In Situ and Context-Aware Target Apps Selection for Unified Mobile Search

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ABSTRACT

With the recent growth in the use of conversational systems and intelligent assistants such as Google Assistant and Microsoft Cortana, mobile devices are becoming even more pervasive in our lives. As a consequence, users are getting engaged with mobile apps and frequently search for an information need using different apps. Recent work has stated the need for a *unified mobile search* system that would act as meta search on users' mobile devices: it would identify the target apps for the user's query, submit the query to the apps, and present the results to the user. Moreover, mobile devices provide rich contextual information about users and their whereabouts. In this paper, we introduce the task of context-aware target apps selection as part of a unified mobile search framework. To this aim, we designed an in situ study to collect thousands of mobile queries enriched with mobile sensor data from 255 users during a three month period. With the aid of this dataset, we were able to study user behavior as they performed cross-app search. We finally study the performance of state-of-the-art retrieval models for this task and propose a simple yet effective neural model that significantly outperforms the baselines. Our neural approach is based on learning high-dimensional representations for mobile apps and contextual information. Furthermore, we show that incorporating context improves the performance by 20% in terms of nDCG@5, enabling the model to perform better for 57% of users. Our data is publicly available for research purposes.

ACM Reference Format:
Mohammad Aliannejadi, Hamed Zamani, Fabio Crestani, and W. Bruce Croft. 2018. In Situ and Context-Aware Target Apps Selection for, Unified Mobile Search. In *The 27th ACM International Conference on Information and Knowledge Management (CIKM '18), October 22–26, 2018, Torino, Italy*. ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3269206.3271679

1 INTRODUCTION

In recent years, mobile devices have become the main means of connecting to the Internet for many people. This has resulted in a tremendous number of apps that are now available on mobile app markets. In particular, Google Play Store now features more than 3.5 million apps and an average user installs only around 35 of them,[1] many of which provide services such as music and location search. In addition, the emergence of intelligent assistants, such as Google Assistant, has made mobile devices even more pervasive, providing users with a universal voice-based search interface. However, as users spend most of their time working with apps (rather than a browser),[2] these systems still have a long way to go to provide a unified interface with the wide variety of the apps. For these reasons, we have recently discussed the need for a *universal mobile search* system that would act as a meta search engine, to which users would submit all their queries. The system should identify the target apps, route the query to them, and display the returned results in an integrated interface. Thus, the first step towards designing a unified mobile search framework is identifying the target apps for a given query, called the *target apps selection* task [2].

As mobile devices provide rich contextual information about users, previous studies [1, 22, 43] have tried to incorporate query context in various domains. In particular, query context is often defined as the information from the previous queries and their corresponding clickthrough data [40, 41], or situational context such as location and time [6, 20, 43]. However, as user interactions on mobile devices are mostly with apps, exploring apps usage patterns reveals important information about the users contexts, information needs, and behavior. For instance, a user who starts spending time on travel-related apps, e.g., TripAdvisor, is likely to be planning a trip in the near future. Carrascal and Church [10] verified this claim by showing that people use certain categories of apps more intensely as they do mobile search.

However, our previous attempt to study unified mobile search through crowdsourcing failed to capture users' contexts while collecting data [2]. In addition, there are some other limitations. For example, we asked the workers to complete a set of given search tasks, which obviously were not their actual information needs, and thus the queries may differ from real search queries. In addition, the workers did not complete their work on mobile devices, which affects their behavior. Furthermore, the user behavior and queries could not be studied in a day-long or week-long period.

The aforementioned limitations have motivated us to conduct the first in situ study on target apps selection for unified mobile

CIKM '18, October 22–26, 2018, Torino, Italy

ACM ISBN 978-1-4503-6014-2/18/10…$15.00
https://doi.org/10.1145/3269206.3271679

[1] https://www.thinkwithgoogle.com/advertising-channels/apps/app-marketing-trends-mobile-landscape/
[2] http://flurrymobile.tumblr.com/post/157921590345/us-consumers-time-spent-on-mobile-crosses-5

search. This enables us to obtain more clear insights into the task. In particular, we are interested in studying the users' behavior as they search for their real-life information needs using their own mobile devices. Moreover, we study the impact of contextual information on the apps they use for search. To this aim, we developed a simple open source app, called uSearch, and used it to build an in situ collection of cross-app queries. Through an open call, we recruited 255 participants who installed uSearch and used it to report their queries as well as the target apps, right after they did a search on their smartphones. With participants' consents, uSearch also ran in the background collecting useful contextual data. We have released the code of uSearch to facilitate research on mobile information retrieval. In fact, uSearch is extendable and can be used for collecting data to study various search tasks on mobile devices. Over a period of 12 weeks, we collected thousands of queries which enables us to investigate various aspects of user behavior as they search for information in a cross-app search environment.

Using the collected data, we conduct an extensive data analysis, aiming to understand how users' behavior vary across different apps while they search for their information needs. The key findings of our analysis include the fact that users conduct the majority of their daily search tasks using specific apps, rather than `Google`. Among various available contextual information, we focus on the users' apps usage statistics as their *apps usage context*, and leave others for future work. This is motivated by the results of our analysis in which we show that users often search on the apps that they use more frequently. Based on the insights we got from our data analysis, we propose a context-aware neural target apps selection model, called CNTAS. In our model, we deal with the problem as a ranking task estimating a relevance score for a given context-query-app triple. Our experiments demonstrate that our model significantly outperforms state-of-the-art retrieval models in this task. Also, we show that incorporating context improves nDCG@5 by an average of 20% on all models and improves the performance with respect to 57% of the users.

In summary, the main contributions of this paper include:

- Designing and conducting an in situ mobile search study for collecting thousands of real-life cross-app queries. Both the app[3] and the collected data[4] are publicly available for research purposes.
- Presenting the first in situ analysis of cross-app queries and users' behavior as they search with different apps. More specifically, we study different attributes of cross-app mobile queries with respect to their target apps, sessions, and contexts.
- Proposing a context-aware neural model for target apps selection.
- Evaluating the performance of state-of-the-art retrieval models for this task and comparing them against our proposed model.

Our analyses and experiments lead to new findings compared to previous studies, opening specific future directions in this research area.

[3]https://github.com/aliannejadi/uSearch
[4]http://aliannejadi.com/istas.html

2 RELATED WORK

Our work is related to the areas of mobile IR, context-aware search, human interaction with mobile devices (mobile HCI), federated search, and aggregated search. Moreover, relevant research has been done in the areas of proactive IR, query classification and neural networks. In the following, we summarize the related research in each of these areas.

Mobile IR. A mobile IR system aims at enabling users to carry out all the classical IR operations on a mobile device [15], as the conventional Web-based approaches fail to satisfy users' information needs on mobile devices [12]. In fact, Song et al. [37] found significant differences in search patterns done using iPhone, iPad, and desktop. Research on mobile IR started by Kamvar and Baluja [21] where they did a large-scale mobile search query analysis, finding mobile search topics were less diverse. Guy [19] and Crestani and Du [14] conducted comparative studies on mobile spoken and typed-in queries showing that spoken queries are longer and closer to natural language. Montanez et al. [25] studied search across multiple devices including smartphones. Park et al. [28] represented apps using online reviews for improving the app retrieval performance. Park et al. [27] inferred users implicit intentions from social media for the task of app recommendation. This work is closely related to our previous work [2] where we introduced the need for a unified mobile search framework as we collected cross-app queries through crowdsourcing. In contrast, in this work, we collect real-life cross-app queries over a longer period of time with an in situ study design.

