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RE-RANKING SEARCH IMAGES USING SEMANTIC SIGNATURE OF QUERY KEYWORD

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ABSTRACT

Web scale image search engines mostly use keyword as queries and rely on surrounding that to search images. They suffer from the ambiguity of query keyword, because it is hard for users to accurately describe the visual content of target images only using keywords. Images re-ranking as an effective way of improve the results of web based image search, has been adopted by current commercial search engine such as 'Bing 'and 'Google'. Given a query keyword, a pool of images is first retrieved based on textual information. By asking the user to select a query image from the pool, the remaining images are re-ranked based on their visual similarities with the query image. A major challenge is that the similarities of visual features do not well correlate with images semantic meaning which interprets users search information. In this project, we proposed novel image re-ranking framework, which automatically offline learns different semantic spaces for different query keyword. The visual features of image are projected into their related semantic spaces to get semantic signatures. At online stage, re-ranked by comparing their semantic signature obtains from the semantic space by the query keyword. The proposed query specific signatures significantly improve both the accuracy &efficiency of image re-ranking. The original visual features of thousands of dimensions can be projected to the semantic signatures as short as 25 dimensions. Experimental results show that 25-40% relative improvement has been achieved on re-ranking precisions compared with the state of the art method.

Keyword – image search, image re-ranking, semantic signature, keyword expansion

I. INTRODUCTION

WEB-SCALE image search engines mostly use keywords as queries and rely on surrounding text to search images. They suffer from the ambiguity of query keywords, because it is hard for users to accurately describe the visual content of target images only using keywords. For example, using "apple" as a query keyword, the retrieved images belong to different categories such as "red apple," "apple logo," and "apple laptop." In order to solve the ambiguity, content- based image retrieval with relevance feedback is widely used. It requires users to select multiple relevant and irrelevant image examples, from which visual similarity metrics are learned through online training. Images are re-ranked based on the learned visual similarities. However, for web-scale commercial systems, users' feedback has to be limited to the minimum without online training. Online image re-ranking which limits users' effort tojust one-click feedback is an effective way to improve search results and its interaction is simpleenough. Majorweb image search engines have adopted this strategy. Given 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 1,000 images. By asking the 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 word image index file and visual features of images are precompiled 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.

Another major challenge is that, without online training, the similarities of low-level visual features may not well correlate with images' high-level semantic meanings which interpret users' search intention. Low-level features are sometimes inconsistent with visual perception. For example, if images of the same object are captured from different viewpoints, under different lightings or even with different compression artefacts, their low-level features may change significantly, although humans think the visual content does not change much. To reduce this semantic gap and inconsistency with visual perception.

There have been a number of studies to map visual features to a set of predefined concepts or attributes as semantic signatures. For example, Kovashka et al. proposed a system which refined image search with relative attribute feedback. Users described their search intention with reference images and a set of pre-defined attributes. These concepts and attributes are pre-trained offline and have tolerance with variation of visual content. However, these approaches are only applicable to closed image sets of relatively small sizes, but not suitable for online web-scale image re-ranking. According to our empirical study, images retrieved by 120 query keywords alone include more than 1,500 concepts. It is difficult and inefficient to design a huge concept dictionary to characterize highly diverse web images. Since the topics of web images change dynamically, it is desirable that the concepts and attributes can be automatically found instead of being manually defined.

