A New Algorithm for Inferring User Search Goals with Feedback Sessions

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ABSTRACT
For a broad-topic and ambiguous query, different users may have different search goals when they submit it to a search engine. The inference and analysis of user search goals can be very useful in improving search engine relevance and user experience. In this paper, we propose a novel approach to infer user search goals by analyzing search engine query logs. First, we propose a framework to discover different user search goals for a query by clustering the proposed feedback sessions. Feedback sessions are constructed from user click-through logs and can efficiently reflect the information needs of users. Second, we propose a novel approach to generate pseudo-documents to better represent the feedback sessions for clustering. Finally, we propose a new criterion "Classified Average Precision (CAP)" to evaluate the performance of inferring user search goals. Experimental results are presented using user click-through logs from a commercial search engine to validate the effectiveness of our proposed methods.

General Terms
K-Means, data mining, clustering, restructuring.

Keywords
Page ranking, feedback sessions, inferring, user search goals, search engine optimization, indexing, re-ranking, and clustering.

1. INTRODUCTION
If we imagine seeing the world from the perspective of a search engine, our only view of user behavior would be the stream of queries users produce. Search engine designers often adopt this perspective, studying these query streams and trying to optimize the engines based on such factors as the length of a typical query. Yet this same perspective has prevented us from looking beyond the query, at why the users are performing their searches in the first place. The "why" of user search behavior is actually essential to satisfying the user's information need. After all, users don't sit down at their computer and say to themselves, "I think I'll do some searches." Searching is merely a means to an end – a way to satisfy an underlying goal that the user is trying to achieve. (By "underlying goal," we mean how the user might answer the question "why are you performing that search?") In fact, in some cases the same query might be used to convey different goals – for example, the query "ceramics" might have been used in any of the three situations above (assuming it is also the title of the book in question).

Therefore, it is necessary and potential to capture different user search goals in information retrieval. We define user search goals as the information on different aspects of a query that user groups want to obtain. Information need is a user's particular desire to obtain information to satisfy his/her need. User search goals can be considered as the clusters of information needs for a query. The inference and analysis of user search goals can have a lot of advantages in improving search engine relevance and user experience. Due to its usefulness, many works about user search goals analysis have been investigated. They can be summarized into three classes: query classification, search result reorganization, and session boundary detection. In the first class, people attempt to infer user goals and intents by predefining some specific classes and performing query classification accordingly. Consider user goals as "Navigational" and "Informational" and categorize queries into these two classes. Define query intents as "Product intent" and "Job intent" and they try to classify queries according to the defined intents. Other works focus on tagging queries with some predefined concepts to improve feature representation of queries.

However, since what users care about varies a lot for different queries, finding suitable predefined search goal classes is very difficult and impractical. In the second class, people try to reorganize search results. Learn interesting aspects of queries by analyzing the clicked URLs directly from user click-through logs to organize search results. However, this method has limitations since the number of different clicked URLs of a query may be small. Other works analyze the search results returned by the search engine when a query is submitted. Since user feedback is not considered, many noisy search results that are not clicked by any users may be analyzed as well. Therefore, this kind of methods cannot infer user search goals precisely. In the third class, people aim at detecting session boundaries. Jones and Klinkner predict goal and mission boundaries to hierarchically segment query logs. However, their method only identifies whether a pair of queries belong to the same goal or mission and does not care what the goal is in detail. In this paper, we aim at discovering the number of diverse user search goals for a query and depicting each goal with some keywords automatically. We first propose a novel approach to infer user search goals for a query by clustering our proposed feedback sessions. The feedback session is defined as the series of both clicked and unclicked URLs and ends with the last URL that was clicked in a session from user click-through logs. Then, we propose a novel optimization method to map feedback sessions to pseudo-documents which can efficiently reflect user information needs. At last, we cluster these pseudo-documents to infer user search goals and depict them with some keywords. Since the evaluation of clustering is also an important problem, we also propose a novel evaluation criterion classified average precision (CAP) to evaluate the performance of the restructured web search results. We also demonstrate that the proposed evaluation criterion can help us to optimize the parameter in the clustering method when inferring user search goals. We propose a framework to infer different user search goals for a query by clustering feedback sessions. We demonstrate that clustering feedback sessions is more efficient than clustering search results or clicked URLs directly. Moreover, the distributions of different user search goals can be obtained conveniently after feedback sessions are clustered. We propose a novel optimization method to combine the enriched URLs in a feedback session to form a pseudo-document, which can effectively reflect the information need of a user. Thus, we can tell what the user search goals are in detail. . We propose a new criterion CAP to evaluate the performance of user search goal inference based on restructuring web search results. Thus, we can determine the number of user search goals for a query.