Context-aware IR. Most of the previous work in context-aware search is based on the user's search history [33, 40, 41]. Shen et al. [33] presented context-sensitive language models based on users' short-term search history. White et al. [40] investigated ways to optimally combine the query and its context by learning a model that predicts the context weight for each query. Bennett et al. [6] estimated the location preference of a document and used it to improve Web search. Most recently, Zamani et al. [43] explored the effect of situational context for personal search.

Mobile HCI. A large body of research has been done on mobile information need analysis. Sohn et al. [36] conducted a diary study in which they found that contextual features such as activity and time influence 72% of mobile information needs. Church and Oliver [11] did a diary and interview study with the aim of understanding users' mobile Web behavior. Pielot et al. [30] conducted an in situ study of mobile phone notifications. They found that depending on the type of notifications, different strategies should be employed for delivering them. Carrascal and Church [10] studied user interactions with respect to mobile apps and mobile search, finding that users' interactions with apps have impact on search. In contrast to this prior research, we conduct a large-scale in situ study, enabling us to collect enough cross-app queries to build a more reliable data collection.

Proactive IR. The aim of proactive IR systems is to anticipate users' information needs and proactively present information cards to them. Shokouhi and Guo [34] analyzed user interactions with information cards and found that the usage patterns of the cards

depend on time, location, and user's reactive search history. Sun et al. [39] proposed a collaborative nowcasting model, tackling the intent monitoring problem, utilizing the collaborative capabilities among users. Benetka et al. [5] showed that information needs vary across activities as well as during the course of an activity, proposing a method to leverage users' check-in activity for recommending information cards. Instead, our work focuses on leveraging context to determine the target apps for a given query.

Federated and aggregated search. Research on unified mobile search has a considerable overlap with federated and aggregated search. While federated search systems assume the environment to be uncooperative and data to be homogeneous, aggregated search systems blends heterogeneous content from cooperative resources [4]. Target apps selection, on the other hand, assumes an uncooperative environment and heterogeneous content. Callan and Connell [7] proposed a query-based sampling approach to *probe* uncooperative resources. Diaz [17] proposed modeling the query dynamics to detect news queries for integrating the news *vertical* in SERP.

Query classification. Different strategies are used to assign a query to predefined categories. Kang and Kim [23] defined three types of queries, each of which requiring the search engine to handle differently. Shen et al. [32] introduced an intermediate taxonomy used to classify queries to specified target categories. Cao et al. [8] leveraged conditional random fields to incorporate users' neighboring queries in a session as context. More recently, Zamani and Croft [44] studied word embedding vectors for the query classification task and proposed a formal model for query embedding estimation.

Neural IR. The successful development of deep neural networks for various tasks has also impacted IR applications. In particular, neural ranking models have recently shown significant improvements in a wide range of IR tasks, such as ad-hoc retrieval [18], question answering [42], and context-aware retrieval [43]. These approaches often rely on learning high-dimensional dense representations that carry semantic information. They can be particularly useful to match queries and documents where minimal term overlap exists. We also take advantage of such latent high-dimensional representations in our model for representing mobile apps.

3 DATA COLLECTION

In this section, we describe how we collected *ISTAS*, which is, to the best of our knowledge, the first in situ dataset on cross-app mobile search queries. We collected the data by recruiting 255 participants through an open call on the Web. The participants installed a simple Android app, called uSearch, for at least 24 hours on their smartphones. We asked them to use uSearch to report their real-life cross-app queries as well as the corresponding target apps. We first describe the characteristics of uSearch. Then, we provide details on how we recruited participants as well as the details on how we instructed them to report queries through the app. Finally, we give details on how we checked the quality of the collected data.

3.1 uSearch

In order to facilitate the query report procedure, we developed uSearch, an Android app shown in Figure 1. We chose the Android platform because, in comparison with iOS, it imposes less

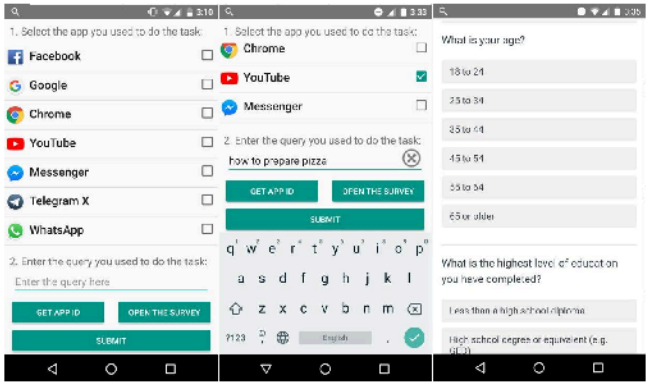


Figure 1: uSearch interface on LG Google Nexus 5 as well as the survey. Checkboxes are used to indicate the target app for a query.

restrictions in terms of sensor data collection and background app activity.

User interface. As shown in Figure 1, uSearch consists of three sections. The upper part lists all the apps that are installed on the phone, with the most used apps ranked higher. The participants were supposed to select the app in which they had done their real-life search (e.g., Facebook). In the second section, the participants were supposed to enter exactly the same query that they had entered in the target app (e.g., Facebook). Finally, the lower part of the app, provided them easy access to a unique ID of their device and an online survey on their demographics and backgrounds.

Collected data. Apart from the participants' input data, we also collected their interactions within uSearch (i.e., taps and scrolling). Moreover, a background service collected the phone's sensors data. We collected data from the following sensors: (i) GPS; (ii) accelerometer; (iii) gyroscope; (iv) ambient light; (v) WiFi; and (vi) cellular. Also, we collected other available phone data that can be used to better understand a user's context. The additional collected data are as follows: (i) battery level; (ii) screen on/off events; (iii) apps usage statistics; and (iv) apps usage events. Note that apps usage statistics indicate how often each app has been used in the past 24 hours, whereas apps usage events provides more detailed app events.[5] Apps usage events record user interactions in terms of: (i) launching a specific app; (ii) interacting with a launched app; (iii) closing a launched app; (iv) installing an app; and (v) uninstalling an app; The background service collected the data at a predefined time interval. The data was securely transferred to a cloud service.

3.2 Collection Procedure

We recruited participants through an online platform. In the announcement, we provided all the details about the intention of the study as well as the data we were collecting. First, we asked them to complete a survey inside uSearch. Moreover, we mentioned all the steps required to be done by the participants in order to report a query. In short, we asked them to open uSearch after every search they did using any installed app on their phones. Then, we asked them to report the app as well as the query they used to perform

[5] https://developer.android.com/reference/android/app/usage/package-summary

their search task. We encouraged the participants to report their search as soon as it occurs, as it is very crucial to capture their context at the right moment.

