I J C T A, 9(15), 2016, pp. 7159-7166

Efficient Image-Based Searching for the Improvement of User Search

Manisha Nath and N. Praveen

ABSTRACT

The analysis of a user search goals for a query can be very useful in improving search engine appropriateness and the user experience. The research on inferring by user goals and intents for text search has received more attention. In this paper, we propose to leverage click session information, which will indicate by the high correlations among the clicked images in a session user logs and combine it with the clicked image visual information for inferring the user image-search. Since the click session information can serve as previous user 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. A classification risk based 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 demonstrating the effectiveness.

Keywords: click-through logs, goal images and image-search Goals, semi-supervised clustering, spectral clustering.

1. INTRODUCTION

In web search applications, the users submit queries (i.e., some keywords) to search engines for representing their search goals. In some cases, the inquiries may not accurately represent 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 examples for user image-search goals which discussed in this paper. In Fig. 1.In this proposed results; can find that the users have the different search goals for the same query due to the following three reasons.

1) Multi-concepts: Here keyword represents different things. For an example, a kind of fruit, “Apple” ends with new concepts by that apple, 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. It can be represented by a real scene and also by the close-up. The user search goals are very important to improve search-engine relevance and user experience. Generally, the captured user image-search goals can also be utilized in many applications. For example, we can take user image-search goals are visual query suggestions to help users reformulate their queries.

During image search. Also, we can also categorize search results for an image-search according to the inferred user image-search goals to make it easier for users to browse. Furthermore, the proposed system can also diversify and also re-rank the results retrieved for a query in image search with the discovered for user image-search. Thus, the user image-search goals are one of the key techniques which improve users search experience. However, there also have much research for text search; few methods were proposed to

* Department of Computer science and engineering SRM University Chennai, India, *Email: Manishanath1991@gmail.com*

** Department of Computer science and engineering SRM University Chennai, India, *Email: npraveencs29@gmail.com*

the user search goals in image search. Sometimes use to discover a user image-search goals based on textual information. However, since external texts are not always reliable and tags are not always available these textual information based on limitations. It should be possible to user image-search goals with visual information of images since different image-search goals to be distinguished from the each other. However, since there are some gaps between two features that are existing image features and the image semantics, inferring user image-search goals by the visual information is still a huge challenge. Therefore, in this paper, we propose to introduce additional information sources to help narrow these semantic gaps.

Intuitively, click-through user information from past users can provide better guidance about to the semantic correlation among images. By mining the click-through user logs, we can obtain two kinds of information the click content information and the click session information. A session in click-through user log is a sequence of the queries and a series of clicks by the user toward addressing single information. In this paper, define a session in image search as a single query and also a series of clicked images in Fig. 2. Usually, clicked images in a session have high interrelations. This correlation information provides hints

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

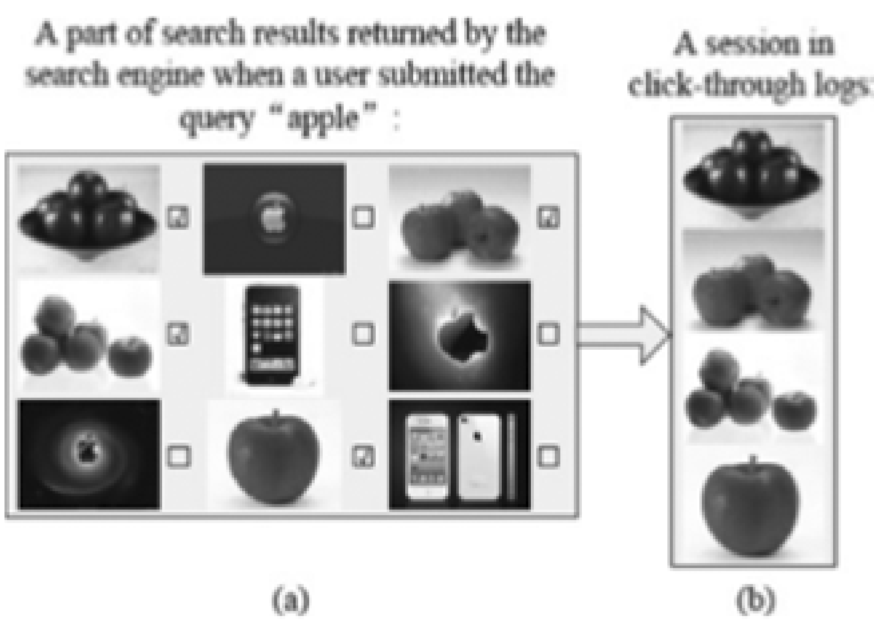

Figure 2: Session for the query apple in user click-through logs. (a) Search results returned by the search engine. The check marks mean that the images were clicked by the user. (b) Session in user click-through logs.

