Behavior Modeling for Point of Interest Search

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ABSTRACT

With the increasing popularity of location-based services, the point-of-interest (POI) search has received considerable attention in recent years. Existing studies on POI search mostly focus on how to construct better retrieval models to retrieve the relevant POI based on query-POI matching. However, user behavior in POI search, i.e., how users examine the search engine result page (SERP), is mostly underexplored. A good understanding of user behavior is well-recognized as a key to develop effective user models and retrieval models to improve the search quality. Therefore, in this paper, we propose to investigate user behavior in POI search with a lab study in which users' eye movements and their implicit feedback on the SERP are collected. Based on the collected data, we analyze (1) query-level user behavior patterns in POI search, i.e., examination and interactions on SERP; (2) session-level user behavior patterns in POI search, i.e., query reformulation, termination of search, etc. Our work sheds light on user behavior in POI search and could potentially benefit future studies on related research topics.

CCS CONCEPTS

• **Information systems → Search interfaces**.

KEYWORDS

point of interest search, mobile search, user behavior, eye tracking

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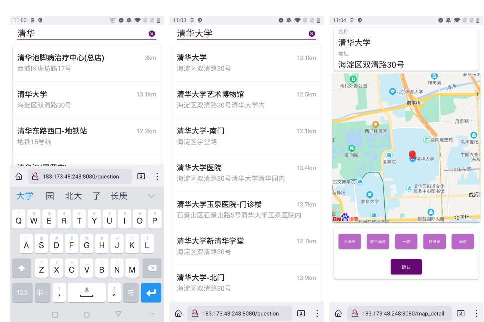
1 INTRODUCTION

With the increasing popularity of location-based services such as Google Map, Uber, and Didi, the point-of-interest (POI) search has received considerable attention in recent years. The POI search is a crucial function provided by map/travel applications with which a large number of users find their points of interest every day. As illustrated in Figure 1, a typical application scenario of POI search is to retrieve and show a list of POIs to the users based on their input query. Thus, existing studies on POI search primarily focus on how to construct better retrieval models to retrieve the relevant POI based on query-POI matching [14, 26, 27, 29].



(a) (b) (c)

Figure 1: Our POI search engine. (a) shows that the SERP is partially covered by virtual keyboard while users is typing, (b) shows the full SERP, and (c) shows the landing page.

Despite the extensive studies on POI search models, the studies of user behaviors in POI search, on the other hand, remain underexplored. User behavior analysis has been widely recognized as an important topic in traditional IR tasks such as ad-hoc retrieval and Web search. For example, eye-tracking studies on the Search Engine Result Pages (SERPs) of Web search [5, 9, 11, 15, 17–19, 31] have led to the development of a variety of user models [2, 3, 6, 10, 30] and retrieval models [12, 16, 23] that help us improve search quality significantly. However, to the best of our knowledge, there is no similar study that analyzes how users interact with search results in POI search. Therefore, how user behaviors in POI search resemble or differ from those in other IR applications are mostly unknown.

While it is reasonable to hypothesize that they could share some common characteristics with how users interact with retrieval results in Web search, there are multiple reasons to believe that user behaviors in POI search could have unique properties in practice. First, search intents in the POI search are usually specific. POI search users often have a single destination in mind when they search. Because most POI search snippets would contain the location name and address simultaneously, users could judge whether the result can satisfy their needs without clicking and checking about the detailed information. Second, Most POI search interfaces provide instant results while users type their queries. On the one hand, users could examine the results without finishing a query, which could directly affect users' query reformulation behavior in search sessions. On the other hand, due to the need for a virtual keyboard for typing on mobile devices, the number of results users can see when and after typing could vary significantly. This could lead to examination and click behaviors that differ from those in standard Web search scenarios.

In this paper, we present one of the first user behavior analyses on POI search. Based on the above observations, we are particularly interested in studying the following research questions: **RQ1:** What are the query-level behavior patterns in POI search? (e.g. SERP examination, result click-through, etc.) **RQ2:** What are the session-level behavior patterns in POI search? (e.g. query reformulation, termination of search, etc.)

To address these questions, we conducted a two-stage lab study to collect participants' eye movement and other behaviors (e.g., clicking and scrolling) in POI search. In the first stage, the initial query is given, and the position of the relevant POI in the query's result list is fixed in advance. Based on the data collected at the first stage, we find that user examination behavior on SERPs in POI search is consistent with the assumptions of Cascade Model [6]. In the second stage, each participant must input the query from the beginning. Based on the data collected at the second stage, we find that users prefer to reform the query than scroll down the current SERPs. These observations could potentially help us better extract user feedback signals from POI search logs and provide essential ideas for the future design of POI search systems.