After running several pilot studies, over the period of 12 weeks we recruited 255 participants, asking them to let the app running on their smartphones for at least 24 hours and report at least 5 queries. Since some people may not submit 5 search queries during the period of 24 hours, we asked them to keep the app running on their phones after the first 24 hours until they report 5 queries. Also, we encouraged them to continue reporting more than 5 queries for an additional reward. As incentive, we paid the participants $0.2 per query. We recruited participants only from English-speaking countries.

3.3 Quality Check

During the course of data collection, we performed daily quality checks on the collected data. The checks were done manually with the help of some data visualization tools that we developed. As we were paying the participants a reward per query, we carefully studied the submitted queries as well as user interactions to prevent participants from reporting false queries. For each query, we checked the apps usage statistics and events for the same day. If a participant reported a query in a specific app (e.g., Facebook) but we could not find any recent usage events regarding that app, we assumed that the query was falsely reported. Moreover, if a participant reported more than 10 queries per day, we took some extra quality measures into account. Finally, we approved 6,877 queries out of 7,750 reported queries.

3.4 Privacy Concerns

Before asking for required app permissions, we made clear statement about our intentions on how we are going to use the participants' collected data as well as what was collected from their devices. We ensured them that their data was stored on secure cloud servers and that they could opt out at any point of the study. In that case we would remove all their data from the servers. While granting apps usage access was mandatory, granting location access was optional. We asked participants to allow uSearch access their locations only if they felt comfortable with that. Note that, through the background service, we did not collect any other data that could be used to identify the identity of participants.

3.5 Limitations

Like any other study, our study has some limitations. First, the study relies on self-reporting. This could result in specific biases in the collected data. For instance, participants may prefer to report shorter queries simply because it requires less work. Also, in many cases, participants are likely to forget reporting queries or do not report all the queries that belong to the same session. Second, the reported queries are not actually submitted to a unified search system and users may formulate their queries differently is such setting. For example, in a unified system a query may be "videos of Joe Bonamassa" but in YouTube it may be "Joe Bonamassa." Both limitations are due to lack of an existing unified mobile search app. Hence, building such app is essential for building a more realistic collection.

Table 1: Statistics of ISTAS.

# queries	6,877
# unique queries	6,262
# users	255
# unique apps	192
# search sessions	3,796
# days data collected	86
Mean queries per user	26.97 ± 50.21
Mean queries per session	1.81 ± 2.88
Mean queries per day	79.96 ± 101.27
Mean days of report per user	7.38 ± 15.95
Mean unique apps per user	5.14 ± 14.06
Mean query terms	3.00 ± 1.96
Mean query characters	17.53 ± 10.46

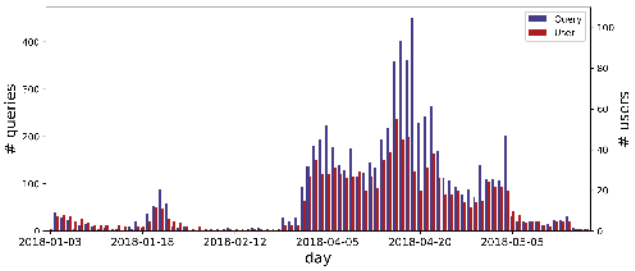


Figure 2: Number of queries and active participants per day, during the course of data collection (best viewed in color).

4 DATA ANALYSIS

In this section, we describe the basic characteristics of ISTAS, and present a thorough analysis of target apps, queries, sessions, and context.

4.1 Basic Statistics

During the period of 86 days, with the help of 255 participants, we were able to collect 6,877 search queries and their target apps as well as sensor and usage data. The collected raw data is over 300 gigabytes. Here, we summarize the main characteristics of the participants based on the submitted surveys. 59% of the participants were female and 50% aged between 25 and 34. Participants were from all kinds of educational backgrounds ranging from high school diploma to PhD. In particular, 32% of them had a college degree, followed by 30% with a bachelor's degree. Smartphone was the main device used for connecting to the Internet for 53% of the participants, followed by laptop (25%). Among the participants, 67% used their smartphones more often for personal reasons rather than work. Finally, half of the participants stated that they use their smartphones 4 hours a day or more. Table 1 lists basic characteristics of ISTAS. Moreover, Figure 2 shows the number of queries and active participants per day during the data collection period. Note that as shown in Figure 2, in the first half collection period, we were mostly developing the visualization tools and did not recruit many participants.

4.2 Apps

How apps are distributed. Figure 3 shows how queries are distributed with respect to the top 20 apps. We see that the top 20 apps

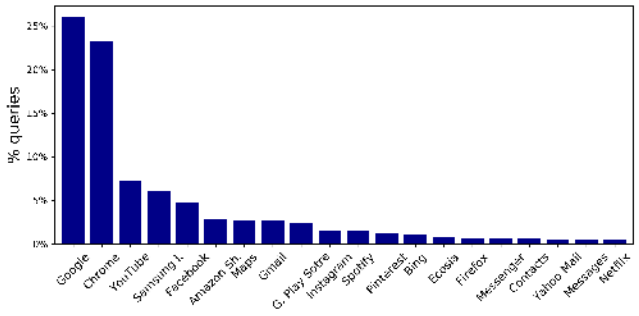


Figure 3: Number of queries per app for top 20 apps.

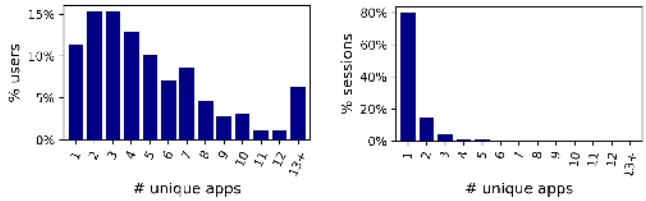


Figure 4: Distribution of unique apps per user and task.

account for 88% of the searches in ISTAS, showing that the app distribution follows a power-law. While Google and Chrome queries respectively attract 26% and 23% of the target apps, users conduct half (51%) of their search tasks using other apps. This finding is inline with what was shown in a previous work [2]. However, we observe a higher percentage of searches done using Google and Chrome apps. This can be due to two reasons: (i) ISTAS is collected in situ and on mobile devices, thus being more realistic; (ii) ISTAS queries reflect real-life information needs rather than a set of given search tasks, hence the information need topics are diverse. Moreover, we observe a notable variety of apps among the top 20 apps, such as Spotify and Contacts. We also see Google Play Store among the top target apps. This suggests that people use their smartphones to search for a wide variety of search tasks, most of which were done by apps other than Google or Chrome. It should also be noted that users seek the majority of their information needs on various apps, even though there exists no unified mobile search system on their smartphones, suggesting that they might even do a smaller portion of their searches using Google or Chrome, if a unified mobile search system was available on their smartphones.

