IMAGE RE-RANKING AS AN EFFECTIVE WAY TO IMPROVE THE RESULTS OF WEB-BASED IMAGE SEARCH.

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ABSTRACT : The Web-Image re-ranking, as an way to improving the results of web-based image search, has been adopted by current search engines like google and Bing .from a query keyword, first a pool of images is retrieved by using google or other search engine based on textual information. For searching the multi media answer we are using the Google search engine as a tool so the answer will get from web data we need to analyze and re-rank the search results. A major challenge is that the similarities of visual features do not well correlate with images' semantic meanings which interpret users' search intention. Recently people proposed to match images in a semantic space which used attributes or reference classes closely related to the semantic meanings of images as basis. However, learning a universal visual semantic space to characterize highly diverse images from the web is difficult and inefficient. In this Project, we propose a novel image re-ranking framework, which automatically offline learns different semantic spaces for different query keywords. The visual features of images are projected into the irrelated semantic spaces to get semantic signatures. At the online stage, images are re-ranked by comparing their semantic signatures obtained from the semantic space specified by the query keyword. The proposed query-specific semantic signatures significantly improve both the accuracy and efficiency of image re-ranking.

Keywords -Image search, image re-ranking, semantic space, semantic signature, keyword expansion

1. INTRODUCTION

Web-scale image search engines mostly use keywords as queries and rely on surrounding text to search images. It is well known that they suffer from the ambiguity of query keywords. For example, using "apple" as query, the retrieved images belong to different categories, such as "red apple", "apple logo", and "apple laptop". Online image reranking has been shown to be an effective way to improve the image search results. Major internet image search engines have since adopted the re-ranking strategy. Its diagram is shown in Figure 1. Given a query keyword input by a user, according to a stored word-image index file, a pool of images relevant to the query keyword are retrieved by the search engine. By asking a user to select a query image, which reflects the user's search intention, from the pool, the remaining images in the pool are re-ranked based on their visual similarities with the query image. The visual features of images are pre-computed offline and stored by the search engine. The main online computational cost of image re-ranking is on comparing visual features. In order to achieve high efficiency, the visual feature vectors need to be short and their matching needs to be fast.
Another major challenge is that the similarities of low level visual features may not well correlate with images' high-level semantic meanings which interpret users' search intention. To narrow down this semantic gap, for offline image recognition and retrieval, there have been a number of studies to map visual features to a set of predefined concepts or attributes as semantic signature. However, these approaches are only applicable to closed image sets of relatively small sizes. They are not suitable for online web- based image re-ranking. According to our empirical study, images retrieved by 120 query keywords alone include more than 1500 concepts. Therefore, it is difficult and inefficient to design a huge concept dictionary to characterize highly diverse web images.

1.1 OUR APPROACH

In this system, a novel framework is proposed for web image re-ranking. Instead of constructing a universal concept dictionary, it learns different visual semantic spaces for different query keywords individually and automatically. We believe that the semantic space related to the images to be re-ranked can be significantly narrowed down by the query keyword provided by the user. For example, if the query keyword is "apple", the semantic concepts of "mountains" and "Paris" are unlikely to be relevant and can be ignored. Instead, the semantic concepts of "computers" and "fruit" will be used to learn the visual semantic space related to "apple". The query-specific visual semantic spaces can more accurately model the images to be re-ranked, since they have removed other potentially unlimited number of non-relevant concepts, which serve only as noise and deteriorate the performance of re-ranking in terms of both accuracy and computational cost. The visual features of images are then projected into their related visual semantic spaces to get semantic signatures. At the online stage, images are re-ranked by comparing their semantic signatures obtained from the visual semantic space of the query keyword.

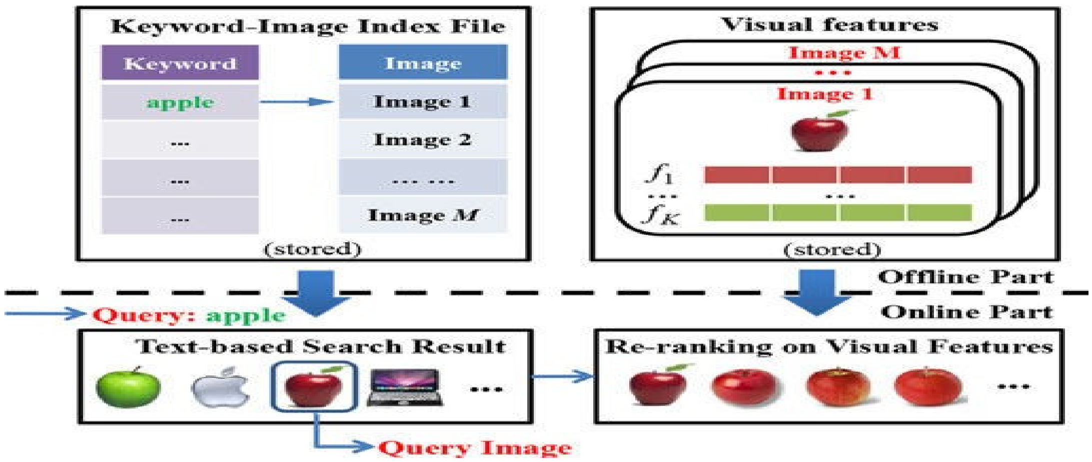

Fig.No.1.The conventional image re-ranking framework.