on which images belong for same search goal from the viewpoint of image semantics. So, here, we propose to introduce this correlation information to reduce semantic gaps between the existing image and the Image semantics. More specifically, this paper proposes the cluster the clicked images for a query in user click through logs under the guidance of click session. 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 visual image information and the click session information for inferring user image-search goals. In this way, for more precise image-search goals can be achieved. 2) We propose the two strategies to proficiently 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, we further propose a classification risk (CR)-based approach

Fig. 2. Session for a query Apple in click-through user logs. (a) Search results returned by the search engine. (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 by introducing some related works. The framework of approach establishes the edge reconstruction based strategy to combine visual image information and familiarizes the goal-image-based strategy. The clustering method for achieving search goals like the CR-based approach to optimize the number of user search.

2. 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 figures and with numbers of unrelated figures. 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 the image provided by the text-based image containing relevant and irrelevant image results. Which all of the existing algorithms require a prior assumption regarding the relevance of the figures in the initial, text-based search result.

2.1. Inferring User Search Goals by Clustering Pseudo-documents

With the proposed pseudo-documents, that can infer user search objective. Here, it will describe how to user search goals and depict them with some meaningful keywords. The feedback session is represented by the pseudo-document, and also, the feature representation of the pseudo-document is FFS. The similarity between two pseudo-documents is used to compute as the cosine score of FFS I, and FFS J, as follows:

$$\text{Sim}_{\text{I: J} = ¼} \cos \left(F_{\text{FS Ii; FFS J}}\right)$$
$$=$$
$$\left(F_{\text{FS I, FFS j}}\right) / |\text{J FFSIK}||F_{\text{FSJK}}|$$

And the distance between two feedback sessions is

$$\text{Dis I: J} = 1\_\text{Simi; j}$$

The pseudo cluster document by K which means clustering which is minimalist and the effective. Here do not know the exact number of the user search goals for the each query, it set K to be five different values and perform clustering based in five values, respectively. So determine the optimal value to the evaluation criterion. After clustering all the pseudo documents, where each cluster can be considered as one user search goal. F centers are utilized to conclude the search goal of the ith set. Finally, the terms of the highest values in center points are used as the keywords to depict the user search objectives. Note that an additional advantage of using this keyword based description is which the extracted keywords can also be utilized to form a meaningful query and thus can represent the user information needs more accurately. Moreover, It can get the number of the feedback sessions from each set, the useful distributions of user search goals can be obtained. The ratio of the number of the feedback sessions in the one set and the total number of all the feedback session is the distribution of the corresponded user search goal.

2.2. Evaluation Based on Restructuring Web Search Results

The assessment of a user search objective into reference is a big problem since user search goals are not predefined, and there is no ground truth. Previously suitable approach in this task was not proposed. Since the optimal number of clusters is still not determined when inferring user search goals, feedback information is needed to determine finally the best set number. Therefore, it is necessary to develop a metric to evaluate the performance of the user search objective inference objectively. Considering that if user search goals are inferred effectively, the search results can also is restructured properly. Therefore, we propose an evaluation method based on restructuring web search results to evaluate whether user search goals are inferred properly or not. Here the propose is criterion “Classified Average Precision” to calculate the restructure results. Based on the proposed criteria, here also describe the method to select the best cluster number. Restructuring web search results since search engines always return; 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. This will introduce how to restructure web search results by inferred the user search 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. Then, we can categorize each URL into a cluster centered on the inferred search goals. In this paper, 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 objectives.

2. METHODOLOGIES

In image search, when users submit a query, they will usually have some vague figures or concepts in their minds. For the query “Apple,” some users want to search the fruit apple. They usually know what an Apple looks. The shape should be round and the color should be red or green, etc. These are the common attributes of the fruit apple to distinguish the fruit apple from other things. Other users may want to search the computer or the cell phone of Apple. These two search goals also have their particular visual patterns. Therefore, users will use these vague figures consisting of those particular visual patterns in their minds rather than external texts.

2.1. Query Image

When in search engines, those corresponding images are loaded in particular time, meanwhile among them there an uncategorized image also spotted. Anyhow producing such databases containing a large number of figures and with high precision is still a manual task. Generally, Image-search-engines apparently provide an easy route. The results of the applicable figures are assembled and our objective in this work is to rank a large number of images of a particular class automatically, to achieve 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 sets into positive and the negative for the class. Second, images and the associated text from these sets are used, and text features.

