Investigating the Learning Process in Job Search: A Longitudinal Study

Jiaxin Mao
BNRist, DCST, Tsinghua University
Beijing, China
maojiaxin@gmail.com

Damiano Spina
RMIT University
Melbourne, Australia
damiano.spina@rmit.edu.au

Sargol Sadeghi
SEEK Ltd.
Melbourne, Australia
ssadeghi@seek.com.au

Falk Scholer
RMIT University
Melbourne, Australia
falk.scholer@rmit.edu.au

Mark Sanderson
RMIT University
Melbourne, Australia
mark.sanderson@rmit.edu.au

ABSTRACT

We investigated the learning process in search by conducting a log-based study involving registered job seekers of a commercial job search engine. The analysis shows that job search is a complex task: seekers usually submit multiple queries over sessions that can last days or even weeks. We find that querying, clicking, and job application rates change over time: job seekers tend to use more filters and a less diverse set of query terms. In terms of click and application behavior, we observed a significant decrease in click rate and query term diversity, as well as an increase in application rates. These trends are found to largely match information seeking models of learning in a complex search task. However, common behaviors are observed in the logs that suggest the existing models may not be sufficient to describe all of the users' learning and seeking processes.

ACM Reference Format:
Jiaxin Mao, Damiano Spina, Sargol Sadeghi, Falk Scholer, and Mark Sanderson. 2019. Investigating the Learning Process in Job Search: A Longitudinal Study. In *The 28th ACM International Conference on Information and Knowledge Management (CIKM '19), November 3–7, 2019, Beijing, China.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3357384.3358169

1 INTRODUCTION

Understanding the learning process in search tasks such as knowledge acquisition can enable better support for complex search tasks. Therefore, learning in search is studied in Interactive Information Retrieval (IIR). Kuhlthau [5] proposed the Information Search Process model that differentiates a learning task into several stages, and showed that users search differently in each stage. Vakkari continued this work [9] and recently surveyed the field [10].

Compared to general web search, job seeking can be more complex [7, 8]. In order to find a suitable job, a job seeker needs to consider the requirements of the desired job, conduct searches, evaluate retrieved available jobs, and finally decide whether to contact the employer or lodge an application. This process can last for days or weeks – if not months [1] – and the collection of jobs that are advertised can change frequently during the process. Job seekers will learn over this period as they acquire more knowledge both about available jobs, the market, and how to effectively search for a job. Therefore, their search behavior is likely to change over the period of a job search and a thorough investigation of this behavioral change is essential for building a better online job search engine.

By examining how job seekers search over time, we revisit the learning process in search, but for a particular complex task: job search. The advantage of investigating the job search environment is that a job seeker's information need, the job, is relatively stable. Therefore, we can investigate behavioral changes within a single job search task by analyzing each job seeker's queries within a time window. So in this work, we conduct a log-based study to address three research questions about job search, and discuss how the empirical findings support or contradict existing models of the learning process in search:

- **RQ1**: How is job seekers' search behavior characterized?
- **RQ2**: How does the behavior change over time?
- **RQ3**: Does information consumption (result clicks) and response behavior (application lodging) change over time?

We collect and analyze a set of logs from SEEK Ltd.[1]. We use a heuristic method to group the logs into different job search tasks. After characterizing the search tasks (**RQ1**), we divide each task into different stages (i.e., disjoint time periods within a job search task) and analyze how job seekers' querying, clicking, and application behavior change during a job search (**RQ2** and **RQ3**). Finally, we discuss the implications of the empirical findings as well as their relationship with existing work on the learning in search and task-based IR.

2 RELATED WORK

As mentioned, Vakkari [9] extended Kuhlthau's model, investigating how information seekers' search tactics and relevance assessment changes over stages. Vakkari later described learning as a two stage process [10]. First, *accommodation* of new knowledge, where new conceptual knowledge structures are formed through

CIKM '19, November 3–7, 2019, Beijing, China

ACM ISBN 978-1-4503-6976-3/19/11…$15.00
https://doi.org/10.1145/3357384.3358169

[1] http://www.seek.com.au

Table 1: Description of the measures used in this study.