How apps are selected. Here, we analyze the behavior of the participants as they searched for real-life information needs, in terms of the apps they chose for performing the search. Figure 4a shows the distribution of unique apps per user. We can see how many users selected a certain number of unique apps, with an average of 5.14 unique apps per user. Again, this indicates that users seek information in a set of diverse apps. It is worth noting that in Figure 4a, we observe a totally different distribution compared to [2], where the average number of unique apps per user was much lower. We believe this difference is due to the fact that the participants in our work reported their real-life queries, as opposed to the crowdsourcing setup of [2].

On the other hand, Figure 4b plots the distribution of unique apps with respect to the sessions, that is how many unique apps were selected during a single search session. We see an entirely different distribution where the average number of unique apps per task is 1.36. This shows that while users seek information using multiple apps, they are less open to switching between apps in a single session. This can partly be due to the fact that switching between apps is not very convenient. However, this behavior requires more investigation that we leave for future work.

Table 2: Corss-app query attributes for 9 apps. The upper part lists the distribution of number of query terms as well as mean query terms per app. The lower part lists the query overlap at different similarity thresholds (denoted by τ) per app. *All* shows query distributions across all apps.

	All	Google	YouTube	Facebook	Amazon Sh.	Maps	Gmail	G. Play Store	Spotify	Contacts
# terms	Query term distribution									
1	22%	13%	11%	22%	12%	25%	57%	49%	29%	81%
2	28%	26%	29%	48%	45%	27%	30%	33%	35%	10%
3	20%	21%	24%	16%	25%	18%	9%	12%	24%	7%
4	12%	13%	18%	10%	10%	13%	3%	4%	7%	2%
> 4	17%	26%	17%	4%	10%	17%	1%	1%	6%	0%
Mean	3.00	3.49	3.19	2.34	2.74	3.07	1.61	1.75	2.31	1.31
τ	Query overlap									
> 0.25	56%	39%	41%	28%	27%	26%	27%	25%	8%	14%
> 0.50	19%	11%	15%	13%	7%	11%	12%	12%	4%	10%
> 0.75	13%	5%	8%	11%	5%	9%	12%	10%	2%	10%

4.3 Queries

In order to understand the differences in user behavior while formulating their information needs using different apps, we conduct an analysis on the attributes of the queries with respect to their target apps. First, we start by studying the number of query terms in each app, for the top 9 apps in ISTAS.

How query length differs among apps. The upper part of Table 2 lists the distribution of the number of query terms in the whole dataset (denoted by *All*) as well as each app. It also lists the average query terms per app. As we can see, the average query length is 3.00, which is slightly lower than previous studies on mobile query analysis [19, 21]. However, the average query length for apps that deal with general web search such as Google is higher (=3.49). This indicates that users submit shorter queries to other apps. For instance, we see that Contacts has the lowest average query length (=1.31). Also Gmail and Google Play Store have an average query length lower than 2. This difference shows a clear behavioral difference in formulating queries using different apps. Moreover, we can see that the distribution of the number of query terms varies among different apps; take Contacts as an example, whose single-term queries constitute 81% of its query distributions. This indicates that the structure of queries vary across the target apps. Studying the most frequent query unigrams of each app also confirms this finding. For example, Google's most popular unigrams are mostly stopwords (i.e., "to", "the", "of", "how"), whereas Facebook's most popular unigrams are not (i.e., "art", "eye", "wicked", "candy").

How query similarity differs across apps. The lower part of Table 2 lists the query similarity or query overlap using a simple function used in previous studies [2, 13]. We measure the query overlap at various degrees and use the similarity function $sim(q_1, q_2) = |q_1 \cap q_2|/|q_1 \cup q_2|$, simply measuring the overlap of query terms. We see that among all queries, 18% of them are similar to no other queries. We see a different level of query overlap in queries belonging to different apps. The highest overlap is among queries from Web search apps such as `Chrome` and `Google`. Lower query similarity is observed for personal apps such as `Facebook` and more focused apps such as `Amazon Shopping`. Note that the query overlap is higher when all app queries are taken into account (All), as opposed to individual apps. This shows that users submit more similar queries as they switch between apps, suggesting that switching between apps is part of the information seeking or query reformulation procedure on mobile devices.

4.4 Sessions

A session is a "series of queries by a single user made within a small range of time" [35]. Similar to previous work [10, 21, 35], we consider a 5-minute range of inactivity to close a session. ISTAS consists of 3,796 sessions, with 1.81 average queries per session. The majority of sessions have only one query (=66%). Similarly, as shown in Figure 4b, participants use only one app in the majority of sessions (=80%). We also studied how similar queries were distributed among single-app sessions as compared to multiple-app sessions. We found that queries are more similar to each other in multiple-app sessions. More specifically, query overlap at the threshold of > 0.25 is 49% and 56% in single-app and multiple-app sessions, respectively. This suggests that users tend to switch between apps to search for the same information need as they reformulate their queries.

4.5 Context

Temporal behavior. We analyze the behavior of users as they search with respect to day-of-week and time-of-day. The distribution across day-of-week among the participants who reported their queries for more than 6 days slightly peaks on Fridays. Moreover, Figure 5 shows the distribution of queries and unique target apps across time-of-day for all participants. As we can see, more queries are submitted in the evenings, however we do not see a notable difference in the number of unique target apps.

Apps usage context. We define a user's *apps usage context* at a given time t as the apps usage statistics of that specific user during the 24 hours before t. Apps usage statistics contain details about the amount of time users spent on every app installed on their smartphones. This gives valuable information on users' personal app preferences as well as their contexts. For example, a user who has interacted with travel guide apps in the past 24 hours is probably planning a trip in the near future. Therefore, we analyze how users' apps usage context can potentially help a target app selection model. Figure 6 shows the histogram of target app rankings in the users' apps usage contexts. We see that participants often looked for information in the apps that they use more frequently. For instance, 19% of searches were done on the most used app, followed by 10% on the second most used app. We also see that, in most cases,

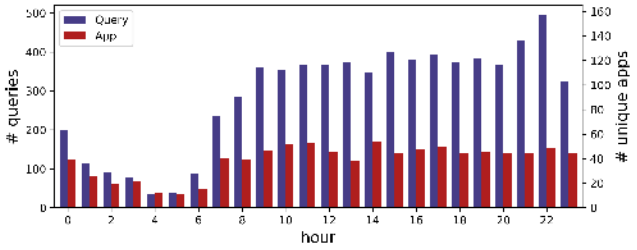


Figure 5: Time-of-the-day distribution of queries and unique apps (best viewed in color).

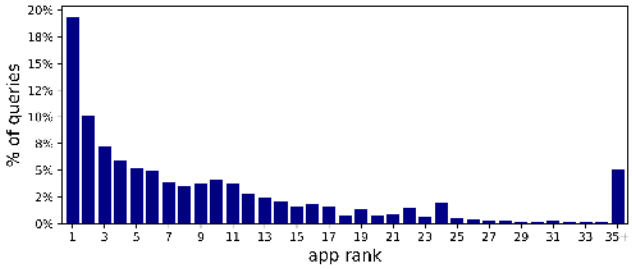


Figure 6: Apps usage context ranking distribution of relevant target apps. Lower values of x axis mean that the app has been used more often in the past 24 hours.

as the ranking increases, the percentage of target apps decreases, suggesting that incorporating users app usage context is critical for target apps selection.

