Exploring Interaction Patterns in Job Search

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ABSTRACT

We analyze interaction logs from Seek.com, a well-known Australasian employment site, with the goal of better understanding the ways in which users pursue their search goals following the issue of each query. Of particular interest are the patterns of job summary viewing and click-through behaviors that arise, and the differences in activity between mobile/tablet-based users (Android/iOS) and computer-based users.

KEYWORDS

Interaction logs; user behavior; job search

1 INTRODUCTION

Interaction logs are valuable resources for improving the quality and effectiveness of the systems they are drawn from. In the area of web search, interaction logs can be leveraged to improve document ranking algorithms [1, 14]; the usability of the system either via query suggestion [5] or query auto-completion [13]; and the presentation of search results [27]. Interaction logs are also important for developing search evaluation methods [2, 8, 21, 28].

Here we examine an English-language interaction log derived from the well-known Australian job search service Seek.com, to characterize the behaviors of users when engaged in post-query reading and evaluating activities. Our emphasis is on chronologically-ordered action sequences, defined as

$$\mathcal{A} = \langle (a_1, r_1, m_1), (a_2, r_2, m_2), \ldots \rangle,$$

where $a_t$ is an action type, $r_t$ is the position in the search ranking that is the site of the action, and $m_t$ is the start time of that action in seconds, normalized so that $m_1 = 0$. Three types of action occur: impressions, when $a_t = "I"$; mouse clicks, when $a_t = "C"$; and job applications, when $a_t = "A"$. An impression occurs when any job summary is completely visible on screen for at least 500 milliseconds, and, in the absence of eye-fixation information, provides at least prima facie evidence that the user was reading that job summary. A click action occurs when a job summary in the result page for the query (the SERP, which itself might be broken into pages by the interface protocol, or might be presented as a single listing via continuous scrolling) is clicked so as to arrive at the corresponding job details page; and an application action is recorded when the job seeker clicks the “apply” button in that job details page, with the presumption being that they will then enter more information, and at some time in the future, lodge their application. We also know the absolute time/date associated with the first action in each sequence.

As an example, consider the action sequence:

$$\mathcal{A}_0 = \langle ("I", 1, 0), ("I", 3, 1), ("C", 3, 3), ("I", 4, 9),
("I", 5, 10), ("C", 5, 11), ("I", 6, 20), ("I", 4, 22),
("C", 4, 25), ("I", 6, 40), ("I", 7, 41) \rangle.$$

In $\mathcal{A}_0$ there are three clicks, at ranks 3, 5, and 4; the user has started by viewing the position summary at rank 1 and ends by viewing the one at rank 7; and it takes 20 seconds until the summary at rank 6 is viewed for the first time.

Many authors have studied the interaction logs from web search services [3, 4, 9–11, 20, 24, 25, 30]. However relatively little attention has been paid to the interaction logs from job search engines. Kudlyak and Faberman [16] analyze the transaction logs from SnagAJob, an online job search service. They observe the relationship between the number of job applications per week and the duration of job search process, measured in weeks. Spina et al. [23] report statistics from the query and click-through logs of an Australasian job search site Seek.com, and compare with general web search patterns in regard to the frequency distribution of click ranks, and the number of distinct queries per user. Most recently, Mansouri et al. [18] examine the job-related search queries issued to a general-purpose Persian-language search service.

Our work here explores a more comprehensive job search interaction log than any of these, in that not only does it include click-through actions, but also impression data and explicit application actions. In addition, the log differentiates between browser-based computer users (that is, those interacting with a web-based service using browsers running on desktop and laptop computers) and Android/iOS-based users using the “seek.com app” on mobile phone and tablet-type devices. We use that distinction as part of our analysis.

Table 1 summarizes some characteristics of the data used in this investigation. For privacy and commercial reasons this data cannot be made public. The terms of service and privacy policies of Seek.com were complied with at all times during the collection and analysis of this data.

2 BACKGROUND

Interaction log study. Silverstein et al. [20] analyze query logs containing approximately one billion search requests, collected...
from AltaVista, one of the first commercial web search engines. Their main focus was on query-specific patterns such as the number of queries per session, the number of terms and operators per query, the frequency distribution of popular queries, and the characteristics of query revisions through the course of each session. Silverstein et al. also carried out a colocation analysis to identify associations between terms across all queries. Their findings included that web search users typically posed short queries, and that the majority of users only examine the first page of the paginated ranked-list of documents. Prior to that work, Jansen et al. [11] had conducted similar studies of query logs, but at a smaller scale, covering 51,473 queries from the Excite service, with similar findings in terms of web search query length and the number of result pages that were viewed.

