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an efficient online image retrieval based on user query expansion

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Abstract—Image re-ranking is a valuable method for an online-based image search. The examine based on only keywords pressed by the users is not proficient and results in unfixed output. The online-based image search recycled by Bing and Google uses image re-ranking technique. In an image that, users' objective is caught by one-click on the query image. This supports in given that better search results towards the users. Now we evaluate the technique in which a query keyword is first recycled to get back an excess of images constructed on the keyword. Image re-ranking structure mechanically learns dissimilar semantic spaces offline for dissimilar query keywords. Their visual structures are projected into their associated semantic spaces to catch semantic signatures for images. Images are re-ranked by differentiating their semantic signatures and the query keyword throughout the wired stage. The query-specific semantic signatures, meaningfully increase both the accuracy and efficiency of the re-ranking procedure. In future, it is proved to be a better method than the conservative online-based image search techniques.

Keywords: Re-ranking, query image, query keyword, semantic signature.

I. INTRODUCTION

Web image search engines use keywords as queries and search images based on the text associated with them. It is difficult for users to accurately describe the visual content of target images only, using keywords and hence text-based image search suffers from the uncertainty of query keywords. For instance, consuming apple as a query keyword, the regained images fit to dissimilar categories, such as apple laptop, apple logo, and apple fruit. To capture users' search intention, additional information has to be used in order to solve the ambiguity. Text-based keyword expansion is one way to make the Textual description of the query more detailed. Existing methods find either synonyms or other linguistics-related words from the thesaurus. However, the intention of users can be highly diverse and cannot be accurately captured by these expansions, even with the same query keywords. Content-based image retrieval with relevance feedback is widely used in order to solve this ambiguity. Users are required to select multiple relevant and irrelevant image examples and the visual similarity metrics are learned through online training from them. Images are re-ranked based on the learned visual similarities. However, for web-scale commercial systems, user's response has to be incomplete to the least lacking online training. In the method reviewed in this paper, a query keyword is first recycled to regain a set of images created on the keyword. Then the user is asked to pick an image from these images. Also, the rest of the images are ranked based on their visual similarities. The major challenge is the correlation of similarities of visual features and images' semantic meaning, which are needed to interpret users' intention to search. Recently, it has been suggested to contest images in a semantic space that used attributes or reference classes closely associated to the semantic meanings of images as base. Conversely, characterizing the highly varied images from the network is challenging because it is impossible to learn a universal visual semantic space. In this, a new framework was proposed to re rank the web images. As a substitute of physically describing a universal conception dictionary, it studies dissimilar semantic spaces for dissimilar query keywords independently and mechanically. The semantic space associated to the

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images to be re ranked and it can be meaningfully pointed down by the query keyword delivered through the user. For instance, if the query keyword is “Paris,” the concepts of “mountain” and “apple” are irrelevant to the query keyword so it will be excluded. As a replacement for, the concept of“computer” and “fruit” will be used as magnitudes to acquire the semantic space associated to the query keyword “apple”. The semantic correlation among perceptions are explored and combined while calculating the resemblance of semantic signatures. Another important issue in this paper is, we didn’t consider increasing the miscellany of search result by eliminating near-duplicate or much related images. The query specific semantic signatures are suggested to diminish semantic gap on the other hand it can’t openly raise the miscellany of search result.

II. RELATED WORK

The fundamental factor of image re-ranking is to calculate visual similarities replicating semantic significance of images. Many visual features have been established in recent years. Though, instead of dissimilar query images, the active low-level visual features are diverse. Consequently, query images are classified into eight predefined significance arrangements and gave dissimilar feature weighting schemes to diverse types of query images. But to cover the large diversity of all the web images it was difficult for the eight weighting schemes. It was also probably for a query image to be categorized to a wrong classification. In order to decrease the semantic gap, query-specific semantic signature was first proposed and it recently increased each image with related semantic features over propagation in excess of a visual graph and a textual graph which were correlated. Alternative way of learning visual resemblances without tallying users’ liability is pseudo relevance feedback. It takes the top N images most visually related to the query image by means of stretched optimistic examples to learn a resemblance metric. Computing the visual similarities that reflect the semantic relevance of images is the key component of image re-ranking. Many visual features have been developed in recent years. However, the operative low-level visual features are dissimilar for different query images. Therefore, Cui *et al*. categorized query images into eight predefined objective categories and offered diverse feature weighting schemes to dissimilar types of query images. But it was difficult for the eight weighting schemes to cover the large diversity of all the network images. It was also expected for a query image to be categorized to a wrong category. Query-specific semantic signature was first proposed in in order to reduce the semantic gap.