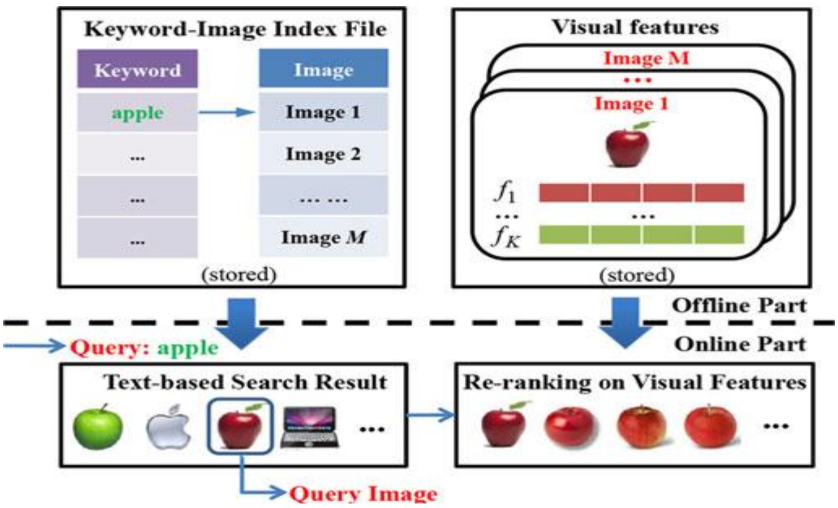

Figure 1: The Conventional Image Re-Ranking Framework

II. RELATED WORK

Learning visual similarities:

Kuok et al.Evaluated each image fetched initially from web on the basis of user query by finding specific semantic features of the images. The semantic features were shown by the use of visual graphs and textual graphs. Finally both the graphs were correlated to learn the similarities. Since the top N images are not necessarily semantically-consistent with the query image, the learned similarity metric may not reliably reflect the semantic relevance and may even deteriorate re-ranking performance.

General image recognition and matching:

Most of the work has been carried out for finding similar images on the basis of attributes or reference classes as image signatures. The classifiers of concepts, attributes, and reference classes are trained from known classes with labelled 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. mapped visual features to a universal concept dictionary for image retrieval. Attributes with semantic meanings were used for object detection,object recognition face recognition image search action recognition 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-specifiedattributes instead of training images. Sharmanska et al. augmented this representationwith additional dimensions and allowed a smooth transition between zero-shot learning, unsupervised training and supervised training. Parikh and Grauman proposed relative attributes to indicate the strength of an attribute in an image with respect to other images. Prakash and Parikh used attributes to guide active learning. In order to detect objects of many categories or even unseen categories, instead of building a new detector for each category, Farhadi et al. learned part and attribute detectors which were shared across categories and modelled the correlation among attributes. Some approaches transferred knowledge between object classes by measuring the similarities between novel object classes and known object classes (called reference classes). For example, Teresina 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. 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 databases and face databases), since image classes in these databases can 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. Intuitively, only a small subset of the concepts are relevant to a specific query. Many concepts irrelevant to the query not only increase the computational cost but also deteriorate the accuracy of reran king. However, how to automatically find such relevant concepts and use them for online web image re-ranking was not well explored in previous studies.

THEORETICALBACKGROUD

Re-ranking:

- Computing Visual similarities of images:

It is important to calculate the visual similarities of the images which seem to be semantically relevant. Many visual features are considered to find the visual similarities between images. However, every image of different query has different visual attributes than every other image retrieved for different query. Hence Cui et al. categorised the images into eight classes and assigned weighing schemes to allthe different kinds of images. But using weighing schemes becomes bottleneck for large and diverse set of images. And it may happen that the images to beplaced in different class other than it were supposed to be placed in.

- Initial text-only search:

Re-ranking is also performed on the basis of visual features of the initially retrieved images from the web without having extra effort for users to select one image of their interest.

III. MODULES OF THE SYSTEM

Re-Ranking Precisions

We invited five labellers to manually label testing images under each query keyword into different categories according to semantic meanings. Image categories were carefully defined by the five labellers through inspecting all the testing images under a query keyword. Defining image categories was completely independent of discovering reference classes. The labellers were unaware of what reference classes have been discovered by our system. The number of image categories is also different than the number of reference classes. Each image was labelled by at least three labellers and its label was decided by voting. Some images irrelevant to query keywords were labelled as outliers and not assigned to any category.