Task Statistics	*Description*
# search tasks	Number of search tasks in our dataset.
Time span, in # days	Number of days that a search task last.
# queries	Number of queries in a search task.
# displayed pages	Number of displayed SERPs (Search Engine Result Pages) within a search task.
# displayed results	Total number of displayed results within a search task.
Querying Behavior	
Length in characters	Number of characters in the text field of the query.
Length in terms	Number of terms in the text field of the query.
Query term diversity	Number of unique terms used in the search task (or task stage), divided by the number of queries in the task (or task stage).
% classification filter	Percentage of queries in the task where the classification filter is used.
% location filter	Percentage of queries in the task where the location filter is used.
% date filter	Percentage of queries in the task where the date filter is used.
% work type filter	Percentage of queries in the task where the work type filter is used.
% salary filter	Percentage of queries in the task where the salary filter is used.
Click and Application Behavior	
Norm. click rate	Number of clicks divided by the number of queries, normalized by the click rate in the 1^{st} stage.
Norm. application rate	Number of applications divided by the number of clicks, normalized by the application rate in the 1^{st} stage.

a process of *restructuring* and subsequent structure *tuning*. Second, *assimilation*: a process of where information is added into existing knowledge structures.

Eickhoff et al. [2] conducted a log-based analysis to identify evidence of learning activities within a search session. Examining behavior recorded in the logs of a major web search engine, including that measured across sessions, the authors were able to identify learning from particular aspects of search behavior. In his survey, Vakkari [10] describes the past work of Liu and Belkin [6] who considered if different search tasks affect learning behavior. No effect was found, however the range of search tasks considered was limited. Jiang et al. [3] also investigated how users' search behaviors change over time when completing different types of search tasks. They found that the Search Engine Result Page (SERP) views and clicks per query tended to decrease in a session.

3 METHODOLOGY

We describe the data, search tasks, and our investigation.

3.1 Data Collection

The query logs of an order of thousands of randomly sampled registered users of SEEK's job search engine were collected from July 2016 to April 2018. The terms of service and privacy policies of SEEK Ltd. were followed and no personally identifiable information was made available or used in our experiments. When using the search engine, a job seeker can submit queries, examine SERPs, and click on posts to display full job details. The user can also choose to apply for a job, an action which is logged by the search engine. The logs contain users' queries, and aggregated statistics of clicks and applications (e.g. # clicks, click-through rate, application rate) on the corresponding SERP. Because users are registered with the system, search interactions are tracked across sessions. Note that the search engine supports faceted search, so a query is an amalgam of keywords and a set of filters on job classification, work type, job location, salary range, and job posting time. The collected dataset contains approximately 125,000 queries.

3.2 Job Search Tasks

A job seeker may have used the search engine to find different jobs at different times across the duration of the logs. Therefore, to investigate search behavior in completing a single job search task, we partitioned the logs of each user into different job search tasks. Task partitioning is non-trivial [4, 11], a major challenges in web search is that users may drift from one information need to another. However, because it is unlikely that a job seeker will be involved in multiple job search tasks at the same time, we assumed such drift was less likely. We therefore used a naïve 14-day gap in logged behavior to signify the boundary of distinct search tasks. Here, we assumed that users had completed or abandoned a job search task if they were inactive for longer than this time period. More sophisticated task extraction methods are left for future work.

3.3 Investigating the Changes of Search Behavior over Time

A common way to investigate how the behavior of searchers changes during a task is to divide the process into different stages over time [5, 9, 10]. We follow previous studies [9] in adopting a three-stage model, dividing each search task into three stages of equal time. Job seekers' search behavior can then be compared across the different stages in terms of the measures defined in Table 1. A one-way ANOVA is used to test whether the measures differ significantly between the three stages.

Differences in task complexity (e.g. finding a part-time job on weekends versus a position for an experienced software engineer) could lead to variation in the time taken to complete a single job search task, as well as in the length of individual stages. Some users without a real intention to apply for a new job may also use the job search engine to survey the job market. Therefore, in this study, we focus on the temporal behavior changes for relatively complex tasks that last longer than a day.

