reinforcement of worn paths through grass and snow on college campuses [3]. On the Web, too, we follow paths — albeit implicitly — when the search results we encounter, videos we watch, and products suggested to us all depend on the interaction patterns of the users who went before us. In this paper we take inspiration from work on path following in physical environments to explore whether sharing explicit search paths between Web searchers can be a useful search aid.

Research in cognitive science suggests that goal-directed cognition is an evolutionary descendant of spatial foraging capacities [4], and an increasing number of studies show that the way humans search in information spaces is deeply

* The first author was an intern at, and the second employed by, Yahoo! Research during study development. Data collection/analyses were done at Indiana University.

linked to the way we search in spatial environments [5, 6]. This conclusion is also bolstered by the embodied view of cognition, which highlights the connections between information processing and bodily movement in space [7].

With this in mind, we developed and tested a prototype interface for applying the notion of path following to a Web search environment. A path, by definition, carries a special kind of information typically lacking from Web-based recommendations and other search tools: It provides not only a destination, but a route from one's current location to that destination, thus delineating what lies between. This may seem a simple point, but the vast majority of tools for guiding information search on the Web — from product recommendations on Amazon to “Also try:” suggestions on Yahoo! search — are pointillistic: You should issue *this* query, or buy *this* product. This is not to say that such recommendation systems are not utilizing path-like data “under the hood” to generate suggestions, but to our knowledge there exist no systems in regular use that explicitly share paths — sequences of activity extended over time — between users.

In a Web context, sharing path information creates opportunities for serendipitous discoveries by exposing the user to content that would be missed by “teleporting” directly to a recommended resource. When these paths are relevant to the current search context, they can provide windows on how to approach a search task that the user might not consider otherwise, and that likely could not be readily communicated via pointillistic recommendations. This of course holds little value in cases where a user's query has a clear, discrete answer (“What is the capital of North Dakota?”). Many search tasks we engage in, however, are simultaneously more complex and less explicitly defined (“What car should I buy?”, “What is fun to do in North Dakota?”). In these cases, paths can capitalize on modern Web users' interest in shared social content and propensity for social copying. We hypothesized that the incorporation of path information into the search interface would lead to increased levels of (1) user engagement and (2) satisfaction with solutions to assigned search tasks. To explore our hypotheses, we developed a custom search engine interface that incorporated path information. Study participants were assigned a series of search tasks, and presented with the paths taken by previous users performing the same task.

A full understanding of search path use requires work at three levels: The cognitive-behavioral (what is the theoretical case for using path information in search and how do people respond to it), the algorithmic (how can search paths be generated and coherently aggregated across multiple users), and design-centric (how should such paths be presented to users). Here we address the first level, as a preliminary attempt to explore how path-like information can be translated to a Web search context. While some of our positive results are suggestive of the power of this approach, our other negative results also indicate that it will be crucial to determine better ways of presenting path information if it is to be helpful to users. Thus a principal goal of this paper is to encourage future work that explores methods for creating and presenting useful path information to individuals searching the Web and other information spaces.

2 Related Work

Cognitive Science: Though following a path in a physical environment bears little surface similarity to a Web searcher’s “movement” on the Internet, the activity of Web searchers create valuable signals that can facilitate future users’ search efforts, much as animals create physical trails. Web path signals are utilized by many modern search systems, both when they are left behind explicitly (as in collaborative tagging or when people share links on a social network) and, more commonly, when they are implicit. These implicit signals, formed as users issue queries and click on results, are integral to intelligent query suggestions and to the ranking of results on modern Web search engines.

In the mid-1990s, Pirolli applied optimal foraging theory — a theory of how organisms search for resources in a physical environment — to Web search with considerable success [8, 9]. More recent work [5] found that participants could be primed by a spatial search task to behave in predictably different ways on a subsequent mental search task. The authors hypothesized the existence of generalized cognitive search processes, and molecular and behavioral evidence [4, 6, 10] supports the hypothesis that evolved capacities for spatial search deeply influence the way we search in other domains. This suggests the usefulness of spatially-inspired data representations, like paths, for information search.