Our experiments show that the semantic space of a query keyword can be described by just 20 □ 30 concepts (also referred as "reference classes" in our paper). Therefore the semantic signatures are very short and online image reranking becomes extremely efficient. Because of the large number of keywords and the dynamic variations of the web, the visual semantic spaces of query keywords need to be automatically learned. Instead of manually defined, under our framework this is done through keyword expansions.


Fig.No. 2. All the images shown in this figure are related to palm trees. They are different in color, shape, and texture.

Another contribution of the paper is to introduce a large scale benchmark database1 with manually labeled ground truth for the performance evaluation of image re-ranking. It includes 120; 000 labeled images of around 1500 categories (which are defined by semantic concepts) retrieved by the Bing Image Search using 120 query keywords. Experiments on this benchmark database show that 20%□35% relative improvement has been achieved on re-ranking precisionswith much faster speed by our approach, compared with the state-of-the-art methods.

1.2 RELATED WORK

Content-based image retrieval uses visual features to calculate image similarity. Relevance feedback was widely used to learn visual similarity metrics to capture users' search intention. However, it required more users' effort to select multiple relevant and irrelevant image examples and often needs online training. For a web-scale commercial system, users' feedback has to be limited to the minimum with no online training. Cui et al. proposed an image re-ranking approach which limited users' effort to just one-click feedback. Such simple image re-ranking approach has been adopted by popular web-scale image search engines such as Bing and Google recently, as the "find similar images" function.

The key component of image re-ranking is to compute the visual similarities between images. Many image features have been developed in recent years. However, for different query images, low-level visual features that are effective for one image category may not work well for another. To address this, Cui et al. classified the query images into eight predefined intention categories and gave different feature weighting schemes to

different types of query images. However, it was difficult for only eight weighting schemes to cover the large diversity of all the web images. It was also likely for a query image to be classified to a wrong category.
Recently, for general image recognition and matching, there have been a number of works on using predefined concepts or attributes as image signature. Rasiwasia et al. mapped visual features to a universal concept dictionary. Lampert et al. used predefined attributes with semantic meanings to detect novel object classes. Some approaches transferred knowledge between object classes by measuring the similarities between novel object classes and known object classes (called reference classes). All these concepts/attributes/reference-classes were universally applied to all the images and their training data was manually selected. They are more suitable for offline databases with lower diversity (such as animal databases and face databases) such that object classes better share similarities. To model all the web images, a huge set of concepts or reference classes are required, which is impractical and ineffective for online image re-ranking. new pseudonyms. Pseudonymizers scheme add a trusted third party (a pseudonymizer) to the basic model. The pseudonymizer mediates between users and providers. Users send their queries to the pseudonymizer, which replaces the real identity of the users (e.g. their IP addresses) by a pseudonym. This way, providers cannot identify users because they become hidden behind the pseudonymizer. Notwithstanding, users must trust pseudonymizers because they have full access to their real locations and identities. Also, if users send several queries from the same location (e.g. from their residence), providers can determine their real identities by using e.g. a public telephone directory. These attacks are known as Restricted Space Identification (RSI) and Observation Identification

2. **PROPOSED SYSTEM**

In this paper, a novel framework is proposed for web image re-ranking. Instead of manually defining a universal concept dictionary, it learns different semantic spaces for different query keywords individually and automatically. The semantic space related to the images to be re-ranked can be significantly narrowed down by the query keyword provided by the user. The query-specific semantic spaces can more accurately model the images to be re-ranked, since they have excluded other potentially unlimited number of irrelevant concepts, which serve only as noise and deteriorate the re ranking performance on both accuracy and computational cost.The main objective is to extend text based QA to multimedia QA. Thus the enrich textual answer with media is grabbed. We use stemming and partial-match retrieval algorithm for getting the best solution. The query-specific semantic spaces can more accurately model the images to be re-ranked, since they have excluded other potentially unlimited number of irrelevant concepts, which serve only as noise and deteriorate the re-ranking performance on both accuracy and computational cost. Different query images, the effective low-level visual features are different. Therefore, queries classified query images into eight predefined intention categories and gave different feature weighting schemes to different types of query images

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3. CONCLUSION

We propose a novel image re-ranking framework, which learns query-specific semantic spaces to significantly improve the effectiveness and efficiency of online image reranking. The visual features of images are projected into their related visual semantic spaces automatically learned through keyword expansions at the offline stage. The extracted semantic signatures can be 70 times shorter than the original visual feature on average, while achieve 20%□35% relative improvement on re-ranking precisions over state-of the- art methods.
In the future work, our framework can be improved along several directions. Finding the keyword expansions used to define reference classes can incorporate other metadata and log data besides the textual and visual fea- tures. For example, the co-occurrence information of key- words in user queries is useful and can be obtained in log data. In order to update the reference classes over time in an efficient way, how to adopt incremental learning [72] under our framework needs to be further investigated. Although the semantic signatures are already small, it is possible to make them more compact and to further enhance their matching efficiency using other technologies such as hashing [76].

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