Spink et al. [24] extended the study of Jansen et al. [11], analyzing a log of approximately one million Excite queries, documenting very similar phenomena. Spink et al. also employed a more principled approach in classifying a random sample of web queries, building insights in terms of common search topics. Lempel and Moran [17] used a different sample of seven million AltaVista queries to study the popularity of query topics and viewed pages, primarily as an argument for and evaluation of a new query caching policy. One of their notable findings is that the frequency distribution of query topics can be modeled as a power law distribution. Other studies explored logs of web queries from BWIE search engine [4]; from AlltheWeb.com [25]; and from Fireball [9]. Jansen and Spink [10] provide a perspective across all of those search engines, including a geographical evaluation of the differences between US and Europe-based services. They report query and session length, query terms, query operators, and viewed pages in a comparative study that provides a clear reference point as to the situation that pertained at the time.

Most of the early query log studies did not examine temporal aspects of web queries. As an exception, Beitzel et al. [3] explore both topical and temporal dimensions from a log of billions of web queries from the AOL search service, examining how particular query topics vary over time. For example, they found that queries related to “personal finance” are popular between 7–10am. Zhang and Moffat [30] conducted an analysis using interaction records that contained click-through information as well as queries. That dataset comprises approximately fifteen millions queries with their corresponding chronologically-ordered click-throughs, sampled from the MSN Live web search engine during May 2006. Zhang and Moffat confirmed findings from the previous query and term-level log studies, and also reported click-through-based findings, including that the distribution of click-throughs across ranks is top-weighted, and that the elapsed time between any two consecutive click-throughs is typically short. The latter suggests that the majority of users only need a few seconds to assess the usefulness or otherwise of most clicked documents.

Table 1: Job search interaction logs used in this study. The data is from Seek.com, a well-known job search engine, and consists of representative samples drawn from the period 30 July 2018 (Monday) to 26 August 2018 (Sunday) for both types of users. To prevent ambiguity, phone/tablet-originated queries via web browser software are excluded from both data sets.

<table>
<thead>
<tr>
<th>Android/iOS</th>
<th>Browser</th>
</tr>
</thead>
<tbody>
<tr>
<td>Users</td>
<td>4,705</td>
</tr>
<tr>
<td>Queries/SERPs</td>
<td>39,545</td>
</tr>
<tr>
<td>SERP size</td>
<td>unlimited</td>
</tr>
</tbody>
</table>

Job search. One of the more comprehensive studies in the job search domain was conducted by Jansen et al. [12], using an Excite dataset that had been filtered to identify job-related queries. Their findings suggest that users seeking jobs usually pose one query before ending the session; and that the majority use three terms when constructing job-related queries. Recently, Kudlyak and Faberman [16] used data from the SnagAJob online job search service to study the correlation between job search effort, measured in the number of weekly applications, and job search duration. They found evidence for an income effect, whereby job seekers with poor job-finding prospects tend to make more job applications and have a longer search duration, suggesting that job seeker behavior is affected by the strength of labor market they stand in.

Spina et al. [23] studied user behavior in job and talent search, and compared those behaviors with those of typical web search users in terms of query popularity and click depth. The datasets used for this comparative evaluation were generated by Seek.com (an Australasian job search company) and Yandex (a Russian web search company) for job/talent search and web search respectively. Finally, Mansouri et al. [18] analyze approximately 500,000 job-related web queries selected from parsijoo.ir, a Persian general-purpose web search engine. They found that job search activities tend to be more intense near the beginning of each week, and to then slowly decline through the balance of the week.

Browser versus mobile users. There have been extensive observational studies based on either lab-setting user studies or interaction logs for both mobile and laptop/desktop (web browser) users. Joachims et al. [15] studied the behavior of participants while they were using the Google search engine (via a desktop computer) to complete ten tasks, where half of them were informational and the remainder were navigational. Click-throughs and eye-fixations occurring during the search process were recorded, providing evidence that on average web searchers had a tendency to scan down the ranking from top to bottom; that prior to a click action at rank i the user had typically viewed the snippets before rank i in preference to those deeper than rank i; and that user clicking behavior varied according to their trust in the search engine being used as well as the quality of the SERPs.