Keyword Expansion

For a keyword q, we define its reference classes by finding a set of keyword expansions most relevant to q. To achieve this, a set of images are retrieved by the search engine using q as query based on textual information. Keyword expansions are found from words extracted from images in according to a very large dictionary used by the search engine. A keyword expansion is expected to frequently appear in. In addition, in order for reference classes to well capture the visual content of images, we require that there are subsets of images which all contain e and have similar visual content. Based on these considerations, is found in a search-and-rank way.

Training Images of Reference Classes

In order to automatically obtain the training images of reference classes, each keyword expansion e combined with the original keyword q is used as query to retrieve images from the search engine and top K images are kept. Since the expanded keywords e have less semantic ambiguity than the original keyword q, the images retrieved by e are much less diverse. After removing outliers by k-meansclustering, these images are used as the training examples of the reference class. The cluster number of k-means is setas 20 and clusters of sizes smaller than 5 are removed as outliers.

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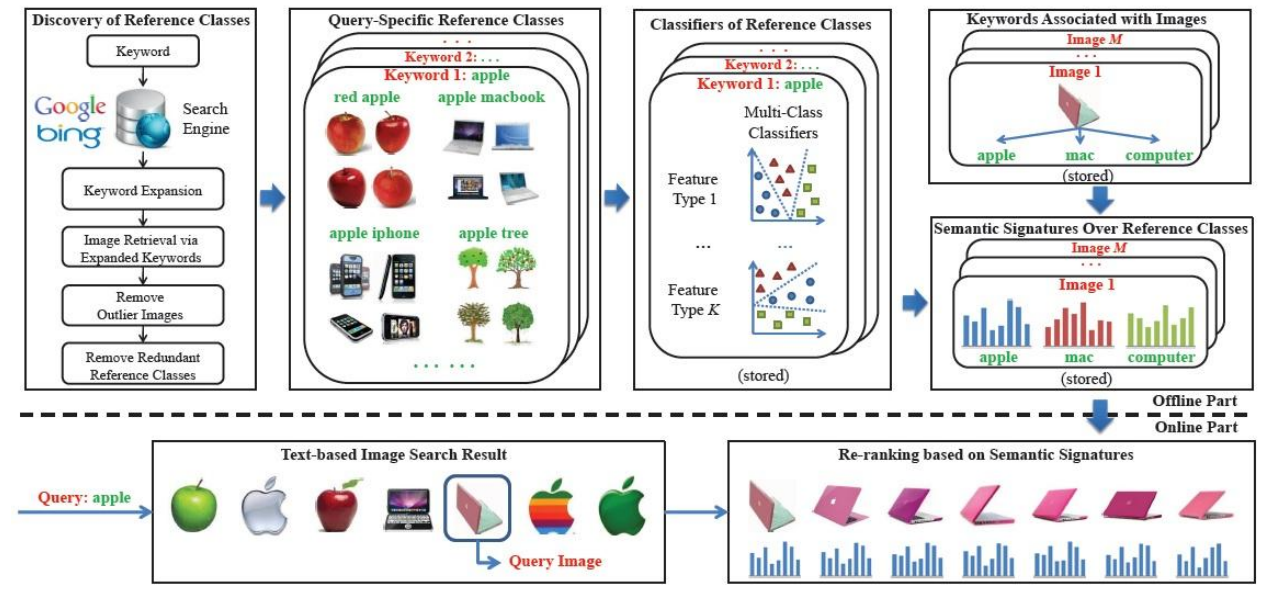

Figure 2:Architecture Of Our New Image Re-Ranking Framework

IV.SEMANTIC SIGNATURES WITH NEW KEYWORD

Given M reference classes for keyword q and their training images, a multi-class classifier on the visual features of images is trained and it outputs an M-dimensional vector p, indicating the probabilities of a new image I belonging to different reference classes. p is used as the semantic signatureof I. The distance between two images Ia and Ib aremeasured as the L1-distance between their semantic signaturespa and pb.