Path-Based Web Search: Recently a few works [11–14] have studied algorithms inspired by physical spatial search to improve web search engine performance, modifying page ranking by enriching link data with collective intelligence information. For each page, the information about Web trails taken by other users (often called Web pheromones) is accumulated and used to modify the global rank of the page. This differs from our approach of showing the paths used by others, but leaving page ranks unchanged. In terms of methodology, only one other study [14] conducted a controlled experiment on real users as we did, but again, participants were not directly presented with search paths.

Search Tool Evaluation: Social search tools can be evaluated via two main criteria: effectiveness (and hence user satisfaction) and elicited engagement [15–18]. Often, shorter time to completion (i.e. the time spent on a search task) is used to assess effectiveness. In a social setting, however, time to completion is not always a good metric: Social interactions can lead to increased engagement, which can in turn increase time to completion, such as through distortions in the subjective perception of time [15, 19]. Since evaluations of social search tools depend on subjective measures, they are typically tested with user studies [15–17], which are limited in number of participants and constrained by the need for extended experience with a new tool [20]. Despite these problems, there is typically no viable alternative for testing users’ subjective responses to search tools.

3 Methodology

Participants completed a sequence of search tasks either with social search information (BestSearcher paths condition) or without (baseline condition). We ran the baseline condition first, and used data from those participants to generate the search path information for the experimental BestSearcher condition. All participants completed the same set of search tasks (in randomized order) for one condition or the other. The study was administered in a modified¹ web browser that allowed for display of path information, presentation of search tasks, collection of task responses, survey administration, and clickstream logging. Baseline condition participants used a standard version of the Yahoo! SERP (Search Engine Results Page), while participants in the experimental condition also saw a sidebar with social search path data (Figure 1). Paths were socially generated sequences of clicks and queries from the baseline condition, and participants could click path elements to visit a URL or issue a query from the path, respectively.

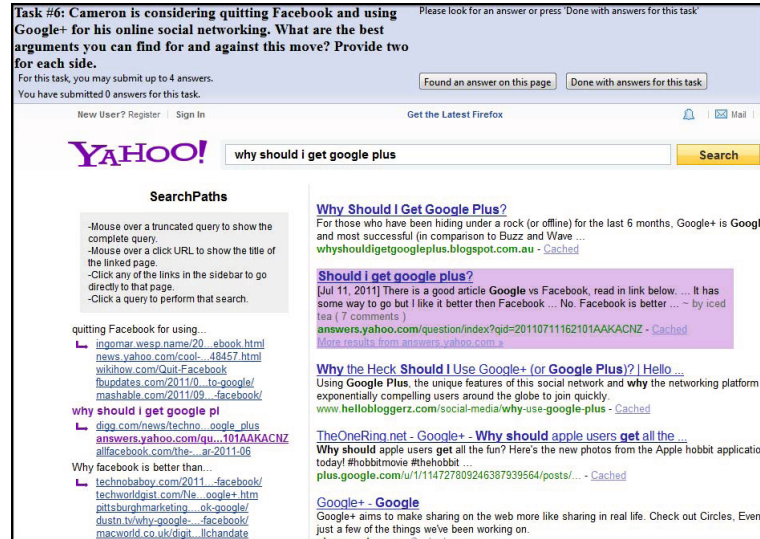


Fig. 1. Screenshot of experiment interface

Participants were given search tasks that we deliberately selected to be both complex and minimally specific; that is, none of them had a particular set of “correct” answers. The goal was to use questions that would enable participants to utilize social information to aid their searches, without the social information leading to a single best answer for any question. Thus all tasks incorporated a level of subjectivity (“find the best...”, etc.) and required multiple answers. Table 1 shows several examples of the tasks used (participants completed eight in total).

¹ Via the HCIbrowser extension [21] and a variety of CSS and Javascript tools that allowed for visual modification of the SERP.

Table 1. Examples of search tasks

“austria”: You’re on a backpacking tour of Europe, and will be stoping in Innsbruck, Austria, but unfortunately you’ll only have a few hours to spend there. Find the two most interesting activities that could both be done in the 4 hours you’ll have.
“disney”: Tammy is planning a two-day trip to Disneyland with her three-year-old daughter (who loves princesses) and is looking for the must-see attractions. She’s already been to disneyland.com, and had little luck, so find three appropriate pages to help her in her trip planning.
“facebook”: Cameron is considering quitting Facebook and using Google+ for his online social networking. What are the best arguments you can find for and against this move? Provide two for each side.
“metal”: A friend wants to take up metal detecting as a hobby. Find the three best resources (books, online tutorials, videos, etc.) you can to get her started.