Cutrell and Guan [7] reported the results from an eye-tracking study to observe user behavior and performance of desktop users across informational and navigational tasks. They confirmed many of the findings of Joachims et al. [15], such as mean arrival time at each rank position and the distribution of viewed positions before clicking at a particular rank, and also developed further results regarding the relationship between task complexity and snippet length. By employing the click rate on relevant results (that is,
We now consider a number of facets of the job search query interaction logs for Seek.com, summarized already in Table 1.

Positional distribution of click-throughs. Clicks were observed in connection with fewer than 40% of the SERPs generated in response to queries, for both the browser- and mobile-sourced queries. For the subset of queries for which click-throughs were noted, we categorized the ranks at which clicks occurred as a function of the total number of clicks in that SERP. Figure 1 shows those distributions. Each cell in Figure 1 represents the observed probability that the user clicked at rank $i$ (vertical axis), given that they clicked on a total of $n$ distinct job summaries (horizontal axis). As expected, the more clicks there are in a SERP, the further down the SERP the clicks reach. But even so, the clicks tend to be top-heavy, and the closer to the top of the ranking a job summary appears, the more likely it is to be clicked, regardless of how many clicks there will eventually be. That is, users tend to click on summaries early in the ranking, even if they end up clicking multiple items.

Impressions deeper than clicks. Prior to actually clicking at some rank $r_t$ at step $t$ in the action sequence, users typically view one or more documents beyond rank $r_t$. For example, in the action sequence $\mathcal{A}_0$ given above, before clicking at rank 4, the user viewed documents at rank 5 and 6. In the same example, that did not occur with the click-throughs at ranks 3 and 5. The second row in Table 2 shows the proportion of all click actions for which one or more documents beyond some rank $r_t$ were registered as an impression at some step $t' < t$, prior to a click-through taking place at rank $r_t$ at step $t$. As can be seen from the table, users inspect summaries beyond rank $r_t$ more than two-thirds of the time, a higher fraction than the corresponding 50% result observed by Joachims et al. [15]. In addition, the difference between the two access modes is statistically significant ($p < 0.05$, z-test), with the difference perhaps a consequence of the scrolling actions of browser users being more precise than those of Android/iOS users.

The next results measure the depth the users reached relative to the rank $r_t$ associated with the $t$th operation in the action sequence, given that they viewed one or more documents beyond rank $r_t$ before clicking at rank $r_t$. Table 3 summarizes the frequency distribution (proportion) of $\max[r_{t'} \mid t' < t] - r_t$ values over all action sequence indices $t$ for which $a_t = "C"$. In the majority of cases, users had viewed the documents one or two further down the ranking than rank $r_t$ within the first $t - 1$ elements of the action sequence, before then deciding at step $t$ to click the document at rank $r_t$. The differences in proportion between the two types of users are statistically significant across all rows ($p < 0.05$ using a two-sided z-test), meaning that browser users are more likely to return back past multiple job summaries to a “mentally bookmarked” potential click point than are Android/iOS users.

Figure 2 confirms the results summarized in Table 3, showing the distribution of impression ranks as a function of click rank $r_t$ when $a_t = "C"$. In Figure 2, each cell represents the observed frequency of user views (impressions) on documents at rank $r_{t'}$ where $t' < t$,
amalgamated over all the available action sequences for which \( a_t = \text{“C”} \). For example, consider the three action sequences:

\[
\mathcal{A}_1 = \langle (\text{“T”}, 1), (\text{“T”}, 2), (\text{“T”}, 3), (\text{“T”}, 4), (\text{“C”}, 3) \rangle
\]

\[
\mathcal{A}_2 = \langle (\text{“T”}, 1), (\text{“T”}, 3), (\text{“T”}, 5), (\text{“T”}, 3), (\text{“C”}, 3) \rangle
\]

\[
\mathcal{A}_3 = \langle (\text{“T”}, 1), (\text{“T”}, 4), (\text{“C”}, 3), (\text{“T”}, 3), (\text{“C”}, 3), (\text{“T”}, 4), (\text{“C”}, 4) \rangle
\]

where for simplicity the timestamp information \( m_t \) is omitted. Across these three sequences the observed “impression before click” likelihood that a user views a summary at rank 1 before clicking at rank 3 is \( 4/4 = 1 \), and of viewing the summary at rank 2 before clicking at rank 3 is \( 1/4 = 0.25 \). The even shading in the upper-right triangular regions in Figure 2 clearly indicates that the user viewed almost all documents above rank \( r_3 \) before it was clicked, and had also viewed one or two documents (three in the case of browser-originated SERPs) documents beyond rank \( r \). As already noted, this phenomenon is stronger for browser-based queries than for Android/iOS-based queries.