5 CONTEXT-AWARE NEURAL TARGET APPS SELECTION

In this section, we propose a context-aware neural model called CNTAS, which is an extension to our recent neural target apps selection model (i.e., NTAS1) [2]. Our model takes a query q, a candidate app a, and the corresponding query context c_q as input and produces a score indicating the likelihood of the candidate app a being selected by the user as the target app for the query q. In the following, we first describe a *general* framework for context-aware target apps selection and further explain how it is implemented and how context is incorporated into the framework.

Formally, the CNTAS framework estimates the probability $p(S = 1|q, a, c_q; A)$, where S is a binary random variable indicating whether the app a should be selected ($S = 1$) or not ($S = 0$). A denotes the set of candidate apps. This set can be all apps, those that are installed on the user's mobile device, or a set of candidate apps that is obtained by another model in a cascade setting. The app selection probability in the CNTAS framework is estimated as follows:

$$p(S = 1|q, a, c_q; A) = \psi(\phi_Q(q), \phi_A(a), \phi_C(c_q)), \quad (1)$$

where ϕ_Q, ϕ_A, and ϕ_C respectively denote query representation, app representation, and context representation components. ψ is a target apps selection component that takes the mentioned representations and generates an app selection score. Any of these components can be implemented in different ways. In addition, c_q can contain various types of query context, including search time, search location, and the users apps usage.

We implement the component ϕ_Q with two major functions: an embedding function $\mathcal{E} : V \rightarrow \mathbb{R}^d$ that maps each vocabulary term

to a d-dimensional embedding space, and a global term weighting function $\mathcal{W} : V \rightarrow \mathbb{R}$ that maps each vocabulary term to a real-valued number showing its global importance. The matrices $\mathcal{E}$ and $\mathcal{W}$ are the network parameters in our model and are learned to provide task-specific representations. The query representation component ϕ_Q represents a given query $q = \{w_1, w_2, \cdots, w_{|q|}\}$ as follows:

$$\phi_Q(q) = \sum_{i=1}^{|q|} \widehat{\mathcal{W}}(w_i) \cdot \mathcal{E}(w_i) \,,$$

which is the weighted element-wise summation over the terms' embedding vectors. $\widehat{\mathcal{W}}$ is the normalized global weights computed using a softmax function as follows:

$$\widehat{\mathcal{W}}(w_i) = \frac{\exp(\mathcal{W}(w_i))}{\sum_{j=1}^{|q|} \exp(\mathcal{W}(w_j))} \,.$$

This is a simple yet effective approach for query representation based on the bag of words assumption, which has been proven to be effective for target apps selection [2], ad-hoc retrieval [16], and query performance prediction [45].

To implement the app representation component ϕ_A, we learn a d-dimensional dense representation for each app. In more detail, this component consists of an app representation matrix $\mathcal{A} \in \mathbb{R}^{N \times d}$ where N denotes the total number of apps. Therefore, $\phi_A(a)$ returns a row of the matrix $\mathcal{A}$ that corresponds to the app a.

Various context definitions can be considered to implement the context representation component. General types of context, such as location and time, has been extensively explored in different tasks, such as web search [6], personal search [43], and mobile search [20]. In this paper, we refer to the *apps usage time* as context, which is a special type of context for our task. As introduced earlier in Section 4.5, the apps usage context is the time that the user spent on each mobile app in the past 24 hours of the search time. To implement ϕ_C, we first compute a probabilistic distribution based on the apps usage context, as follows:

$$p(a'|c_q) = \frac{\text{time spent on app } a' \text{ in the past 24 hours}}{\sum_{a'' \in A} \text{time spent on app } a'' \text{ in the past 24 hours}} \,,$$

where A is a set of candidate apps. ϕ_C is then computed as:

$$\phi_C(c_q) = \sum_{a' \in A} p(a'|c_q) \cdot \mathcal{A}_C[a'] \,,$$

where $\mathcal{A}_C \in \mathbb{R}^{N \times d}$ denotes an app representation matrix which is different from $\mathcal{A}$ used in the app representation component. This matrix is supposed to learn app representations suitable for representing the apps usage context. $\mathcal{A}_C[a']$ denotes the representation of app a' in the app representation matrix $\mathcal{A}_C$.

In summary, each of the representation learning components ϕ_Q, ϕ_A, and ϕ_C returns a d-dimensional vector. The app selection component is modeled as a fully-connected feed-forward network with two hidden layers and the output dimensionality of 1. We use rectified linear unit (ReLU) as the activation function in the hidden layers of the network. Sigmoid is used as the final activation function. To avoid overfitting, the dropout technique [38] is employed. For each query, the following vector is fed to this network:

$$(\phi_Q(q) \circ \phi_A(a)) \cdot |\phi_Q(q) - \phi_A(a)| \cdot (\phi_C(c_q) \circ \phi_A(a)) \cdot |\phi_C(c_q) - \phi_A(a)| \,,$$

where $\circ$ denotes the Hadamard product, i.e., the element-wise multiplication, and $\cdot$ here means concatenation. In fact, this component computes the similarity of the candidate app with the query content and context, and estimates the app selection score based on the combination of both.

We train our model using pointwise and pairwise settings. In a pointwise setting, we use mean squared error (MSE) as the loss function. MSE for a mini-batch b is defined as follows:

$$\mathcal{L}_{MSE}(b) = \frac{1}{|b|} \sum_{i=1}^{|b|} (y_i - \psi(\phi_Q(q_i), \phi_A(a_i), \phi_C(c_{q_i})))^2 \,,$$

where q_i, c_{q_i}, a_i, and y_i denote the query, the query context, the candidate app, and the label in the i^{th} training instance of the mini-batch. For this training setting, we use a linear activation for the output layer.

CNTAS can be also trained in a pairwise fashion. Therefore, each training instance consists of a query, the query context, a target app, and a non-target app. To this end, we employ hinge loss (max-margin loss function) that has been widely used in the learning to rank literature for pairwise models [24]. Hinge loss is a linear loss function that penalizes examples violating the margin constraint. For a mini-batch b, hinge loss is defined as below:

$$\mathcal{L}_{Hinge}(b) = \frac{1}{|b|} \sum_{i=1}^{|b|} \max\{0, 1 - \text{sign}(y_{i1} - y_{i2})(\widehat{y}_{i1} - \widehat{y}_{i2})\} \,,$$

where $\widehat{y}_{ij} = \psi(\phi_Q(q_i), \phi_A(a_{ij}), \phi_C(c_{q_i}))$.

6 EXPERIMENTS

In this section, we evaluate the performance of the proposed models in comparison with a set of state-of-the-art IR models. We also study the performance of the models with respect to the apps and users.

6.1 Experimental Setup

Dataset. We evaluate the performance of our proposed models on the ISTAS dataset. We follow two different strategies to split the data: (i) In *ISTAS-R*, we randomly select 70% of the queries for training, 10% for validation, and 20% for testing set; (ii) In *ISTAS-T*, we sort the queries of each user chronologically and keep the first 70% of each user's queries for training, the next 10% for validation, and the last 20% for testing set. ISTAS-T is used to evaluate the methods when information about users' search history is available. To minimize random bias, for ISTAS-R we repeated the experiments 10 times and report the average performance. The hyper-parameters of all models were tuned based on the nDCG@3 value on the validation sets.