2 RELATED WORK

User behavior analysis has long been an important topic in IR research. For example, user behavior in web search has been extensively studied in the last two decades. Existing studies found several behavior biases in web search, including position bias [7], attention bias [4, 24] and novelty bias [28]. Granka et al. [11], Joachims et al. [15] and Richardson et al. [22] focused on user's eye movement and browsing patterns during the search process by eye-tracking. Dumais et al. [9] paid attention to user's gaze distribution on the whole SERP and investigated individual differences in gaze patterns. Diaz et al. [8] used cursor movements to estimate user visual attention on the SERPs. Liu et al. [20] proposed a two-stage examination model for web search, consisting of a "from skimming to reading" stage and a "from reading to clicking" stage. Liu et al. [21] investigated the influence of vertical results in web search examination. Wang et al. [25] investigated examination behavior in mobile search based on large-scale search logs with viewport information and found that click positions mostly happen in the top two-thirds portion of the viewport. Zheng et al. [31] investigated user's browsing pattern and attention distribution on the SERPs in mobile search and found that the focus of attention transfers from the top to the bottom half after the initial viewport. In contrast to web search, user behavior analysis in POI search is mostly underexplored in the existing literature. To the best of our knowledge, this paper is one of the first studies investigating user behavior patterns in POI search.

3 DATA COLLECTION

To investigate user behavior in POI search, we conduct a two-stage lab-based study with 80 search tasks. Participants are asked to find a specific POI through the provided POI search engine in each task. The first stage is designed with 60 query-level tasks, and the second stage is designed with 20 session-level tasks. In this section, we describe the details of the user study and the dataset we collected.

3.1 Task Design and Procedure

We construct our tasks with the search logs of a commercial POI search engine in Dec. 2020. In the logs, the search session is defined as a sequence of queries issued by the user, and the session ends with the user's click on a result. The log of each session consists of a sequence of queries, the result POI lists of each query, and the clicked POI in the POI list of the last query. We randomly selected 80 sessions and extracted the clicked POIs as the target POIs of our search tasks. These session data are randomly divided into two groups to form the tasks for each stage of our lab study, i.e., 60 for the first stage and 20 for the second.

Before the start of the user study, we calibrate the eye-tracker for each participant. To introduce the experiment, participants are guided through five training tasks, consisting of two query-level tasks and three session-level tasks. The participants are first presented with the description of the task, which consists of the name and the address of the target POI (e.g. "You want to go to the National Stadium. The address is 1 Guojiatiyuchang S Rd, Chaoyang, Beijing"). After reading, they are required to search the POI by our POI search engine on the provided mobile phone. The search process of query-level tasks and session-level tasks will be described in detail in the following paragraphs. After finding the target POI, participants are asked to assess their satisfaction on a five-grade scale with their whole search process on the detail page (as shown in the bottom of Figure 1c). After assessing the satisfaction, participants can switch to the next task. For each task, we recorded participants' eye movements using the eye-tracker (including both fixations and saccades), as well as their clicks and scrolling information using our search engine.

In the first stage, we focus on user examination behavior at the query level (i.e., on a single SERP). Here, when the participants enter the search page, a initial query is already shown in the search box with its results shown below and the virtual key board collapsed. That initial query is the last query in the log of the task's corresponding session, and the results shown on the page is the result POI list of the query in the log. The participant can examine the current results or change the query to get new results, but we only focus on the user behavior on the SERP of the initial query, and the user behavior corresponding to other queries will not be analysed. Besides, we manipulated the position of the target POI in the result list to investigate the effect of the result position. Since the full screen of our smartphone can display seven results of each SERP, we control the position of the target POI in the result list at 1,4,7,9, corresponding to top, middle, bottom, and out of the first screen. The pre-processed result list will be shown to participants.

In the second stage, we focus on analyzing user behavior at the session level. For each session-level task, the participants enter the search page with an empty search box and they need to construct the queries by themselves. They can freely examine and interact with the results or change the query to get new results. and all the behavior in the search session are recorded for further analysis.

3.2 Participants

We recruited 30 participants on campus, including undergraduate and graduate students, as well as university staff members. Among the participants, 20 were female and 10 were male, ranging in age from 19 to 32, with majors spanning across arts and humanities, natural sciences, and engineering disciplines. All participants had prior experience with mobile devices and daily Point of Interest (POI) search experience. To ensure the validity of the collected eye movements data, we required all participants to have normal corrected eyesight, including correction for astigmatism and strabismus. Participants completed 60 query-level tasks and 20 session-level tasks, taking approximately 60 minutes to complete. We compensated each participant with US$15 upon completion of all tasks.