**Click ordering.** It is also interesting to examine the extent to which the click actions are ordered in terms of rank position. We define the last click point, \( lc \), as the index in the action sequence of the final click-through, \( lc = \max(t \mid a_t = \text{“C”}) \). For example, in the earlier action sequence \( \mathcal{A}_0 \) we have \( lc = 9 \), since the action ("C", 4) at step 9 is the last click action. Given that the users clicked on two to four distinct documents, Table 4 shows that for 87.3%–91.1% of the queries the last click is the deepest, suggesting that users do indeed proceed through the ranked list mostly sequentially.

We also examined the extent of the ordering in the full set of clicks occurring in each action sequence, stratifying the queries based on number of click-throughs, and then computing a Kendall’s \( \tau \) score for each action sequence based on the sequence of click ranks when ordered by the step number. That is, the sequences \( \langle t, r_{tk} \rangle \mid (a_t, r_t, m_t) \in \mathcal{A} \rangle \) were formed, and \( \tau \) coefficients used to determine the extent to which \( t \) and \( r_t \) correlate. Contiguous duplicate clicks to the same rank position were removed as part of the filtering process. Looking again at the example action sequence \( \mathcal{A}_0 \), that derived sequence would be \( \langle (3, 3), (6, 5), (9, 4) \rangle \), with a \( \tau \) score of \( 1/3 = 0.33 \).

Table 5 shows that most users click on summaries in generally increasing order. To further reinforce that observation, Figure 3 depicts the distribution of click-through jumps for the two types of users, where a positive jump arises if two consecutive click-throughs correspond to concords when computing \( \tau \) coefficients, and negative jumps correspond to discords. The fact that positive click-through jumps dominate the distribution is strong evidence that job search users in general click from the top towards the bottom. Note that Android/iOS-based job search users exhibit a slightly stronger tendency to do this.

**After the last click.** The bars in Figure 4 show the distribution of each of the deepest impression before the last click-through in the action sequence; the deepest impression following the last click-through; and the last impression following the last click action. The overall pattern is clear: even after their last click-through, users continue to inspect further summaries in the SERP. For browser-based queries, it is also interesting to see that the lower side of the third element in each group of three (last impression after last click) extends to the shallowest rank position of the page, that is, rank 1 for the first page, and rank 21 for the second page. This

**Table 4: Proportion of queries for which the last click action (at step \( lc \) in the action sequence) is also the deepest click-through rank in the sequence.**

<table>
<thead>
<tr>
<th></th>
<th>Android/iOS</th>
<th>Browser</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clicks on 2 distinct summaries</td>
<td>87.0%</td>
<td>88.1%</td>
</tr>
<tr>
<td>Clicks on 3 distinct summaries</td>
<td>87.9%</td>
<td>87.4%</td>
</tr>
<tr>
<td>Clicks on 4 distinct summaries</td>
<td>88.3%</td>
<td>91.1%</td>
</tr>
</tbody>
</table>

**Table 5: Mean value of Kendall’s \( \tau \) for extracted click sequences, stratified by number of clicks, and the percentage of positive \( \tau \) values in each group.**

<table>
<thead>
<tr>
<th></th>
<th>Android/iOS</th>
<th>Browser</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>freq.</td>
<td>mean ( \tau )</td>
</tr>
<tr>
<td>2</td>
<td>48.5%</td>
<td>0.78</td>
</tr>
<tr>
<td>3</td>
<td>23.3%</td>
<td>0.81</td>
</tr>
<tr>
<td>4</td>
<td>10.7%</td>
<td>0.86</td>
</tr>
<tr>
<td>5</td>
<td>5.9%</td>
<td>0.87</td>
</tr>
</tbody>
</table>

**Figure 2:** Distribution of impression ranks preceding click actions at rank \( r_t \). The left plot is for Android/iOS users, the right one for browser-initiated queries.

