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Efficient Image Based Searching for Improving User Search Image Goals

Manisha Nath, Mr. N Praveen

Department of Computer science and engineering, SRM University, Chennai, India

Abstract— *The analysis of a user search goals for a query can be very useful in improving search engine relevance and the user experience. Although the research on inferring by user goals and intents for text search has received much attention, so small has been proposed for image search. In this paper, we propose to leverage click session information, which will indicate by high correlations among the clicked images in a session in a user click-through logs, and combine it with the clicked image visual information for inferring the user image-search goals. Since the click session information can serve as past users' implicit guidance for the clustering the images, more precise user search goals can be obtained. The two strategies are proposed because of combine image visual information for the click session information. Furthermore a classification risk based on approach is also proposed for automatically selecting the optimal number of search goals for a query. Experimental results based on the popular commercial search engine for demonstrate the effectiveness of the proposed method.*

Keywords— click-through logs, goal images, image-search goals, semi-supervised clustering, spectral clustering.

I. INTRODUCTION

In web search applications, the users submit queries (i.e., some keywords) to search engines for represent their search goals. However, in many cases, the queries may not exactly represent what they want since the keywords may be polysemous and cover the broad topic with the users tend to formulate short queries rather than to take the trouble of constructing long and carefully stated ones. Besides, the even for the same query, users may have different search goals. Fig.1 shows some of the example for user image-search goals which discussed in this paper. Each goal in Fig. 1 is represented an image example. From Fig. 1.Our experimental results, we find that users have the different search goals for the same query due to the following three reasons.

Fig. 1. Different user image-search goals represented by image examples in image search by our experiment.

1) Multi-concepts: here a keyword may represent different things. For a example, a kind of fruit, "apple" is end with new concepts by that apple, Inc. 2) Multi-forms: the same thing may have different forms. Which Take "Bumblebee" in the film Transformers as an example. It has two modes: the car mode and the humanoid mode. These two modes are the two forms of "Bumblebee." 3) Multi-representations: in image search, the same thing can be represented from the different angles of view such as the query leaf. It can be represented by a real scene and by close-up. The user search goals is very important to improving search-engine relevance and user experience. Normally, the captured user image-search goals can also be utilized in many applications. For example, we can take user image-search goals is a visual query suggestions to help users reformulate their queries during image search. Also we can also categorize search results for a image search according to the inferred user image-search goals to make it easier for a users to browse. Furthermore, we can also diversify and also re-rank the results retrieved for a query in image search with the discovered for user image-search goals. Thus, inferring user image-search goals is one of the key techniques which to improving users search experience. However, although there has been much research for text search, few methods were proposed to the user search goals in image search. Some works try to discover a user image-search goals based on textual information. However, since external texts are not always reliable (i.e., not guaranteed to precisely describe the image contents) and tags are not always available these textual information based methods still have limitations. It should be possible to user image-search goals with visual information of images since different image-search goals usually have been particular visual patterns to be distinguished from the each other. However, since there are semantic gaps between two features that exist image features and the image semantics, inferring user image-search goals by the visual information is still big challenge. Therefore, in this paper, we propose to introduce additional information sources to help narrow these semantic gaps.

Intuitively, click-through information from past users can provide good guidance about to the semantic correlation among images. By mining the user click-through logs, we can obtain two kinds of information the click content information and the click session information. a session in user click-through logs is a sequence of the queries and a series of clicks by the user toward addressing a single information need. In this paper, we define a session in image search as a single query and also a series of clicked images as illustrated in Fig. 2. Usually, clicked images in a session have highly correlations. This correlation information provides hints on which images belong for same search goal from the viewpoint of image semantics. So, in this paper, we propose to introduce this correlation information (named as click session information in this paper) to reduce semantic gaps between the existing image features and the image semantics. More specifically,

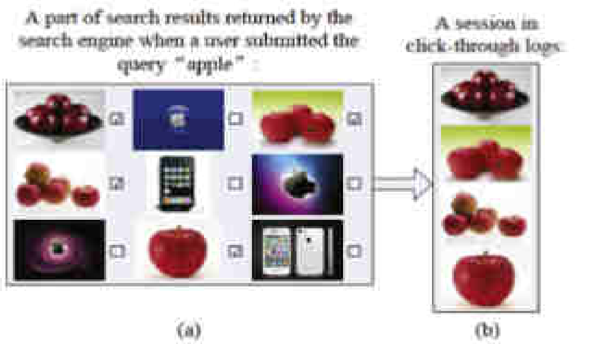

Fig. 2. Session for the query apple in user click-through logs. (a) Search results returned by the search engine. The check marks mean that the images were clicked by the user. (b) Session in user click-through logs.