3.3 Experiment System and Platform

We used a Tobii X2-30 eye tracker mounted on a mobile-specific platform to record participants' eye movements. To ensure the accuracy of the gaze position data, participants were required to be present within a specific range from the eye tracker. The eye-tracker was calibrated according to the settings outlined in the usage manual of the Tobii X2-30 eye-tracker to maintain optimal distance from the smartphone. The user study was conducted on an Android smartphone, specifically the OnePlus 5T, equipped with a 6-inch screen, which is a mainstream specification for smartphones in recent years. We developed a web application using JavaScript, which could record participants' behavior on the Search Engine Results Page (SERP).

4 USER BEHAVIOR IN POI SEARCH

Based on the collected data in the user study, we would like to investigate user behavior in POI search and address **RQ1** and **RQ2**:
RQ1: What are the query-level behavior patterns in POI search?
RQ2: What are the session-level behavior patterns in POI search?

4.1 Query-Level Behavior

To address **RQ1**, we analyze the data collected at the first stage of lab study, including users' eye-tracking data and implicit feedback.

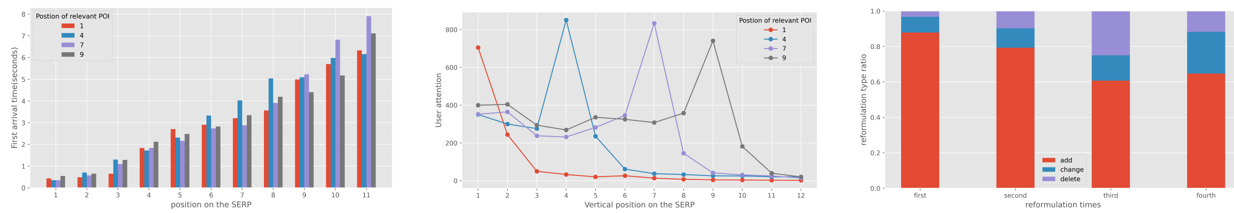
Table 1: The statistics of viewports and related examination behavior. The LEP means the lowest examined position on each viewport. The mean column is the metrics on all four kinds of positions.

position of target POI	1	4	7	9	mean
scrolling ratio	0.022	0.265	0.798	1.000	0.501
#Avg viewports	1.053	1.349	1.747	2.464	1.669
#Avg normalized LEP	0.365	0.624	0.771	0.712	0.661
forward transition ratio	0.688	0.736	0.938	0.943	0.908
#Avg forward distance	0.178	0.155	0.197	0.230	0.211
#Avg backward distance	0.219	0.269	0.221	0.290	0.264
#Avg viewport duration(ms)	1517	2133	1988	1730	1858

The implicit feedback consists of the timestamp of scrolling and clicking, through which we can recover the viewport information.

First, we investigate user behavior through the statistics of the viewports, shown in Table 1. The *scrolling ratio* means the ratio of the sessions that have scrolling behavior to all sessions, and *#Avg viewports* means the average number of viewports per session. The table shows that there is a gradual increase in the number of these two metrics with the increase of the position of the relevant POI. The scrolling ratio of position 9 is 1.0 because position 9 is out of the first screen so that users have to scroll down to check position 9. This indicates that if the relevant POI is on the top positions in the viewport, which probably has been examined, the user will stop scrolling to examine more results. Then, we investigate the lowest examined position (*LEP*) in each viewport. We normalized the position by the height of the screen. The average LEP of all viewports is 0.661, which shows that users may not examine the whole viewport when they scroll. On average, the participants examined the top 67% content of each viewport. The viewport transition direction, including forward to view the results in the bottom and backward to view top results, can be used as an indicator for the users' examination order. Among all viewports, the ratio of forward is 90.8%, indicating that users examine the SERPs in a top-down order, which is consistent with the behavior in mobile web search [25, 31]. In our study, there are at most seven results displayed in each viewport. The average scroll distance of forward and backward is 0.211 (standard deviation=0.156) and 0.264 (standard deviation=0.212) of the full viewport, which shows that the participants usually scrolled for about the height of two to three results and scroll a longer distance at backward than forward. This distance is shorter than the one in mobile web search, which is usually half screen [31], while the number of results corresponding to the scroll distance is similar – both are two to three results. The cause may be that the number of results in each viewport of POI search (7 in our study) is more than those in mobile web search (usually 3 to 5). Besides, we investigate the examination order by measuring the first time of positions on the SERP being examined by the users, shown in Figure 2a. It is observed that the first arrival time has a strong correlation with the position, verifying that, users browse the SERP from top to bottom.