There is a lot of work on using visual features to re-rank images retrieved by initial text-only search, however, without requiring users to select query images. Jing and Baluja proposed Visual Rank to analyze the visual link structures of images and tofind the visual themes for re-ranking. Cai*et al*. re-ranked images with attributes which were manually defined and learned from manually labeled *Harshil Jain et al* training samples. These approaches assumed that there was one major semantic category under a query keyword. Images were re-ranked by modeling this dominant category with visual and textual features.

A. Re-Ranking without Query Images

Query-specific semantic signature can be applied to image re-ranking without selecting query images. This application also requires the user to input a query keyword. But it assumes that images returned by initial text-only search have a dominant topic and images belonging to that topic should have higher ranks. Existing approaches typically address two issues: (1) how to compute the similarities between images and reduce the semantic gap; and (2) how to find the dominant topic with ranking algorithms based on the similarities. The query-specific semantic signature is effective in this application since it can improve the similarity measurement of images.

The query-specific semantic signature is also effective in this application, where it is crucial to reduce the semantic gap when computing the similarities of images. Due to the ambiguity of query keywords, there may be multiple semantic categories under one keyword query. These approaches cannot accurately capture users’ search intention without query images selected by users. In recent times, general image appreciation and toning, there have been a amount of works on using projections over predefined concepts, attributes or reference classes as image signatures. The classifiers of concepts, attributes, and reference classes are trained from known classes with labeled examples. But the knowledge learned from the known classes can be transferred to recognize samples of novel classes which have few or even no training samples. Since these concepts, attributes, and reference classes are defined with semantic meanings, the projections over them can well capture the semantic meanings of new images even without further training. Rasiwasia *et al* plotted visual features to a worldwide concept vocabulary for image retrieval. Attributes with semantic meanings were used for object detection and recognition, face recognition, action recognition, image search and 3D object retrieval. Lampert *et al*. predefined a set of attributes on an animal database and detected target objects based on a combination of human-specified attributes instead of training images. Parikh and Grauman proposed relative attributes to indicate the strength of an attribute in an image with respect to other images. Some methods transportedinformation between object classes by calculating the similarities amongst novel object

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classes and known object classes are called reference

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classes. For example, Torresani*et al.* proposed an image descriptor which was the output of a number of classifiers on a set of known image classes, and used it to match images of other unrelated visual classes.

Online image re-ranking limits users' effort to just one-click feedback is an effective way to improve search results and its query not only increase the computational cost but also deteriorate the accuracy of re-ranking. However, how to find such relevant concepts automatically and use them for online web image re-ranking was not well explored in the conventional.

III. PROPOSED SYSTEM

The new image re-ranking framework focusses on the semantic signatures associated with the images. These semantic signatures are derived from the visual features associated with the images but are much shorter than the visual features. The diagram of the approach is shown in Fig. 2. It has offline and online portions. At the offline point, the reference classes (which represent different concepts) related to query keywords are automatically discovered and their training images are automatically collected in several steps. For a query keyword (for example apple), automatic selection of a set of maximum related keyword expansions (such as red apple and apple MacBook) is performed utilizing both textual as well as visual information. This set of keyword expansions describes the reference classes for the query keyword. In order to robotically acquire the training instances of a reference class, the keyword expansion (e.g., red apple) is recycled to regain images by the search engine originated on textual information over again. Images retrieved by the keyword expansion (red apple) are much fewer unrelated than those regained by the unique keyword (apple). The recovered top images are used as the working out examples of the reference class after robotically eliminating outliers. some reference classes (such as apple laptop and apple macbook) have related semantic meanings and their exercise sets are visually related. The redundant reference classes are removed in order to increase the proficiency of online image re-ranking. To better measure the similarity of semantic signatures, the semantic correlation between reference classes is estimated with a web-based kernel function. For each query keyword, its reference classes forms the basis of its semantic space. A multi-class classifier on visual and textual features is skilled from the exercise sets of its reference classes and deposited offline. Under a query keyword, the semantic signature of an image is extracted by computing the resemblances amongst the image and the reference classes of the query keyword using the trained multiclass classifier. If there are K types of visual/textual features, such as color, texture, and shape, one could combine them together to train a single classifier, which extracts one semantic signature for an image. A separate classifier for each type of feature can also be trained. Then, the K classifiers based on different types of features extract K semantic signatures, which are combined at the later stage of image matching. An image may be associated with multiple query key-words, which have different semantic spaces affording to the word- image index file. Hence, it may have different semantic signatures. The query keyword input by the user decides which semantic signature to choose. As an example shown in Fig. 2, an image is associated with three keywords apple, mac and computer. When using any of the three keywords as query, this image will be retrieved and re-ranked. However, under different query keywords, different semantic spaces are used. Therefore an image could have several semantic signatures obtained in different semantic spaces. They all need to be calculated and deposited offline.