3.1 Generating Search Paths

To generate the social search path data displayed in the sidebar, we had to extract meaningful paths from users’ search activity in the baseline condition. After comparing several options, we settled on “BestSearcher” paths for this study, which show the complete path (sequence of queries and clicks) of the “best” participant from the baseline condition for each task — requiring a measure of query success.² Our ranking metric used the total number of queries (because the tasks require multiple answers, issuing more queries should increase the probability of finding more unique pages), the total number of long dwell-time (i.e. time spent on page) clicks per query, and the inverse of the time required to reach the first long dwell-time result. The path followed by the baseline condition participant with the greatest score on this metric for each task was then used as the BestSearcher path for that task, such that all participants in the experimental condition saw that same path for any given task (but the source “best” searcher for paths varied from task to task).

3.2 Participants and Procedure

Participants were Indiana University undergraduates compensated with course credit. 26 female and 42 male students (12 female and 12 male in the baseline condition, 14 female and 30 male in the BestSearcher condition) participated. All were between 18 and 24 years old. Participants in the baseline condition were informed that they would be presented with a series of questions for which they should search the web for answers. Those in the experimental condition were given the same instructions, but were also told that they would have “access to information about how previous IU students have completed the search tasks.”

² The technical details of this metric, along with expanded discussion of our methodology and results, appear in an extended version of this paper available online at <http://mypage.iu.edu/~jlorince/papers/lorince.donato.todd.2014.sbp.extended.pdf>

Participants first completed a practice trial to get familiar with the interface, then eight experimental search tasks (in randomized order). They then rated task difficulty, satisfaction with results, engagement with the task, and, for the BestSearcher condition, the usefulness of the search path information.

4 Results and Discussion

We focus here on determining if participants found the social path data engaging and/or helpful. Analyses discussed below reflect only participants who utilized the social path information (by clicking a query or URL) at least once (33 of 44).

Subjective Ratings: Unsurprisingly, we found a general pattern of anticorrelation between task difficulty and satisfaction (baseline: $r(209) = -.59, p < .0001$), experimental: $r(317) = -.60, p < .0001$), as well as weak but significant correlation between engagement and search satisfaction (baseline: $r(209) = .35, p < .0001$, experimental: $r(317) = .26, p < .0001$) across both conditions. As subjective difficulty went up, engagement went down in the Baseline condition ($r(209) = -.29, p < .0001$), but not in the BestSearcher condition. This suggests that social facilitation did ameliorate the negative effect of task difficulty on engagement. In contrast to our initial predictions, we found no significant difference in mean satisfaction or engagement between conditions. Problematically, participants did not report the experimental tasks to be of strong personal relevance, rating them on average below the midpoint of a Likert scale (i.e. disagreeing with the statement “This is a realistic search task for you in particular.”).

Behavioral Measures: The key metrics for each task (Figure 2) were mean time to completion, mean dwell time (i.e. the average time spent on each clicked page), proportion of trials successfully completed, and total number of search events (i.e. sum of queries and clicked URLs for each task). Again, there was little difference between conditions. The data suggest a trend towards faster completion times and fewer total search events when path information was available, with the notable exception of the “indiana” task, which required significantly more time and search events in the BestSearcher condition compared to baseline. This may stem from the difficulty of the task (highest subjective difficulty rating), along with the possibility that the information in the sidebar was not particularly useful, but participants still explored the social data in detail in an effort to solve the difficult task. This task also had the greatest proportion of activity originating from the sidebar across participants. There is, in fact, a weak but significant ($r(209) = -.29, p < .0001$) correlation between the proportion of activity originating from the sidebar and the perceived difficulty of tasks, indicating that participants relied more on socially available data when search tasks were more challenging.