4 RESULTS

We characterize job search tasks and describe how search behavior changes over time.

4.1 Characterizing Job Search Tasks

Following the methodology in Section 3.2, the logs were partitioned into 11,267 search tasks. Table 2 shows the statistics for the search tasks, demonstrating that job search can be a relatively complex task. On average, a job search lasts for 8.56 days, in which a job seeker submits 11.14 queries. 45.75% of the tasks exceed one day in duration; for this set of longer tasks, the average duration is 17.51

Table 2: The statistics of job search tasks. The means are shown in the table and the standard deviations of the measures are shown in parentheses.

	All search tasks		*Search tasks last longer than one day*	
# search tasks	11,267		5,159	
Time span, in # days	8.56	(16.04)	17.51	(20.36)
# queries	11.14	(35.29)	20.75	(50.39)
# displayed pages	15.66	(47.02)	29.13	(66.83)
# displayed results	268.63	(837.17)	503.35	(1 191.65)

Table 3: The statistics of job seekers' querying behavior. The means are shown in the table and the standard deviations of the measures are shown in parentheses.

	All search tasks		*Search tasks last longer than one day*	
# search tasks	11,267		5,159	
Length in characters	11.95	(10.30)	12.30	(13.08)
Length in terms	1.65	(1.58)	1.69	(2.11)
Query term diversity	0.923	(0.69)	0.646	(0.46)
% classification filter	0.239	(0.37)	0.236	(0.34)
% location filter	0.704	(0.37)	0.720	(0.31)
% date filter	0.105	(0.28)	0.108	(0.27)
% work type filter	0.099	(0.26)	0.105	(0.24)
% salary filter	0.105	(0.27)	0.112	(0.26)

days, and seekers submit 20.75 queries and examine 29.13 SERPs that contain around 500 job posts.

Job seekers' querying, click, and application behavior can be used to further characterize searcher behavior. Table 3 shows that, for querying behavior: (1) job seekers tend to use short queries, that on average contain 1.65 terms; (2) query term diversity measure is 0.923 for all search tasks, and 0.646 for search tasks that last longer than one day, indicating that job seekers are likely to reuse query terms across multiple queries; and (3) the location filter is widely used in job search, with 70.4% of the queries having a non-default location filter.

We also find that clicks and applications are sparse in job search.[2] This is probably because substantial information about a job post – such as the job title, hiring company's name, location, and salary range – is shown as part of each item summary on the SERP, to help seekers assess the potential relevance of each result. Therefore, job seekers may only click the most relevant job posts, which results in a low click rate.

4.2 Changes in Search Behavior over Time

Recall that to analyse changes in search behavior, tasks were partitioned into three equal stages. The average behavior measures are shown for each stage in Table 4, together with the F-values and p-values from a one-way ANOVA F-test. For querying behavior, the query term diversity, and the ratio where a location filter is used (% location filter) change significantly over time, while for click and application behavior, both the click rate and application rate change significantly. Figure 1 shows the trends and the standard deviations dgraphically for those measures where changes are significant at

[2]Due to commercial sensitivity, we only show relative numbers of clicks and applications.

Table 4: The statistics of search behavior in three stages ($n = 5,159 \times 3 = 15,477$). For click and application rate, we show the relative values w.r.t. the values in the first stage.

	1^{st} *stage*	2^{nd} *stage*	3^{rd} *stage*	F*-value*	p*-value*
Querying Behavior					
Length in characters	12.263	12.304	12.325	0.03	0.974
Length in terms	1.680	1.693	1.692	0.05	0.953
Query term diversity	1.001	1.016	0.908	33.21	< 0.001
%classification filter	0.240	0.237	0.234	0.38	0.686
%location filter	0.707	0.726	0.728	4.87	0.008
%date filter	0.105	0.110	0.109	0.42	0.658
%work type filter	0.098	0.110	0.109	2.78	0.062
%salary filter	0.107	0.117	0.116	1.67	0.189
Clicking and Application Behavior					
Norm. click rate	1.000	0.872	0.882	10.44	< 0.001
Norm. application rate	1.000	0.921	1.038	7.30	0.001

the 0.01 level or lower. For querying behavior, we first find that the query term diversity remains relatively stable between the first and second stages, with the level falling notably in the third stage. The fact that job seekers tend to explore using a wider query vocabulary at the beginning of a search task, and then use more narrow and specific query terms towards the end of the task, suggests that they may be learning about the job market. This allows them to be more effective in specifying a query that meets their needs and uses the required vocabulary.