Evaluation metrics. Effectiveness is measured by four standard evaluation metrics that were also used in [2]: mean reciprocal rank (MRR), and normalized discounted cumulative gain for the top 1, 3, and 5 retrieved apps (nDCG@1, nDCG@3, nDCG@5). We determine the statistically significant differences using the two-tailed paired t-test with Bonferroni correction at a 95% confidence interval ($p < 0.05$).

Compared methods. We compared the performance of our model with the following methods:

Table 3: Performance comparison with baselines on ISTAS-R and ISTAS-T. The superscript * denotes significant differences compared to all the baselines.

Methods	ISTAS-R Dataset				ISTAS-T Dataset			
	MRR	nDCG@1	nDCG@3	nDCG@5	MRR	nDCG@1	nDCG@3	nDCG@5
StaticRanker	0.4502	0.2597	0.4435	0.4891	0.4786	0.2884	0.4752	0.5173
QueryLM	0.3556	0.2431	0.3534	0.3900	0.2706	0.1486	0.2713	0.3097
BM25	0.4205	0.3134	0.4363	0.4564	0.3573	0.2447	0.3771	0.3948
BM25-QE	0.4319	0.2857	0.4371	0.4727	0.3930	0.2411	0.4053	0.4364
k-NN	0.4433	0.2761	0.4455	0.4811	0.4067	0.2294	0.3982	0.4655
k-NN-AWE	0.4742	0.2937	0.4815	0.5211	0.4859	0.2950	0.4919	0.5392
ListNet	0.5170	0.3330	0.5211	**0.5623**	0.5118	0.3219	**0.5208**	0.5572
NTAS-pointwise	0.5221	0.3427	0.5231	0.5586	0.5162	0.3385	0.5162	0.5550
NTAS-pairwise	**0.5257**	**0.3468**	**0.5236**	0.5618	**0.5214**	**0.3427**	0.5183	**0.5580**
Context-Aware Methods								
StaticRanker-CR	0.4903	0.3015	0.4901	0.5268	0.5289	0.3576	0.5358	0.5573
QueryLM-CR	0.4540	0.2773	0.4426	0.5013	0.4696	0.3023	0.4597	0.5145
BM25-CR	0.5398	0.3653	0.5394	0.5871	0.5249	0.3496	0.5255	0.5723
BM25-QE-CR	0.5215	0.3398	0.5223	0.5693	0.5230	0.3474	0.5260	0.5728
k-NN-CR	0.4978	0.3114	0.4926	0.5431	0.5161	0.3481	0.4956	0.5555
k-NN-AWE-CR	0.5144	0.3233	0.5142	0.5632	0.5577	0.3722	0.5612	**0.6086**
ListNet-CR	0.5391	0.3544	0.5417	0.5845	0.5599	0.3780	0.5657	0.6037
ListNet-CX	0.5349	0.3580	0.5343	0.5784	0.5019	0.3139	0.5153	0.5521
NTAS-pointwise-CR	0.5532	0.3745	0.5580	0.5883	0.5627	0.3865	0.5663	0.5965
NTAS-pairwise-CR	0.5576	0.3779	0.5568	0.5870	0.5683	0.3923	0.5661	0.6047
CNTAS-pointwise	0.5614*	0.3833*	**0.5592**	0.5901	0.5702*	0.4146*	0.5655	0.5938
CNTAS-pairwise	**0.5637***	**0.3861***	0.5586	**0.5924***	**0.5738***	**0.4182***	**0.5679***	0.6071

- *StaticRanker:* For every query we rank the apps in the order of their popularity in the training set as a static (query independent) model.
- *QueryLM, BM25, BM25-QE:* For every app we aggregate all the relevant queries from the training set to build a document representing the app. QueryLM is the query likelihood retrieval model [31]. For BM25-QE, we adopt Bo1 [3] for query expansion. We use the Terrier [26] implementation of these methods.
- *k-NN, k-NN-AWE:* To find the nearest neighbors in k nearest neighbors (k-NN), we consider the cosine similarity between the TF-IDF vectors of queries. Then, we take the labels (apps) of the nearest queries and produce the app ranking. As for k-NN-AWE [44], we compute the cosine similarity between the average word embedding (AWE) of the queries obtained from GloVe [29] with 300 dimensions.
- *ListNet, ListNet-CX:* For every query-app pair, we use the scores obtained by BM25-QE, k-NN, k-NN-AWE, and StaticRanker as features to train ListNet [9] implemented in RankLib[6]. For every query, we consider all irrelevant apps as negative samples. ListNet-CX also includes users' apps usage context as an additional feature.
- *NTAS*: A neural model approach that we designed for the target apps selection task in our previous work [2]. We use the NTAS1 model due to its superior performance compared to NTAS2.
- *Contextual baselines:* In order to carry out a fair comparison between CNTAS and other context-aware baselines, we apply a context filter to all non-contextual baselines. We create the context filter as follows: for every app α in the training samples of user u, we take the time that u has spent on α in the past 24 hours as its score. We then perform a linear interpolation with the scores of all the mentioned baselines. Note that all scores are normalized. All these models are denoted by a *-CR* suffix.

[6]https://sourceforge.net/p/lemur/wiki/RankLib/

6.2 Results and Discussion

In the following, we evaluate the performance of CNTAS trained on both data splits and study the impact of context on the performance. We further analyze how the models perform on both data splits.

Performance comparison. Table 3 lists the performance of our proposed methods as well as the compared methods. First, we compare the relative performance drop between the two data splits. We see that almost all non-contextual models perform worse on ISTAS-T compared to ISTAS-R, whereas almost all context-aware models perform better on ISTAS-T. Among the non-contextual methods, ListNet is the most robust model with the least performance drop and k-NN-AWE is the only method that performs better on ISTAS-T (apart from StaticRanker). On the other hand, QueryLM exhibits the most performance drop (−27% on average), as opposed to Contextual-k-NN-AWE with the highest performance improvement on ISTAS-T (+10% on average). This indicates that k-NN-AWE is able to capture similar queries more effectively, whereas QueryLM relies heavily on the indexed queries. It should also be noted that StaticRanker performs better on ISTAS-T indicating that it is more biased towards more popular apps.

Among the non-contextual baselines, we see that NTAS-pairwise performs best in terms of most evaluation metrics on both data

Table 4: Performance analysis based on query length, dividing the test queries into three evenly-sized length buckets.