At the online point, the search engine, affording to the query keyword, regains a pool of images. Meanwhile all the images in the pool are connected with the query keyword according to the word-image index file; they all have pre-computed semantic signatures in the same semantic space identified by the query keyword. Once the user chooses a query image, these semantic signatures are used to compute image similarities for re-ranking. The semantic correlation of reference classes is incorporated when computing the similarities and interaction is simple enough. Major web image search engines have adopted this strategy. Its diagram is shown in Fig. 1. Given a query keyword input by a user, a pool of images relevant to the query keyword is retrieved by the search engine according to a stored word-image index file. Usually the size of the returned image pool is fixed, e.g., containing 1000 images.

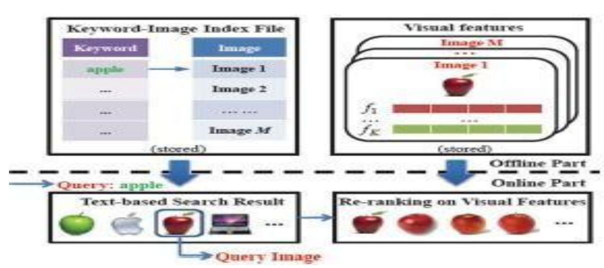

Fig. 1. The conventional framework for image re-rankinThe user is asked to select a query image from the pool.

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This image reflects the user's search intention and

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the remaining images in the pool are re-ranked based on their visual similarities with the query image. The word-image index file and visual features of images are pre-computed offline and stored. The main online computational cost is on comparing visual features. To achieve high efficiency, the visual feature vectors need to be short and their matching needs to be fast. Some popular visual features are in high dimensions and efficiency is not satisfactory if they are directly matched. In the current approaches, all the concepts/ attributes/ reference-classes are universally applied to all the images and they are manually defined. They are more suitable for offline databases with lower diversity (such as animal data- bases and face databases), since image classes in these databases can share similarities in a better way. A huge set of concepts or reference classes are required to model all the web images, which is impractical and ineffective for online image re- ranking. Intuitively, only a small subset of the concepts is relevant to a specific query.

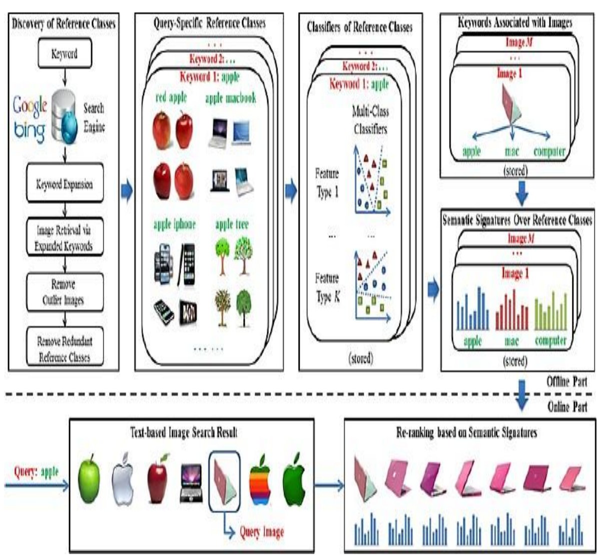

Fig.2.A new image re-ranking frame work

The conventional framework compares images based upon their visual features. The length of these visual features is much longer than that of the semantic signatures used in the new framework. Hence, the computational cost is higher. Compared with the conventional image re-ranking diagram in Fig. 1, the new approach is much more efficient at the online stage, because the main online computational cost is on comparing semantic signatures and the lengths of semantic signatures are much shorter than those of low-level visual features.