2.2. DOWNLOAD ASSOCIATE IMAGES

The first approach, named Web Search, submits the query word to Google Web search, and all images that are linked within the returned Web pages are downloaded. The Google limit the number of returned Web pages to 1,000, but many of the Web pages contain multiple figures. 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 more images are downloaded from the Web page.

The third approach, Google Images, includes only the images directly returned to Google search. The query can consist of a single word and more particular descriptions. The Images should be smaller than 120 where 120 are discarded. In addition to the images, text surrounding the HTML image tag is downloaded, together with other meta-data such as the figure file name. The Image Search gives a lower precision and is not used for the harvesting experiments. This lower precision is probably due to the fact of that Google selects many images from Web gallery pages which contain figures of all sorts. Google can select in-class images from those pages, e.g., the ones with the class object in the file name; however, if we use the Web pages as seeds, the overall precision decreases. So, user only uses 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.

2.3. SVM Implementation

A support vector machine (SVM) is a concept in a statistics and computer science for a set of related supervised methods which analyze data and recognize patterns. This used for classification and regression analysis. The standard support vector machine takes a set of input data and predicts, for given input, which of two possible classes comprises in the data, making the support vector machine a non-probabilistic binary linear classifier. Given a examples, each marked as belonging to one of the two categories, a support training algorithm builds a model that assigns with new examples into one category to the other. A 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.

2.4. Filtering Process

The text re-ranker performs well, on average, and significantly improves to quite a high recall level. To re-ranking the filtered images, that applied the text and vision system to all images downloaded for one particular 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 difficult to remove the drawings and the symbolic images at 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 sequentially, 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 the expected for short periods of time.

3. RELATED WORK

The new framework, which combines visual image 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. The classification risk (CR) is based on the approach to automatically decide the optimal number of search goals. Where we will get the images as per output so, that its efficiency is high. To complete online process and achieve the accuracy of the image search. 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 the proposed method can also be extended for a new query. In recent years, the researches on inferring user goals and intents for text search have much attention. In searches define user aim as navigational and informational, or by some of specific

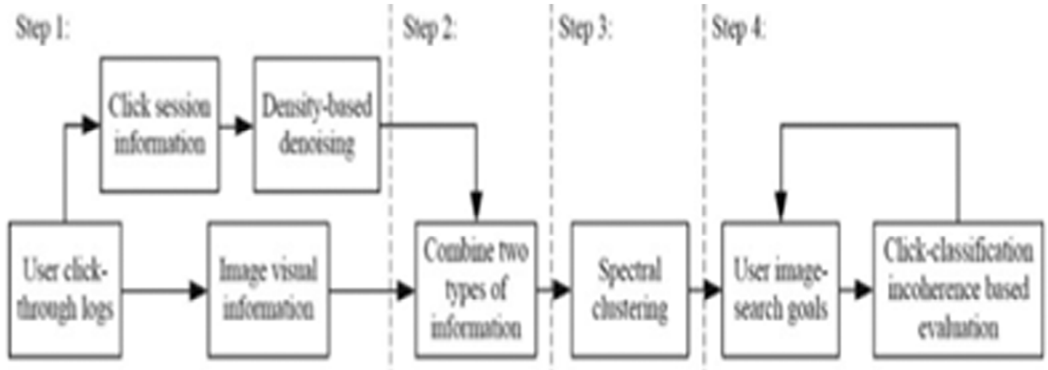

Figure 3: Framework of our approach.

predefined aspects, such as product aim and job aim. Some works focus on tagging queries with more hierarchical predefined concepts to improve feature representation. However, in fact, these applications belong to query classification. The user search for goals and the number of them should be arbitrary. Some works analyze the 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. It 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 another one is informativeness. Then, they collect the images associated with a suggested keyword and also cluster these images for the keyword. However, the better performance of their method depends on the precision of tags and many web image search engines, manual tags are not available, and only extrinsic words are achievable In these cases, the performance of may be decreased by using 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 satisfy the user. In early works, Carbonell et al. Introduced marginal relevance into the text retrieval by combining query. This information-novelty can be considered as the 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. This difference can be considered as high-level semantic diversity. The research on the diversity in image retrieval has just started. It considers the diversity and newness of image retrieval as a high-level image semantic diversity and the low-level visual content newness, respectively. The inferred user image-search goals in this paper can exactly utilize to diversify the image search results from high-level image. Our goal-inference method is based on image clustering. There has been some research on image clustering with different types of information. The textual and the link information to cluster the images in web pages, and then they use visual information to further cluster the images. They consider that as a single web page often contains multiple semantics and the blocks in a page containing different linguistic should be regarded units to be analyzed. They define link information as the relationships between the page, block, and image. When we cluster the images for the query to infer user goals, there are no such blocks or link information. Instead, It 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 fractions into portions lets only, if the positive fractions contain an image in common, and the edges between chunk lets are then added if the figures in ξ+ and ξ" of a session appear in two chunk lets. Finally, the clustering is implemented on the chunk let graph. Although their approach tried to introduce user information for facilitating visual information 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 undirected bipartite graph, whose edges connect a set of the related queries.However, if the set of this queries are irrelative, there may be few or no images shared by the numerous queries. In this case, the queries and their clicked images in the bipartite graph are independent. This situation often happens if we randomly select a small set of queries from query logs.In this paper, use the clicks by different users for the same query to reduce the semantic gap. Thus, the algorithm is flexible to construct the semantic similarity graph for an individual query.