2. LITERATURE SURVEY

In a typical information retrieval setting, the user describes their information need with a query Q, in response the retrieval system returns a ranked list of documents D1,D2,D3, · · · as results. If the initial ranking is poor, one way for improvement is to ask the user to provide feedback, i.e., to evaluate the relevance of some top-ranked documents. According to the cluster hypothesis, which states that relevant documents tend to be more similar to each other than to irrelevant ones, if some example relevant documents are identified from user feedback, one may find more relevant documents by seeking similar ones. A feedback loop is introduced: relevance judgment on the initial results are fed back to the system to perform a second-round retrieval, presumably generating a better ranking. Typically this is done by extracting informative terms from the feedback documents and adding them to the original query, producing a refined query Q_ that better represents the user's information need.

In collective feedback when a user issues a query, the log database is usually looked up for feedback from other users on the same query, rather than from the same user on other queries in his/her history. In contrast, single-user feedback from past search history. This has several implications: compared to a gigantic search log containing millions of users' records, a single-user one is small enough to reside on the user's client side, which alleviates privacy concerns, and more importantly, allows for more computation-intensive feedback algorithms.

In recent years, many works have been done to infer the so called user goals or intents of a query. But in fact, their works belong to query classification. Some works analyze the search results returned by the search engine directly to exploit different query aspects. However, query aspects without user feedback have limitations to improve search engine relevance. Some works take user feedback into account and analyze the different clicked URLs of a query in user click-through logs directly, nevertheless the number of different clicked URLs of a query may be not big enough to get ideal results. Wang and Zhai clustered queries and learned aspects of these similar queries, which solves the problem in part. However, their method does not work if we try to discover user search goals of one single query in the query cluster rather than a cluster of similar queries. For example, in, the query "car" is clustered with some other queries, such as "car rental," "used car," "car crash," and "car audio." Thus, the different aspects of the query "car" are able to be learned through their method. However, the query "used car" in the cluster can also have different aspects, which are difficult to be learned by their method. Some other works introduce search goals and missions to detect session boundary hierarchically. However, their method only identifies whether a pair of queries belong to the same goal or mission and does not care what the goal is in detail. A prior utilization of user click-through logs is to obtain user implicit feedback to enlarge training data when learning ranking functions in information retrieval. Thorsten Joachims did many works on how to use implicit feedback to improve the retrieval quality. In our work, we consider feedback sessions as user implicit feedback and propose a novel optimization method to combine both clicked and unclicked URLs in feedback sessions to find out what users really require and what they do not care. One application of user search goals is restructuring web search results. There are also some related works focusing on organizing the search results. In this paper, we infer user search goals from user click-through logs and restructure the search results according to the inferred user search goals.

3. METHODOLOGY

Fig. 4.1 shows the framework of our approach. Our framework consists of two parts divided by the dashed line. In the upper part, all the feedback sessions of a query are first extracted from user click-through logs and mapped to pseudo-documents. Then, user search goals are inferred by clustering these pseudo-documents and depicted with some keywords. Since we do not know the exact number of user search goals in advance, several different values are tried and the optimal value will be determined by the feedback from the bottom part. In the bottom part, the original search results are restructured based on the user search goals inferred from the upper part. Then, we evaluate the performance of restructuring search results by our proposed evaluation criterion CAP. And the evaluation result will be used as the feedback to select the optimal number of user search goals in the upper part.