IV. SYSTEM DESIGN

Figure 3 demonstrates the framework of our proposed approach. In that user have to enter the query keyword into the search engine. Then search engine will return thousands of images based on text-based search. At that point our new framework will do re-rank the images by the following modules:

A. Keyword Expansion

Database keyword search (DB KWS) has received a lot of attention in the database research community. Although much of the research has been motivated by improving performance, recent research has also paid increased attention to its role in the database contents exploration or data mining. In this paper, we explore aspects related to DB KWS in two steps: First, we expand DB KWS by incorporating ontologies to better capture users' intention. Furthermore, we examine how KWS or ontology-enriched KWS can offer useful hints for better understanding of the data and in-depth analysis of the data contents, or data mining

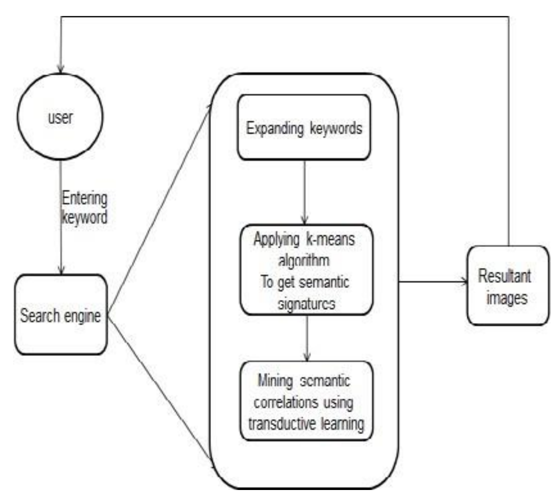

Fig. 3. System architecture

B. Semantic Signatures

Choosing keywords plays a main role in scheming semantic signatures; careful choice of keywords leads to a more accurate analysis, especially in English, which is sensitive to semantics. It is interesting to note that when words appear in different contexts they carry a different meaning. We have incorporated stemming within the framework and its effectiveness is demonstrated using a large corpus. We haveconducted experiments to demonstrate the sensitivity of semantic signatures to subtle content differences between closely related documents. These experiments show that the newly developed

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framework can identify subtle semantic differences substantially.

C. Semantic Correlations

Although multimedia objects such as images, audios and texts are of different modalities, there is a great amount of semantic correlations among them. In this paper, we propose a method of transductive learning to mine the semantic correlations among media objects of different modalities so that to achieve the cross-media retrieval. Cross-media retrieval is a new kind of searching technology by which the query examples and the returned results can be of different modalities, e.g., to query images by an example of audio. First, according to the media object features and their co-existence information, we construct a uniform cross-media correlation graph, in which media objects of different modalities are represented uniformly.

To perform the cross-media retrieval, a positive score is assigned to the query example; the score spreads along the graph and media objects of target modality or MMDs with the highest scores are returned. To boost the retrieval performance, we also propose different approaches of long-term and short-term relevance feedback to mine the information contained in the positive and negative examples.

V. CONCLUSION

In this paper, we have reviewed an Internet based image search approach. We have also discussed the conventional web-based image search techniques and pointed out their shortcomings. The reviewed image re-ranking framework overcomes the shortcomings of the previous methods and also significantly increases together the accuracy and efficiency of the re-ranking procedure. It captures users' intention using a query image. It learns query-specific semantic spaces to significantly improve the effectiveness and efficiency of online image re-ranking. The visual features of images are estimated into their related semantic spaces mechanically learned through keyword expansions offline. The extracted semantic signatures are shorter than the original visual features. In future work, image re-ranking can be further improved by incorporating other metadata and log data along with the textual and visual features for finding the keyword expansions used for defining the reference classes. The log data of user queries provides useful co-occurrence information of keywords for keyword expansion. Finally, in order to further improve the quality of re-ranked images, they should be re-ranked not only by content similarity but also by the visual quality of the images.

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