Evaluation of Search Paths: Participants in the experimental condition also rated the usefulness of seeing search paths, whether it made the task more interesting/engaging, whether they actually used paths, and whether path information allowed them to complete the task more quickly than they would have

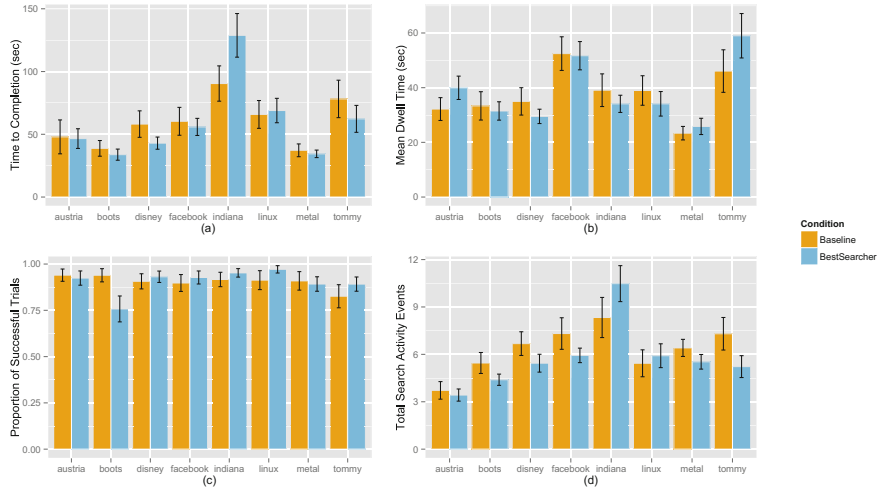


Fig. 2. Summary of behavioral measures by condition and task. (a): Mean time to complete task (seconds). (b): Mean dwell time (seconds). (c): Mean proportion of successfully completed trials. (d): Total search activity (number of clicks + number of queries). (a),(b), and (d) normalized by the number of responses required for each task. Error bars show ± 1 standard error.

otherwise. Responses hovered around the middle of the response scale on average, indicating that participants found the search paths moderately helpful overall. There appears to be a general pattern of paths being more positively evaluated on the more difficult tasks, though the only measure here that correlates (weakly) with difficulty in a statistically reliable way is participants' reported usage levels ($r(258) = .23, p < .001$). These responses were not particularly strongly aligned with the respective behavioral measures we collected, though; ratings of how much participants actually used the paths, for instance, had only a weak correlation ($r(258) = .22, p < .001$) with their total sidebar activity (i.e. sum of clicked queries and URLs from the sidebar).

Notable here is that all responses to the search paths evaluation questions were moderately to highly inter-correlated ($r > .6, p < .0001$ in all pairwise correlations). So, even though their subjective responses may not correlate well with their behavioral patterns, these results indicate (consistent with our hypotheses) that a useful search tool is one that enhances both engagement and the speed with which a user can achieve his or her search goal. Unexpected here is the weak correlation between how much participants reported using the sidebar by actually clicking queries and URLs and the true use of the sidebar we logged experimentally. The unexpected low correlation between perceived and actual use could have come about because participants had an inflated sense of how much they used the sidebar when they found the sidebar path information to be useful. Nevertheless, these data suggest that the SearchPaths tool may have been of help to participants in ways not apparent from our collected behavioral measures.

5 Conclusions

We have made a theoretical case for leveraging cognitive science research linking spatial and information search in the development of social search aids, specifically in the context of sharing search paths between users. We also presented a preliminary effort at designing and testing a simple system with such social functionality. In the end, our empirical results do not allow for strong conclusions to be drawn from our user study, but our methods will likely be useful in future comparative work that considers other path-based search tools.

Our study faced a number of limitations, many stemming from its relatively small scale. While our hypothesis that path information should be helpful for moderately complex search tasks like those we assigned may hold true, we doubt such an effect can be clearly measured when study participants are presented with tasks in which they have little intrinsic interest or stake in the outcome. Subsequent work on such search tools must ensure that participants are provided with tasks that capture their interest in an ecologically valid manner. Further, larger-scale work is also required to determine how to aggregate path information from many searchers and how to effectively present that information to users.

Our study does nonetheless suggest that path information may be useful to Web searchers. Research in cognitive science has revealed that human search mechanisms in non-physical environments remain deeply connected to evolved foraging and spatial search processes, and work of this nature thus can inform both our understanding of how individuals interact with information search systems, and the design of tools to facilitate search in such environments. Our study focused on one particular application, namely applying notions of spatial path following to a Web search environment. Our hope is that this work can serve as inspiration for further exploration of how path information can be leveraged in Web search, and for applications of cognitive science research about search behavior to the improvement of online information search systems more generally.

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