**Figure 3:** Distribution of click-through jumps. Note the logarithmic scale on the vertical axis.
Two assumptions arise when considering click sequences:

1. If a user clicks at some rank $r_t$, they have already examined the documents at ranks 1 to $r_t$.
2. The last click-through action is the last element in the action sequence.

Zhang et al. [31] develop their observation model based on the first assumption, but also use the average interval between the clicks within that zone to extrapolate further impressions beyond the last click-through. The second assumption is used by Smucker and Clarke [21] to approximate the time spent by user to examine the SERP, by computing the time duration between the search commencement and the last click. Carterette [6] and Azzopardi et al. [2] also employ the second assumption as a basis to meta-evaluate their proposed user models (and hence dual effectiveness metrics) by measuring how well their proposed models predict user stopping behavior.

The first of these two assumptions seems to be supported by the results depicted in Figure 2. However, the second assumption is at odds with our results, which clearly record users inspecting multiple job summaries beyond the last click. Table 6 provides further information about the relationship between the last click and the deepest (highest rank) click.

![Figure 4](image_url) Distribution of the deepest impression prior to the last click action (left element in each group of three); the deepest impression following the last click (middle element in each group); and the last impression following the last click (right element). The green triangle represents the mean value of each box-whisker element. Only odd-depth last click-throughs are shown, with Android/iOS queries in the left-hand pane, and browser-based queries in the right-hand pane; and only action sequences in which impressions occurred both before and after the last click are included, so that all three elements in each group are over the same set of action sequences.

![Figure 5](image_url) Fraction of action sequences, categorized by the number of previously-unseen items viewed beyond the last click-through. Note the logarithmic vertical scale.

A further question that then arises is whether the impressions that occur following the last click-through are to items that have been previously viewed, or to new items being looked at for the first time. Figure 5 shows the frequency distribution (proportion) of the number of distinct “first impression” items viewed following the last click action, not counting impressions for job summaries that had previously generated one or more impressions in the action sequence. For example, in the example provided by $A_0$ (see Section 1), the number of new items viewed beyond the last click is one (the item at rank 7). Figure 5 shows that only around 40–50% of last click actions (for both Android/iOS and browser users) were followed by impressions that exposed hitherto unviewed summaries.

**Job applications.** The second row of Table 2 shows the proportion of job application actions for which the user viewed one or more documents beyond some rank $r_t$ before initiating the application process for a job whose summary was at rank $r_t$. Table 7 expands on that summary information, listing how deep the users go relative to the application ranks $r_t$ at which $a_t = "A"$, showing the frequency distribution of the differences $\max(r_{t'} | t' < t) - r_t$.

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Table 6: Statistics in regard to the last click and the deepest click across the set of action sequences. All paired differences are significant ($p < 0.05$, two-sided z-test).
Figure 6: Distribution of impression ranks observed before a job application action took place at rank $r_t$. The left plot is for Android/iOS users, the right one for browser-initiated queries.

| max($r_{t'} | t' < t$) = $r_t$ | Android/iOS | Browser |
|-----------------------------|-------------|---------|
| 1                           | 56.0%       | 36.8%   |
| 2                           | 29.5%       | 24.2%   |
| 3                           | 7.5%        | 7.6%    |
| 4                           | 1.4%        | 4.6%    |
| ≥ 5                         | 5.6%        | 26.8%   |

Table 7: Distribution of the set of values max($r_{t'} | t' < t$) = $r_t$, given that $a_t$ = "A". All Android/iOS versus browser relationships are significant ($p < 0.05$, two-sided z-test), except in row "3".

Figure 7: Distribution of click-through ranks observed before a job application action took place at rank $r_t$. The left plot is for Android/iOS users, the right one for browser-initiated queries.

Figure 8: Job application rate as a function of click-throughs per query. In general, the likelihood of making an application increases as the number of distinct summaries clicked increases. The vertical scale is linear; but for commercial reasons is not labeled.

Figure 6 elaborates on Table 7, showing the distribution of impression ranks observed before a job application action took place at rank $r_t$. Each cell in Figure 7 represents the observed likelihood of the user clicking the job summary at that rank $r_{t'}$, where $t' < t$, before they apply for job advertised at rank $r_t$, the "click before application" ratio. The most notable and predictable effect here is that an application at rank $r_t$ is always preceded at some point in the action sequence by a click-through at rank $r_{t'}$. But click-throughs also occur at other ranks, including greater than $r_t$.