	Short queries	Med. queries	Long queries
	MRR	MRR	MRR
w/o context	0.5302	0.4924	0.4971
w/ context	**0.5733**	**0.5190**	**0.4977**

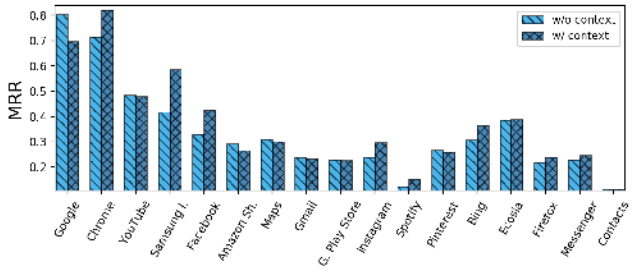
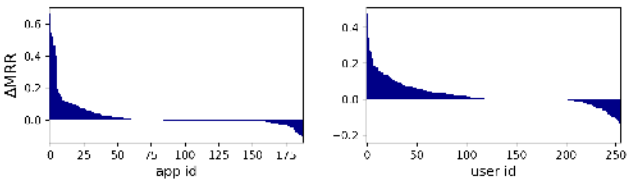


Figure 7: Performance comparison with respect to certain apps with and without context.



(a) ΔMRR per app **(b) ΔMRR per user**

Figure 8: MRR differences on ISTAS-R with and without context per app and user.

splits, this is because it learns high dimensional app and query representations which help it to perform more effectively. We see that applying the contextual filter improves the performance of all models. These improvements are statistically significant in all cases, so are not shown in the table. Although this filter is very simple, it is still able to incorporate useful information about user context and behavior into the ranking. This also indicates the importance of apps usage context, as mentioned in Section 4.5. Among the context-aware baselines, we see that NTAS-pairwise-CR performs best in terms of MRR and nDCG@1, while k-NN-AWE-CR and ListNet-CR perform better in terms of other evaluation metrics. It should be noted that ListNet-CR performs better than ListNet-CX. This happens due to the fact that ListNet-CX integrates the apps usage context as an additional feature, whereas ListNet-CR is the result of the combination of ListNet and the contextual filter.

We see that our proposed CNTAS outperforms all the baselines with respect to the majority of evaluation metrics. In particular CNTAS-pairwise exhibits the best performance. The achieved improvements in terms of MRR and nDCG@1 are statistically significant. The reason is that CNTAS is able to learn latent features from the interaction of mobile usage data in the context. These interactions can reveal more information for better understanding of the user information needs.

Impact of context on performance per app. In this experiment we demonstrate the effect of context on the performance with respect to various apps. Figure 7 shows the performance for queries that are labeled for specific target apps (as listed in the figure). We see that the context-aware model performs better while predicting social media apps such as Facebook and Instagram. However, we see that the performance for Google drops as it improves for Chrome. This happens because users do most of their browsing activities on Chrome, rather than Google; hence the usage statistics of Chrome helps the model to predict it more effectively. Moreover, we study the difference of MRR between the model with and without context for all apps. Our goal is to see how context improves the performance for every target app. We see in Figure 8a that the performance is improved for 39% of the apps. As shown in the figure, the improvements are much larger compared with the performance drops. Among the apps with the highest context improvements, we can mention Quora, Periscope, and Inbox. We saw that these apps were less popular among our participants and their representations were weaker than the other apps, that is why the contextual information shows the highest improvement for them.

Impact of context on performance per user. Here we study the difference of MRR between the model with and without context for all users. Our goal is to see how many users are impacted positively by incorporating context in the target apps selection model. Figure 8b shows how performance differs per user when we apply context compared with when we do not. As we can see, users' apps usage context is able to improve the effectiveness of target apps selection for the majority of users. In particular, the performance for 57% of the users is improved by incorporating the apps usage context. In fact, we observed that users with the highest impact from context use less popular apps.

Impact of context on performance per query length. Following Zamani et al. [46], we create three buckets of test queries based on query length uniformly. Therefore, the buckets will have approximately equal number of queries. The first bucket, called Short queries, contains the shortest queries, the second one, called Med. queries, constitutes of medium-length queries and the last bucket, called Long queries, includes the longest queries of our test set. Table 4 lists the performance of the model with and without context in terms of MRR. As we see, the average MRR for all three buckets is improved as we apply context. However, we observe that as the queries become shorter, the improvement increases. The reason is that shorter queries tend to be more general or ambiguous, and thus query context can have higher impact on improving search for these queries.

7 CONCLUSIONS AND FUTURE WORK

In this paper, we conducted the first in situ study on the task of target apps selection, which was motivated by the growing interest in intelligent assistants and conversational search systems where users interact with a universal voice-based search system. To this aim, we developed an app, called uSearch, and recruited 255 participants, asking them to report their real-life cross-app mobile queries via uSearch. We observed notable differences in length

and structure among queries submitted to different apps. Furthermore, we found that while users search using various apps, few apps attract most of the search queries. We found that even though `Google` and `Chrome` are the most popular apps, users do only 26% and 23% of their searches in these apps, respectively. The in situ data collection enabled us to collect valuable information about users' contexts. For instance, we found that the target app for 29% of the queries were among the top two most used apps of a particular user. Inspired by our data analysis, we proposed a model that learns high-dimensional latent representations for the apps usage context and predicts the target app for a query. The model was trained with an end-to-end setting. Our model produces a score for a given context-query-app triple. We compared the performance of our proposed method with state-of-the-art retrieval baselines splitting data following two different strategies. We observed that our approach outperforms all baselines, significantly.

An immediate future work can be exploring the influence of other types of contextual information, such as location and time, on the target apps selection task. In addition, it would be interesting to explore result aggregation and presentation in the future, considering two important factors: information gain and user satisfaction. This direction can be studied in both areas of information retrieval and human-computer interaction. Furthermore, based on our findings in the analyses, we believe that mobile search queries can be leveraged to improve the user experience. For instance, a user searches for a restaurant using a unified search system and finds some relevant information on `Yelp`. In this case, considering the user's personal preference as well as the context, the system could push a notification with information about the traffic near the restaurant.

Acknowledgements. This work was supported in part by the RelMobIR project of the Swiss National Science Foundation (SNSF), and in part by the Center for Intelligent Information Retrieval. Any opinions, findings and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect those of the sponsors.