Combined Features versus Separate Features

In order to train the SVM classifier, we adopt six typesof visual features used in [6]: attention guided color signature,color spatiality, wavelet [73], multi-layer rotationinvariant edge orientation histogram, histogram of orientedgradients [37], and GIST [74]. They characterizeimages from different perspectives of color, shape, andtexture. The total dimensionality around 1:700.A natural idea is to combine all the visual features totrain a single powerful SVM better distinguishing referenceclasses. However, the purpose of using semantic signaturesis to capture the visual content of an image, which maybelong to none of the reference classes, instead of classifyingit into one of the reference classes.

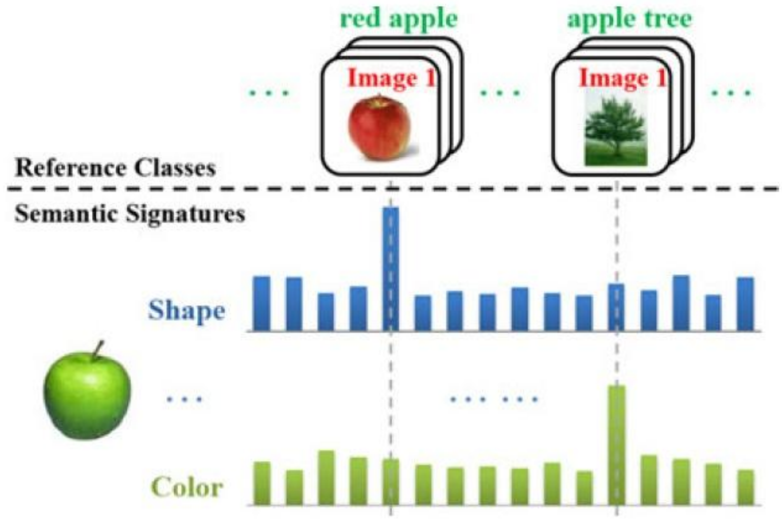

Figure 3: Describe "green apple" with reference classes. Its shape is captured by the shape classifier of "red apple" and its color is captured by the color classifier of "apple tree."

If there are K types ofindependent visual features, it is more effective to train separateSVM classifiers on different types of features and tocombine the K semantic signatures fpkgKk¼1 from the outputsof the K classifiers. The K semantic signatures describethe visual content from different aspects (e.g., color, texture,and shape) and can better characterize images outside thereference classes. For example, in Fig. 4, "red apple" and"apple tree" are two reference classes. A new image of"green apple" can be well characterized by two semanticsignatures from two classifiers trained on color features andshape features separately, since "green apple" is similar to"red apple" in shape and similar to "apple tree" in color. IfWANG ET AL.: WEB IMAGE RE-RANKING USING QUERY-SPECIFIC SEMANTIC SIGNATURES 815the color and shape features are combined to compute a singlesemantic signature; it cannot well characterize the imageof "green apple." Since the "green apple" is dissimilar toany reference class when jointly considering color andshape, the semantic signature has low distributions over allthe reference classes.

V. APPLICABILITY

The Image Re-ranking system that is developed can be applicable with the current web search engines, where users get bulk of images. On selection of a particular image, the system retrieves and returns the best possible images similar to the user selected image. The search engines that can adopt this system are:

– Google Images
– Bing
– CC Search
– Photo Pin
– PicFindr
– Veezzle
– Every Stock Photo
– Behold

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VI. CONCLUSION

The system re-ranks the shortlisted images very accurately.The system works in both modes, online and offline.The images are found similar based on RGB value of the images.The visual features of images are projected to find the similarity and to re-rank as well.The system finds the similarity features between images so as to decide the similar images. Once the similar images are found, re-ranking is performed to find the final ranking of the images.While working online, system stores the intermediate results in the database so that while working offline, we have the set of images for further ranking.

VII. FUTURE SCOPE

The future scope of the project can be aimed to find more features of the image such as shape, contrast, etc. to find more accurate similar images. Once all the related features are extracted, there is a vast room of comparing images based on these features so as to get more accurate re-ranking. The images have many semantic features using which we can extend the project for re-ranking the images in best possible way.

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