We also stratified the action sequences based on the number of click-throughs they contained, as described earlier. Within each stratum the application rate was computed, the total number of job applications in those action sequences divided by the number of SERPs served. Figure 8 plots the resultant data, and shows that the application rate broadly increases as the number of click-throughs increases, especially for Android/iOS-sourced queries. (For commercial reasons we cannot provide labels on the vertical scale.) In the case of the Android/iOS-based users, there is a clear relationship between number of clicks and application rate. The relationship is less apparent for browser-based users, with the reasons behind the difference in behavior not currently known.

4 TIME-BASED TRENDS

This section explores the timestamps that are associated with each item in the action sequences.

Time of day. Figure 9 shows the times during the day at which click-throughs (top) and job applications (bottom) occur. Not unexpectedly, job search intensity is low during the night (sleeping time) and highest during the day ("working" time) and into the evening (leisure time). Others – see, for example, Zhang and Moffat [30] – have also observed the same patterns in terms of click-throughs and queries for web search. It is also interesting to note that the proportion of click-throughs of desktop-based browser users is higher than that of Android/iOS users during working hours (10am to 6pm), but the opposite happens in the early morning and in the evening. It seems possible that users are using office computers in one job to search for new positions elsewhere. This finding is also in agreement with the observational studies on Bing search logs conducted by Song et al. [22].
Day of week. Figure 10 similarly shows the distribution of click-throughs and applications across the seven days of the week, as identified during the four-week data collection period. Job search intensity, measured via the number of click-throughs and applications, peaks between Monday and Wednesday, and then slowly decreases through to the end of the week, in agreement with the trends observed by Mansouri et al. [18]. Note, however, that none of the four-element day-versus-day comparisons showed significant differences at $p = 0.05$, and hence that the pattern in Figure 10 should be regarded as being indicative rather than definitive.

Figure 11 compares the click-through intensity between weekend days and weekdays for Android/iOS users. On weekdays users tend to be more active in the morning, whereas at the weekend there is also considerable activity occurring in the evening before midnight.

Reading Time. Figure 12 plots the distribution of job description reading times, stratified by click rank position, and measured as the elapsed time from when each click-through action is recorded through until the next action (of any sort) appears in the action sequence. Browser-based users take longer that app-based users on average (the green triangles), but are faster if the median is used as the central tendency.

5 CONCLUSION

We have analyzed interaction logs provided by Seek.com, an online job search service, covering 39,545 queries and SERPs for mobile/tablet-based Android/iOS app-originated queries, and 20,129 SERPs for desktop/laptop computer browser-originated queries. Our evaluation has resulted in a number of observations, some of which were already known in the more general web search context. These include that:

- Users tend to view job description summaries (impressions on “snippets”) in order from top downward in the SERP, and similarly tend to undertake their click-through actions from top downward.
- Users are more likely to click-through job summaries at early rank positions.
- Users tend to examine a small number of job description summaries beyond any given rank $r$ before deciding to click-through (and then perhaps apply for) the job situated at rank $r_1$ in the SERP.
- Users tend to examine several further job summaries after the last click-through action associated with each SERP.
- In general, as the number of distinct documents clicked in the SERP increases, the chance of making a job application also increases.
- Measured elapsed SERP reading durations are several times longer for browser-based queries than for app-based queries, perhaps suggesting that computer-based users interleave job search activity with other activities in a way that is less achievable on mobile devices.

Taken together, these observations provide an improved understanding of the ways in which job seekers interact with this particular job search engine, and may be transferable not only to other job search tools, but also to online marketplaces, perhaps including those for other major decisions, such as home and car purchase.

That is, while this current work has been primarily an observational study, without a modeling overlay in which the observed actions are motivated and explained, we nevertheless believe that the analysis of action sequences in the way that we have done so...
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[27] Y. Wang, D. Yin, L. Jie, P. Wang, M. Yamada, Y. Chang, and Q. Mei. Beyond document reading time, stratified by rank. The left element in each pair is for Android/iOS queries, the right one for browser-based queries.

Figure 11: Click-throughs in two-hour periods, comparing week days and weekend days for Android/iOS users (upper pane) and browser users (lower pane).

Figure 12: Document reading time, stratified by rank. The left element in each pair is for Android/iOS queries, the right one for browser-based queries.