Image semantics. More specifically, we propose the cluster the clicked images for a query in user click through logs under the guidance of click session information to infer user image-search goals. With the introduction of the correlation information, the reliability of visual features can be improved. The contributions in this paper can be described as follows. 1) We propose a new framework which combines image visual information and the click session information for inferring user image-search goals for a query. In this way, for more precise image-search goals can be achieved by 2) we propose the two strategies (i.e., the edge-reconstruction based strategy and the goal-image-based strategy) to effectively implement the process of the combining image visual information with click session information. We also propose to introduce spectral the clustering for handling the arbitrary cluster shape scenario during the clustering. 3) Since different queries may have different number of search goals (e.g., some queries may have two goals while others may have three goals as in Fig. 1), we further propose a classification risk (CR)-based approach

Fig. 2. Session for a query apple in user click-through logs. (a) Search results returned by the search engine. The check marks mean that the images were clicked by a user. (b) Session in user click-through logs.

To automatically decide the optimal number of search goals for a query. The rest of this paper is organized a. by introduces some related works. The framework of our approach is introduces the edge reconstruction based strategy to combine image visual information with the click session information and for introduces the goal-image-based strategy. The clustering method for achieving search goals like the CR-based approach to optimize the number of user search goals.

II. PROBLEM STATEMENT

The existing methods for image search suffered from the unreliability of the assumption under where initial text-based image searches result. However, such results containing a large number of images and with more number of irrelevant images. Image search engines can apparently provide an effortless route, but currently are limited by the poor precision of the returned images and also restrictions on the total number of image provided. The text based image are contains relevant and irrelevant image results. Which all of the existing algorithms require a prior assumption regarding to the relevance of the images in the initial, text-based search result with less efficiency.

A.INFERRING USER SEARCH GOALS BY CLUSTERING PSEUDO-DOCUMENTS

With the proposed pseudo-documents, we can infer user search goals. Here, we will describe how to infer user search goals and depict them with some meaningful keywords. Feedback session is represent by the pseudo-document and also the feature representation of the pseudo-document is Ffs. The similarity between two pseudo-documents is use to computed as the cosine score of Ffs i and Ffs j, as follows:

$$Sim_{i;j} = ¼ \cos (F_{fs_i} ; F_{fs_J})$$
$$=$$
$$(F_{fs_i}, F_{fs_j}) / |jF_{fs_i}k||F_{fs_j}j|$$

And the distance between two feedback sessions is

Disi; j=1_Simi;j

The cluster pseudo document by K which means clustering which is simple and effective. We do not know the exact number of the user search goals for the each query, we set K to be five different values and perform clustering based on these five values, respectively. So determine the optimal value through the evaluation criterion. After clustering all the pseudo documents, where each cluster can be considered as one user search goal. Fcenteri is utilized to conclude the search goal of the i th cluster. Finally, the terms with the highest values in center points are used as the keywords to depict the user search goals. Note that an additional advantage of using this keyword based description is which the extracted keywords can also be utilized to form a more meaningful query in a query recommendation and thus can represent the user information needs more effectively. Moreover, we can get the number of the feedback sessions from each cluster; the useful distributions of user search goals can be obtained. The ratio of the number of the feedback sessions in the one cluster and the total number of all the feedback session is the distribution of the corresponding user search goal.

B. EVALUATION BASED ON RESTRUCTURING WEB SEARCH RESULTS

The evaluation of a user search goal into ference is a big problem, since user search goals are not predefined and there is no ground truth. Previously has not proposed a suitable approach on this task. Since the optimal number of clusters is still not determined when inferring user search goals, a feedback information is needed to finally determine the best cluster number, Therefore, it is necessary to develop a metric to evaluate the performance of the user search goal inference objectively. Considering that if user search goals are inferred properly, the search results can also be restructured properly, to restructuring web search results is one application of inferring user search goals. Therefore, we propose an evaluation method based on restructuring web search results to evaluate whether user search goals are inferred properly or not. Here we propose this novel criterion "Classified Average Precision" to evaluate the restructure results. Based on the proposed criterion, we also describe the method to select the best cluster number. Restructuring web search results since search engines always return millions of search results, it is necessary to organize them to make it easier for the users to find out what they want. Restructuring web search results is an application of inferring user search goals. Which we will introduce how to restructure web search results by inferred user search goals at first.Then, the evaluation based on restructuring the web search results will be described. The inferred user search goals are represented by the vectors in and the feature representation of each of the URL in the search results can be computed. Then, we can categorize each URL into a cluster centered by the inferred search goals. In this paper, we perform categorization by choosing the smallest distance between the URL vector and user-search-goal vectors. So the search results can be restructured according to the inferred user search goals.