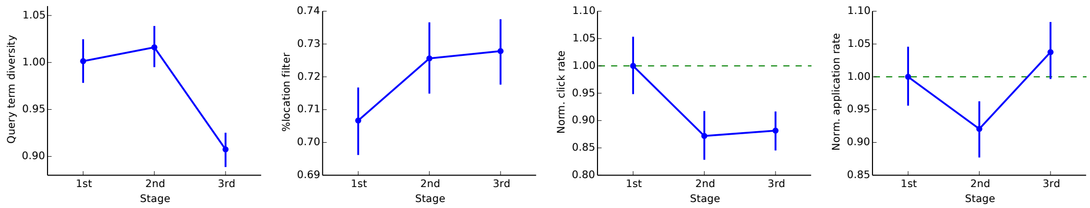
For the use of filters, only the change of the usage ratio of the location filter is significant (Figure 1b). The increase of usage could be explained by the job seeker learning to use filters, to further refine the search results, after a few rounds of interactions with the job search engine.

For click and application behavior (Figure 1c), the click rate decreases after the first stage. After exploration in the first stage, job seekers appear to develop more specific criteria for a job and become more selective in clicking. The application rate decreases from stage one to stage two, then increases at the last stage of the search task. We speculate that the relatively high initial application rate in the first stage is because job seekers have been found to often make an application to test the functionality of the search system at the beginning of a search task. The increase for the last stage suggests that job seekers may have become more certain about which job they should apply for.

5 DISCUSSION

Before discussing the findings, we acknowledge the limitations of this study. First, a naïve method was used to partition the job search logs into tasks. Second, the influence of job seeker profiles (and therefore corresponding search tasks) on search behavior was largely ignored in this study. For example, whether seekers are finding a temporary, part-time job or a regular full-time job may alter their search behavior.

We believe our results can be mainly explained by models of the learning effect in search [10] but the existing models may need extension. Vakkari described restructuring, tuning, and assimilation. At the last stage, Vakkari states that users will reformulate queries less, while using more unique terms, writing longer queries, having clear usefulness criteria, a lower click rate, and a high use/selection ratio of retrieved items.



(a) Query term diversity
1st>3rd, 2nd>3rd****

(b) % location filter
1st<2nd*, 1st<3rd*

(c) Norm. click rate
1st>2nd, 1st>3rd****

(d) Norm. application rate
1st>2nd*, 2nd<3rd**

Figure 1: The changes of (a) Query term diversity, (b) % location filter, (c) Norm. click rate, and (d) Norm. application rate across three different stages. */ indicate the difference is significant at $\alpha = 0.05/0.01$ level with a post hoc comparison using the Tukey's HSD test.**

The model suggests that across the duration of a job seeking task, seekers will learn how to search more effectively and efficiently during the completion of search tasks. Our results show that seekers learn how to effectively use the filters provided by the job search engine, as well as which terms are the best to describe the job they are trying to find. They also develop better criteria for the relevance and usefulness of job posts, and thus, click retrieved jobs in a more selective manner and achieve a higher application rate. We see that these changes of behavior are mainly in line with the predictions given by Vakkari.

However, there are also differences between our results and past work. Vakkari suggested that as users learn, the number of search terms they employ would increase as would term specificity [10]. Eickhoff et al. described such an effect in web search logs across a short search session; in that work, they measured "Query Complexity" [2], which they saw rise. In our results, we see the opposite: the query term diversity decreases over time. The explanation for this is likely due to the nature of the task. Past work examined learning in the context of relatively static collections and an information seeking problem that was complex. In the job seeking task the descriptions of work are maybe easier to learn, and the collection of advertised jobs is updated regularly.