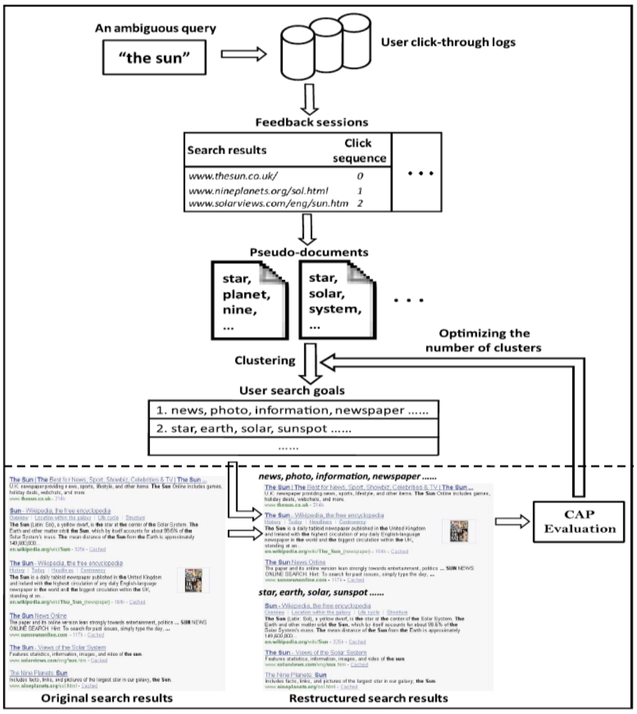

Fig 1: Block Diagram

4. EXPERIMENTS AND RESULTS

In this section, we will show experiments of our proposed algorithm. The data set that we used is based on the click through logs from a commercial search engine collected over a period of two months, including totally 2,300 different queries, 2.5 million single sessions and 2.93 million clicks. On average, each query has 1,087 single sessions and 1,274 clicks. However, these queries are chosen randomly and they have totally different click numbers. Excluding those queries with less than five different clicked URLs, we still have 1,720 queries. Before using the data sets, some preprocesses are implemented to the click-through logs including enriching URLs and term processing. In our approach, when clustering feedback sessions of a query, we try five different K (1, 2…5) in K-means clustering. Then, we restructure the search results according to the inferred user search goals and evaluate the performance by CAP, respectively. At last, we select K with the highest CAP. We select 20 queries and empirically decide the number of user search goals of these queries. Then, we cluster the feedback sessions and restructure the search results with inferred user search goals. We tune the parameter γ to make CAP the highest when K in K-means accord with what we expected for most queries. Based on the above process, the optimal γ is from 0.6 to 0.8 for the 20 queries. The mean and the variance of the optimal γ are 0.697 and 0.005, respectively. Thus, we set γ to be 0.7. Moreover, we use another 20 queries to compute CAP with the optimal γ (0.7) and the result shows that it is proper to set γ to be 0.7. In the following, we will first give intuitive results of discovering user goals to show that our approach can depict user search goals properly with some meaningful words. Then, we will give the comparison between our method and the other two methods in restructuring web search results.

4.1 Intuitive Results of Inferring User Search Goals

We infer user search goals for a query by clustering its feedback sessions. User search goals are represented by the center points of different clusters. Since each dimension of the feature vector of a center point indicates the importance of the corresponding term, we choose those keywords with the highest values in the feature vector to depict the content of one user search goal. Table 1 gives some examples of depicting user search goals with four keywords that have the highest values in those feature vectors. From these examples, we can get intuitive results of our search goal inference. Taking the query "Lamborghini" as an example, since CAP of the restructured search results is the highest when (K = 3), there are totally three clusters (i.e., three lines) corresponding to "Lamborghini" and each cluster is represented by four keywords. From the keywords "car, history, company, overview," we can find that this part of users are interested in the history of Lamborghini. From the keywords "new, auto, picture, vehicle," we can see that other users want to retrieve the pictures of new Lamborghini cars. From the keywords "club, oica, worldwide, Lamborghini club," we can find that the rest of the users are interested in a Lamborghini club. We can find that the inferred user search goals of the other queries are also meaningful. This confirms that our approach can infer user search goals properly and depict them with some keywords meaningfully.

4.2 Object Evaluation and Comparison

In this section, we will give the objective evaluation of our search goal inference method and the comparison with other two methods.

Three methods are compared. They are described as follows:

Our proposed method clusters feedback sessions to infer user search goals.

Method I clusters the top 100 search results to infer user search goals [2], [3]. First, we program to automatically submit the queries to the search engine again and crawl the top 100 search results including their titles and snippets for each query. Then, each search result is mapped to a feature vector according to (1) and (2). Finally, we cluster these 100 search results of a query to infer user search goals by K-means clustering and select the optimal K based on CAP criterion. . Method II clusters different clicked URLs directly [1]. In user click-through logs, a query has a lot of different single sessions; however, the different clicked URLs may be few. First, we select these different clicked URLs for a query from user click- through logs and enrich them with their titles and snippets as we do in our method. Then, each clicked URL is mapped to a feature vector according to (1) and (2). Finally, we cluster these different clicked URLs directly to infer user search goals as we do in our method and Method I. In order to demonstrate that when inferring user search goals, clustering our proposed feedback sessions are more efficient than clustering search results and clicked URLs directly, we use the same framework and clustering method. The only difference is that the samples these three methods cluster are different. Note that in order to make the format of the data set suitable for Method I and Method II, some data reorganization is performed to the data set. The performance evaluation and comparison are based on the restructuring web search results.

5. CONCLUSION

In this paper, a novel approach has been proposed to infer user search goals for a query by clustering its feedback sessions represented by pseudo-documents. First, we introduce feedback sessions to be analyzed to infer user search goals rather than search results or clicked URLs. Both the clicked URLs and the unclicked ones before the last click are considered as user implicit feedbacks and taken into account to construct feedback sessions. Therefore, feedback sessions can reflect user information needs more efficiently. Second, we map feedback sessions to pseudo documents to approximate goal texts in user minds. The pseudo documents can enrich the URLs with additional textual contents including the titles and snippets. Based on these pseudo documents, user search goals can then be discovered and depicted with some keywords. Finally, a new criterion CAP is formulated to evaluate the performance of user search goal inference. Experimental results on user click-through logs from a commercial search engine demonstrate the effectiveness of our proposed methods. The complexity of our approach is low and our approach can be used in reality easily. For each query, the running time depends on the number of feedback sessions. Therefore, the running time is usually short. In reality, our approach can discover user search goals for some popular queries offline at first. Then, when users submit one of the queries, the search engine can return the results that are categorized into different groups according to user search goals online. Thus, users can find what they want conveniently.

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