III. METHODOLOGIES

In image search, when users submit a query, they will usually have some vague figures or concepts in their minds as shown in Fig. 8. For the query "apple," some users want to search the fruit apple. They usually know what an apple looks like. The shape should be round and the color should be red or green, etc. These are the common attributes (i.e., visual patterns) of the fruit apple to distinguish the fruit apple from other things. Meanwhile, other users may want to search the computer or the cell phone of Apple Inc. These two search goals also have their own visual patterns. Therefore, users will use these vague figures consisting of those particular visual patterns in their minds rather than external texts to decide whether an image satisfies their needs.

A. QUERY IMAGE

When an image searches in search engines, that corresponding images are loaded in particular time, meanwhile among them there is a un-categorized images are also spotted. However, producing such databases containing a large number of images and with high precision is still manual task. Generally Image search engines apparently provide an effortless route. For this type of obtaining images which can be filter and arrange. The results of the applicable images are assembled and our objective in this work is to rank a large number of images of a particular class automatically, to achieved with high precision.

Image clusters for each topic are formed by selecting image where nearby text is top of the ranked by the topic. A user then partitions the clusters into positive and the negative for the class. Second, images and the associated text from these clusters are used and text features.

B. DOWNLOAD ASSOCIATE IMAGES

The first approach, named Web Search, are submits the query word to Google Web search and all images that are linked within the returned Web pages are downloaded. The Google limits the number of returned Web pages to 1,000, but many of the Web pages contain multiple images, The thousands of images are obtained. The second approach, Image Search, starts from Google image search. Google image and search limits the number of returned images to 1,000, but here, each of the returned images is treated as a "seed"—for further images are downloaded from the Web page where the seed image originated.

The third approach, Google Images, includes only the images directly returned to Google image search. The query can consist of a single word and more specific descriptions such as "penguin animal" or "penguin OR penguins." the Images should be smaller than 120 where 120 are discarded. In addition to the images, text surrounding the image HTML tag is downloaded, together with other Meta data such as the image file name. The Image Search gives a very low precision and is not used for the harvesting experiments. This low precision is probably due to the fact of that Google selects many images from Web gallery pages which contain images of all sorts. Google is able to select in-class images from those pages, e.g., the ones with the object-class in the file name; however, if we use the Web pages as seeds, the overall precision greatly decreases. So, we only use Web Search and Google Images, which is use to merged into one data set per object class. Here the query has to be transformed to the protocol, authority, host name, port number, path, query, file name, and reference from a URL using some methods.

C. SVM Implementation

A support vector machine (SVM) is a concept in a statistics and computer science for a set of related supervised learning methods which analyze data and recognize patterns, used for classification and regression analysis. The standard support vector machine takes a set of input data and predicts, for each of given input, which of two possible classes comprises in the input, making the support vector machine a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of the two categories, an support training algorithm builds a model that assigns with new examples into one category or the other. An support vector machine model is a representation of the examples as points in the space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

D.FILTERING PROCESS

The text re-ranker performs well, on average, and significantly improves to the precision up to quite a high recall level. To re-ranking the filtered images, which applied the text and vision system to all images downloaded for one specific class. It is interesting to note that the performance which is comparable to the case of filtered images. It means that the learned visual model is strong enough to remove the drawings and the symbolic images during the ranking process. So that, the filtering is only necessary to train the visual classifier and this is not required to rank new images, However, using unfiltered images during training decreases the performance significantly, so, the main exception here is the airplane class, where the training with filtered images is a lot worse than with unfiltered images.

Handled by the surveillance system will effectively mean that reliable results could only be expected for short periods of time.

IV. RELATED WORK

The new Framework which combines image visual information and click session information for inferring user image-search goals for a query. Spectral clustering With K Means for handling the arbitrary cluster and shape scenario during clustering. The classification risk (CR) is based on approach to automatically decide the optimal number of search goals for a query. Where we will get the images as per output so, that its efficiency is high. To complete online process and achieve accuracy of the image. The system should be robust and performance of the proposed method is more compared with existing methods. By Inferring the user image search goals for those popular queries can be very useful, and our proposed method can also be extended for a new query. In recent years, the research on inferring user goals and intents for text search has been received much attention. In early researches define user intents as navigational and informational, or by some specific predefined aspects, such as product intent and job intent.