In this context, we speculate that job seekers move through Vakkari's three stages of learning, but then, as available jobs update, they enter a fourth stage: *monitoring*. The stage is similar to assimilation, but one where the seeker – fresh with their new found knowledge of how to find jobs in a particular field – now monitors updates as time progresses. New jobs are assimilated into the job seeker's knowledge structures, but queries remain relatively static.

Other search tasks may also have such a monitoring stage, for example a PhD student learning a new research field will learn while searching, but also learn strategies to monitor publication forums to stay on top of their subject. Our findings suggest that the search systems for a dynamic collection should be able to detect the monitoring behavior and provide better support – such as tracking the results of a specific query – in the monitoring stage.

6 CONCLUSIONS

In this paper, search behavior was analyzed over a relatively unusual data set, allowing us to study searches that run for many days. We used the logs of job searches to characterize search behaviors, and how such behaviors change over time. We addressed three research questions.

- **RQ1**: *How is job seekers' search behavior characterized?* We found that overall, the job search task is a complex search task for seekers, usually requiring the submission of multiple queries over a relatively long time period to complete it. The analysis also showed that during a job search, the job seekers liked to use short query terms repeatedly, and they often used different filters, especially for location, to narrow the scope of the search.
- **RQ2**: *How does the behavior change over time?* We found that for querying behavior, job seekers tend to use more filters and less diverse query terms in their formulated queries as the search proceeds.
- **RQ3**: *Does information consumption (result clicks) and response behavior (application lodging) change over time?* Over time, a decrease in click rate and an increase in application rate was observed, suggesting that searchers become better able to focus on jobs of interest.

Overall, these findings demonstrate that job searchers do learn over the duration of their job finding task. In future work, we plan to extend our study to a larger log of registered job seekers, examining the duration of search tasks and their changes in more detail.

ACKNOWLEDGMENTS

This research was partially supported by Australian Research Council Project LP150100252 and SEEK Ltd.

REFERENCES

[1] Bureau of Labor Statistics, U.S. Department of Labor. 2012. Length of job search for the unemployed on the Internet. *The Economics Daily* (2012). https://www.bls.gov/opub/ted/2012/ted_20120424.htm Accessed: 2019-05-20.
[2] Carsten Eickhoff, Jaime Teevan, Ryen White, and Susan Dumais. 2014. Lessons from the journey: A query log analysis of within-session learning. In *WSDM'14*.
[3] Jiepu Jiang, Daqing He, and James Allan. 2014. Searching, browsing, and clicking in a search session: Changes in user behavior by task and over time. In *SIGIR'14*.
[4] Alexander Kotov, Paul N Bennett, Ryen W White, Susan T Dumais, and Jaime Teevan. 2011. Modeling and analysis of cross-session search tasks. In *SIGIR'11*.
[5] Carol Collier Kuhlthau. 1993. Seeking meaning: A process approach to library and information services. *Norwood, NJ: Ablex* (1993).
[6] Jingjing Liu and Nicholas J Belkin. 2012. Searching vs. writing: Factors affecting information use task performance. In *ASIST'12*.
[7] Behrooz Mansouri, Mohammad Sadegh Zahedi, Ricardo Campos, and Mojgan Farhoodi. 2018. Online Job Search: Study of Users' Search Behavior using Search Engine Query Logs. In *SIGIR'18*.
[8] Damiano Spina, Maria Maistro, Yongli Ren, Sargol Sadeghi, Wilson Wong, Timothy Baldwin, Lawrence Cavedon, Alistair Moffat, Mark Sanderson, Falk Scholer, and Justin Zobel. 2017. Understanding user behavior in job and talent search: An Initial Investigation. In *SIGIR Workshop on eCommerce (eCom'17)*.
[9] Pertti Vakkari. 2001. A theory of the task-based information retrieval process: a summary and generalisation of a longitudinal study. *J. Documentation* 57, 1 (2001).
[10] Pertti Vakkari. 2016. Searching as learning: A systematization based on literature. *Journal of Information Science* 42, 1 (2016).
[11] Hongning Wang, Yang Song, Ming-Wei Chang, Xiaodong He, Ryen W White, and Wei Chu. 2013. Learning to extract cross-session search tasks. In *WWW'18*.