REFERENCES

[1] Mohammad Aliannejadi and Fabio Crestani. 2017. Venue Appropriateness Prediction for Personalized Context-Aware Venue Suggestion. In *SIGIR*. 1177–1180.
[2] Mohammad Aliannejadi, Hamed Zamani, Fabio Crestani, and W. Bruce Croft. 2018. Target Apps Selection: Towards a Unified Search Framework for Mobile Devices. In *SIGIR*. 215–224.
[3] Giambattista Amati. 2003. *Probability models for information retrieval based on divergence from randomness.* Ph.D. Dissertation. University of Glasgow, UK.
[4] Jaime Arguello. 2017. Aggregated Search. *Foundations and Trends in Information Retrieval* 10, 5 (2017), 365–502.
[5] Jan R. Benetka, Krisztian Balog, and Kjetil Nørvåg. 2017. Anticipating Information Needs Based on Check-in Activity. In *WSDM*. 41–50.
[6] Paul N. Bennett, Filip Radlinski, Ryen W. White, and Emine Yilmaz. 2011. Inferring and using location metadata to personalize web search. In *SIGIR*. 135–144.
[7] James P. Callan and Margaret E. Connell. 2001. Query-based sampling of text databases. *ACM Trans. Inf. Syst.* 19, 2 (2001), 97–130.
[8] Huanhuan Cao, Derek Hao Hu, Dou Shen, Daxin Jiang, Jian-Tao Sun, Enhong Chen, and Qiang Yang. 2009. Context-aware query classification. In *SIGIR*. 3–10.
[9] Zhe Cao, Tao Qin, Tie-Yan Liu, Ming-Feng Tsai, and Hang Li. 2007. Learning to rank: from pairwise approach to listwise approach. In *ICML*.
[10] Juan Pablo Carrascal and Karen Church. 2015. An In-Situ Study of Mobile App & Mobile Search Interactions. In *CHI*. 2739–2748.
[11] Karen Church and Nuria Oliver. 2011. Understanding mobile web and mobile search use in today's dynamic mobile landscape. In *Mobile HCI*. 67–76.
[12] Karen Church, Barry Smyth, Keith Bradley, and Paul Cotter. 2008. A large scale study of European mobile search behaviour. In *Mobile HCI*. 13–22.
[13] Karen Church, Barry Smyth, Paul Cotter, and Keith Bradley. 2007. Mobile information access: A study of emerging search behavior on the mobile Internet. *TWEB* 1, 1 (2007), 4.
[14] Fabio Crestani and Heather Du. 2006. Written versus spoken queries: A qualitative and quantitative comparative analysis. *JASIST* 57, 7 (2006), 881–890.
[15] Fabio Crestani, Stefano Mizzaro, and Ivan Scagnetto. 2017. *Mobile Information Retrieval.* Springer.
[16] Mostafa Dehghani, Hamed Zamani, Aliaksei Severyn, Jaap Kamps, and W. Bruce Croft. 2017. Neural Ranking Models with Weak Supervision. In *SIGIR*. 65–74.
[17] Fernando Diaz. 2009. Integration of news content into web results. In *WSDM*. 182–191.
[18] Jiafeng Guo, Yixing Fan, Qingyao Ai, and W. Bruce Croft. 2016. A Deep Relevance Matching Model for Ad-hoc Retrieval. In *CIKM*. 55–64.
[19] Ido Guy. 2016. Searching by Talking: Analysis of Voice Queries on Mobile Web Search. In *SIGIR*. 35–44.
[20] Shun Hattori, Taro Tezuka, and Katsumi Tanaka. 2007. Context-Aware Query Refinement for Mobile Web Search. In *SAINT Workshops*.
[21] Maryam Kamvar and Shumeet Baluja. 2006. A large scale study of wireless search behavior: Google mobile search. In *CHI*. 701–709.
[22] Maryam Kamvar and Shumeet Baluja. 2007. The role of context in query input: using contextual signals to complete queries on mobile devices. In *Mobile HCI*. 405–412.
[23] In-Ho Kang and Gil-Chang Kim. 2003. Query type classification for web document retrieval. In *SIGIR*. 64–71.
[24] Hang Li. 2011. *Learning to Rank for Information Retrieval and Natural Language Processing.* Morgan & Claypool Publishers.
[25] George D. Montanez, Ryen W. White, and Xiao Huang. 2014. Cross-Device Search. In *CIKM*. 1669–1678.
[26] Iadh Ounis, Gianni Amati, Vassilis Plachouras, Ben He, Craig Macdonald, and Douglas Johnson. 2005. Terrier Information Retrieval Platform. In *ECIR*. 517–519.
[27] Dae Hoon Park, Yi Fang, Mengwen Liu, and ChengXiang Zhai. 2016. Mobile App Retrieval for Social Media Users via Inference of Implicit Intent in Social Media Text. In *CIKM*. 959–968.
[28] Dae Hoon Park, Mengwen Liu, ChengXiang Zhai, and Haohong Wang. 2015. Leveraging User Reviews to Improve Accuracy for Mobile App Retrieval. In *SIGIR*. 533–542.
[29] Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. GloVe: Global Vectors for Word Representation. In *EMNLP*. 1532–1543.
[30] Martin Pielot, Karen Church, and Rodrigo de Oliveira. 2014. An in-situ study of mobile phone notifications. In *Mobile HCI*. 233–242.
[31] Jay M. Ponte and W. Bruce Croft. 1998. A Language Modeling Approach to Information Retrieval. In *SIGIR*. 275–281.
[32] Dou Shen, Jian-Tao Sun, Qiang Yang, and Zheng Chen. 2006. Building bridges for web query classification. In *SIGIR*. 131–138.
[33] Xuehua Shen, Bin Tan, and ChengXiang Zhai. 2005. Context-sensitive information retrieval using implicit feedback. In *SIGIR*. 43–50.
[34] Milad Shokouhi and Qi Guo. 2015. From Queries to Cards: Re-ranking Proactive Card Recommendations Based on Reactive Search History. In *SIGIR*. 695–704.
[35] Craig Silverstein, Monika Rauch Henzinger, Hannes Marais, and Michael Moricz. 1999. Analysis of a Very Large Web Search Engine Query Log. *SIGIR Forum* 33, 1 (1999), 6–12.
[36] Timothy Sohn, Kevin A. Li, William G. Griswold, and James D. Hollan. 2008. A diary study of mobile information needs. In *CHI*. 433–442.
[37] Yang Song, Hao Ma, Hongning Wang, and Kuansan Wang. 2013. Exploring and exploiting user search behavior on mobile and tablet devices to improve search relevance. In *WWW*. 1201–1212.
[38] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *Journal of Machine Learning Research* 15 (2014), 1929–1958.
[39] Yu Sun, Nicholas Jing Yuan, Xing Xie, Kieran McDonald, and Rui Zhang. 2017. Collaborative Intent Prediction with Real-Time Contextual Data. *ACM Trans. Inf. Syst.* 35, 4 (2017), 30:1–30:33.
[40] Ryen W. White, Paul N. Bennett, and Susan T. Dumais. 2010. Predicting short-term interests using activity-based search context. In *CIKM*. 1009–1018.
[41] Biao Xiang, Daxin Jiang, Jian Pei, Xiaohui Sun, Enhong Chen, and Hang Li. 2010. Context-aware ranking in web search. In *SIGIR*. 451–458.
[42] Lei Yu, Karl Moritz Hermann, Phil Blunsom, and Stephen Pulman. 2014. Deep Learning for Answer Sentence Selection. In *NIPS Deep Learning Workshop*.
[43] Hamed Zamani, Michael Bendersky, Xuanhui Wang, and Mingyang Zhang. 2017. Situational Context for Ranking in Personal Search. In *WWW*. 1531–1540.
[44] Hamed Zamani and W. Bruce Croft. 2016. Estimating Embedding Vectors for Queries. In *ICTIR*. 123–132.
[45] Hamed Zamani, W. Bruce Croft, and J. Shane Culpepper. 2018. Neural Query Performance Prediction using Weak Supervision from Multiple Signals. In *SIGIR*. 105–114.
[46] Hamed Zamani, Bhaskar Mitra, Xia Song, Nick Craswell, and Saurabh Tiwary. 2018. Neural Ranking Models with Multiple Document Fields. In *WSDM*. 700–708.