Second, we investigate users' attention allocation mechanism by measuring users' attention distribution at a different position on the SERP. Figure 2b shows users' attention distribution with the result's rank on the SERP, where we view the average fixation time as the users' attention. The average fixation time of the irrelevant result is about 300ms, while the average fixation time of the relevant result



(a) (b) (c)

Figure 2: (a) The average arrival time at different position on the SERPs. (b) The fixation distribution with the position of the results on the SERP. (c) The ratio of different query reformulation types in the first four reformulations.

is about 750ms. It indicates that the participants have paid more attention to the relevant results than the irrelevant results, even if the latter has a higher position. It also indicates that for positions before the relevant result, users' attention distributes evenly.

In summary, we get three main conclusions: (1) Users examine the SERP from in a top-down order; (2) Before the relevant POI is examined, users' attention distributes evenly on the results; and (3) After the relevant POI is examined, users do not examine the following results and end the session.

4.2 Session-Level Behavior

To address **RQ2**, we analyze the data collected at the second stage lab study, including users' eye-tracking data and implicit feedback on the SERP. Because practical POI search engines usually support instant search, users can see the instant results when they are typing the query. Therefore, the process of query reformulation and the process of result examination is mixed up, which means that we need methods that are different from those in web search (in which queries can be easily identified and split) to capture the sequence of queries and reformulations in POI search. In our study, we use users' examination behavior to split the queries in the session. Specifically, during the period between two consecutive queries, if there exists scrolling behavior or the user's total examination time on the results exceeds a certain limit, we view these two queries as different queries. Otherwise, we treat the first query as a part of the input process of the second query and only use the second query as an actual query submitted by the user. We set this limit as 300ms, according to the average fixation time in the first stage.

Based on the above definition, we first analyze user's click behavior in POI search sessions. The average clicks per session are 1.04, indicating that other than the click on the relevant results, the number of clicks on irrelevant results is highly limited. It is consistent with the fact that users can judge whether the result can satisfy their needs through the POI's name and address in the snippets. In other words, the clicked result usually is the relevant result of the users' information needs. In POI search, whenever users have issued a query, they should make a choice between scrolling down to examine more results in the current SERP or reforming the query to retrieve a new SERP. In more than 72% search sessions there is no scrolling behavior, while in more than 65% search sessions there is query reformulation behavior, indicating that users prefer reforming the query rather than scrolling down to examine more results. On the one hand, collapsing and expanding the virtual keyboard increases users' effort of scrolling down. On the other hand, since the results change instantly, users may see the relevant result before they complete the whole query, which reduces users' effort in reforming the query. Besides, in more than 87% sessions, the clicked result is one of the top 3 results, and the average rank of all clicked result is 1.75, verifying that users tend to reform the query and focus on the top 3 instant results.

Second, we analyze users' query reformulation behavior in the session. We divide the query reformulation into three types, which are adding, deleting, and changing, similar to existing study[1, 13]. Figure 2c shows the distribution of the three types in the first four reformulations of each session. It shows that with the increase of query reforming times, the ratio of the adding type decreases and the ratio of the deleting type and the changing type increases. However, the ratio of the adding type is above 60% in all distributions, which means that users usually have clear information needs, and they can submit correct keywords in sequence (thus, no need to revise previous query terms). Further, we investigate the ratio of the sessions in which the query length increases monotonically. It shows that in more than 79% sessions, users always add more information to the query, which verifies the above conclusion.

In summary, we get three main conclusions: (1) There are few clicks on the irrelevant results; (2) Users prefer reforming the query to retrieve new results rather than scrolling down to examine more results on the current SERP; (3) Users usually constantly add information to the query during the whole session.

5 DISCUSSION AND CONCLUSION

In this paper, we investigate user examination behavior in POI search by conducting a two-stage lab study. By analyzing the eye-tracking behavior and other interaction behavior, we find several patterns of users' examination behavior in the POI search. When examining the SERP, users examine the results in top-down order, and the attention distributes evenly before the relevant result is examined. In the whole search session, users prefer reforming the query to retrieve new results rather than scrolling down to examine more results on the current SERP.

We believe that these observations could provide valuable insights into the understanding of user behavior in POI search and may benefit lots of other IR tasks in POI search. For example, the observations of users' examination behavior suggests that the instant search function in query writing could significantly affect user's interaction patterns with POI search engines in sessions. Thus, a joint consideration of instant search and search session evaluation might be a good direction to pursue. We hope that our observations can guide the design of POI search systems to provide a better search experience for users.

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