4. CONCLUSION

In this paper, we proposed a click session information and combine it with image visual information to the infer user image search. By click session, information, can serve as the implicit guidance of the previous users to help the cluster. Based on this framework, we proposed two strategies which use to combine visual image information with click session information. Furthermore, a click-classification incoherence based on approach was also recommended to automatically select by the optimal search objective numbers. Experimental results demonstrated that the 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. The inferring user image search goals for those popular inquiries which can be very useful and the proposed method can also extend for a new query. For example, we can infer user image search for such goals to a group of similar inquiries instead of a particular query. The new query will classify into a query of group at first. Then the user search goals for the inquiry group can be considered.

REFERENCES

[1] D. Tjondronegoro, A. Spink, and B. Jansen, a Study, and Comparison of Multimedia Web Searching: 1997–2006, vol. 60, Wiley Online Library, 2009, pp.

[2] B. Jansen, A. Spink, and J. Pedersen, “The effect of specialized multimedia on web searching,” J. Web Eng., vol. 3, pp. 182–199, 2004.

[3] B. Jansen, A. Goodrum, and A. Spink, “Searching for multimedia: Analysis of audio, video and image web queries,” World Wide Web, vol. 3, 2000.

[4] Z. Zha, L. Yang, T. Mei, M. Wang, Z. Wang, T. Chua, and X. Hua, “Visual query suggestion: Toward capturing user intent in internet image search,” ACM Trans. Multimedia Comput., Commune, vol. 6, no. 3, , 2010.

[5] H. Chen and S. Dumas, “Bringing order to the web: Automatically categorizing search results,” in Human Factors 2000, pp. 145–152.

[6] S. Wan, Y. Xue, X. Yu, F. Guan, and X. Cheng, ICTNET at Web Track 2011 Diversity Task. MD, USA.

[7] R. Santos, C. Macdonald, and I. Ounis, “Exploiting query reformulations for web search result diversification Conf. WWW, 2010, pp. 881–890.

[8] U. Lee, and J. Cho, “Automatic identification of user goals in web search,” in Proc., 2005, pp. 391–400.

[9] D. Rose and D. Levinson, “Understanding user goals in web search,” in 2004, pp. 13–19.

[10] X. Li, Y. Wang, and A. Acero, “Learning query intent from regularized click graphs,” in Proc. 31st Annu. Int. ACM SIGIR Conf. Res. Develop. vol. 339. 2008, p. 346.

[11] X. Wang and C. Zhai, “Learn from web search logs to organize search results,” in Proc. 30th Ann. Int. ACM SIGIR Conf. Res. Develop. Retrieval, 2007, pp. 87–94.

[12] Z. Lu, X. Yang, W. Lin”A new algorithm for inferring user search goals with feedback sessions,” 2011.

[13] Z. Lu, X. Yang, W. Lin, and H. Zha, “Inferring users’ image search goals with pseudo-images,” in Proc. IEEE Visual Commun. Image Process. 2011, pp. 1–4.

[14] D. CAI, X. He, Z. Li, W. Ma, and J. Wen, “Hierarchical clustering of www image search results using visual, textual and link information, “in Proc. 12th Annu. ACM Int. Conf. Multimedia, 2004, pp. 952–959.

[15] P. Ensor and C. Sandom, “Toward a comprehensive survey of the semantic gap in visual image retrieval,” in Proc, 2003, pp. 163–168.

[16] R. Jones and K. Klinkner, “Beyond the session timeout: Automatic hierarchical segmentation of search topics in query logs,” in Proc. 17th ACM Conf. Inform. Knowl. Manage. 2008, pp. 699–708.

[17] D. Shen, J. Sun, Q. Yang, and Z. Chen, "Building bridges for web query classification image search," in Proc. 29th Annu. Int. ACM SIGIR, 2006, pp. 131–138.

[18] R. Baeza-Yates, C. Hurtado, and M. Mendoza, "Query Recommendation Using Query Logs in Search Engines," Proc. Concurrent Trends in Database Technology, pp. 588-596, and 2004.