Some works focus on tagging queries with more hierarchical predefined concepts to improve feature representation of queries. However, in fact, these applications belong to query classification. The user search for goals and the number of them should be arbitrary and not predefined. Some works analyze the

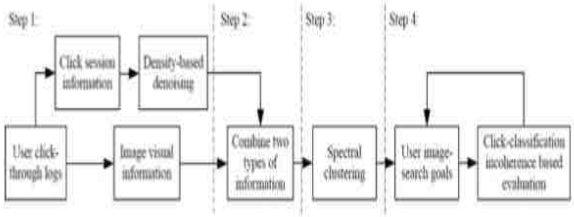

Fig. 3. Framework of our approach.

Clicked documents for a query in user click by the logs to explore user goals. However, the click session information is not fully utilized. Although there has been much more research on the inferring user goals for text search, few methods were proposed in image search. Zha et al. who try to capture user goals to give visual suggestions for a query in the image search. They first select some tag words as textual suggestions by satisfying two properties: one of that is relatedness and other one is in formativeness. Then, they collect the images associated with a suggested keyword and also cluster these images to select representative images for the keyword. However, the good performance of their method depends on the precision of tags. n many web image search engines, manual tags are not available and only external texts are achievable In these cases, the performance of may be decreased by using external texts as the external texts are not as reliable as tags. The research on diversity in retrieval is relevant to user goal inference .It aims to diversify the results retrieved for an ambiguous query, with the hope which at least one of the interpretations of the query intent will be satisfy the user. In early works, Carbonell et al. Introduced marginal relevance into the text retrieval by combining query relevance with information-novelty. This information-novelty can be considered as low-level textual content novelty. Recent works model the diversity based on a set of sub-queries. The sub-queries are generated by simply clustering the documents for search results or by query expansion. This diversity can be considered as high-level semantic diversity. The research on the diversity in image retrieval has just started. We consider the diversity and novelty of image retrieval as a high-level image semantic diversity and the low-level visual content novelty, respectively. The inferred user image-search goals in this paper can exactly utilized to diversify the image search results from high-level image semantics. Our goal-inference method is based on image clustering using similarity graphs. There has been some research on image clustering with different types of information. Cai et al. first use textual and the link information to cluster the images in web pages, and then they use visual the information to further cluster which the images in each cluster. They consider that as a single web page often contains multiple semantics and the blocks in a page containing different semantics should be regarded as information units to be analyzed. They define link information as the relationships between the page, block, and image. However, when we cluster the images for the query to infer user goals, there are no such blocks or link information. Instead, we use click information in this paper. Cheng et al. first divide a session into the positive part ξ+ and the negative part ξ−. After that, they merge the positive parts into chunk lets only, if the positive parts contain an image in common, and the edges between chunk lets are then added if the images in ξ+ and ξ− of a session appear in two chunk lets, respectively. Finally,the clustering is implemented on the chunk let graph. Although their method tried to introduce user information for facilitating visual information, it still has limitations since this method requires the users to identify ξ+ and ξ− in each session. However, in real data, it is difficult to divide ξ+ and ξ− precisely and ensure that the images in a chunk let will not appear in both ξ+ and ξ− of a session simultaneously. Poblete et al. propose to use queries to reduce the semantic gap. They define the semantic similarity graph as an un directed bipartite graph, whose edges connect a set of the relative queries and the clicked images of these queries.However, if the set of this queries are irrelative, there may be few or no images shared by multiple queries . In this case, the queries and their clicked images in the bipartite graph are independent and the semantic similarity graph can not provide any semantic information. This situation often happens if we randomly select a small set of queries from query logs.In this paper, we use the clicks by different users for the same query to reduce the semantic gap. Thus, our algorithm is flexible to construct the semantic similarity graph for an individual query instead of a set of queries.

V. CONCLUSION

In this paper, we proposed to leverage a click session information and combine it with image visual information to the infer user image search for finding the goals. By click session information can serve as the implicit guidance of the past users to help clustering. Based on this framework, we proposed two strategies which use to combine image visual information with click session information. Furthermore, a click-classification incoherence based on approach was also proposed to automatically select by the optimal search goal numbers. Experimental results demonstrated that our method can infer by user image search goals precisely. It is worth noting that the proposed method in this paper focused on analyzing a particular query appearing which in the query logs. The inferring user image search goals for those popular queries which can be very useful, and our proposed method can also be extended for a new query. For example, we can infer user image search for such goals to a group of similar queries instead of a particular query. The new query will be classified into a query of Group at first. Then the user search goals for the query group can be considered as the ones for this new query.

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