

An Efficient Image Re-Ranking using Short Query based Semantic Spaces

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Abstract:- Image re-ranking is an effective way to improve the results of web-based image search has been adopted by current commercial search engines such as Bing and Google. Given a query keyword, a group of images are first retrieved based on textual information. By asking the user to choose a query image from the group, 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 meanings which interpret users' search intention. Recently people proposed to match images in semantic space which used attributes or references classes closely related to 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 paper, 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 their related semantic spaces to get semantic signatures. At the online stage, images are re-ranked by comparing their semantic space specified by the query keyword. The proposed query-specific semantic monograms considerably improve both the accuracy and efficiency of images re-ranking. The original visual features of thousands of dimensions can be projected to the semantic spaces as short as 25 dimensions. Experimental outcomes show that 25% -40% relative improvement has been achieved on re-ranking precisions compared with the state-of-the-art methods.

Index Terms- Image investigate, Image re-rank, Semantic gap, Semantic autograph, Keyword extension.

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 (also called concepts in my project), such as "red apple", "apple logo", and "apple laptop". In order to solve the ambiguity, content-based image retrieval [1], [2] with relevance feedback [3] 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 [4] which limits users' effort to just one-click feedback, is an effective way to improve search results and its interaction is simple enough. Major web image search engines have adopted this strategy [5]. Its diagram is shown in Figure 1. Given a query keyword input by a user, a pool of images relevant to the query keyword

are 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 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.

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. Some examples are shown in Figure 2. Moreover, 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 artifacts, 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 [6]

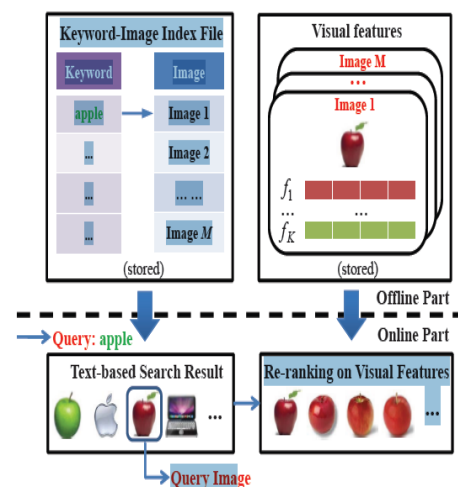


Fig. 1. The conventional image re-ranking framework.



Fig. 2. All the images shown in this figure are related to palm trees. They are different in color, shape, and texture.

II LITERATURE SURVEY

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. For example, if the query keyword is “apple”, the concepts of “mountain” and “Paris” are irrelevant and should be excluded. Instead, the concepts of “computer” and “fruit” will be used as dimensions to learn the semantic space related to “apple”. 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 visual and textual features of images are then projected into their related semantic spaces to get semantic signatures. At the online stage, images are re-ranked by comparing their semantic signatures obtained from the semantic space of the query keyword. The semantic correlation between concepts is explored and incorporated when computing the similarity of semantic signatures.

The semantic signatures are very short and online image re-ranking becomes extremely efficient. Because of the large number of keywords and the dynamic variations of the web, the semantic spaces of query keywords are automatically learned through keyword expansion.

III EXISTING SYSTEM

In Existing system one way is text-based keyword Expansion , making the textual description of the query more detailed. Existing linguistically-related methods find either synonyms or other other linguistic-related words from thesasaures,or find words frequently co occurring with the query keywords.

For example, Google image search provides the “Related searches “ features to suggest likely keyword expansion. However , even with the same query keywords , the intension of users can be highly diverse and cannot be

accurately captured by these expansions. Search by image is optimized to work well for content that is reasonably well described on the web. For this reason , you will likely get more relevant results for famous landmarks or paintings than you will for more personal images like your toddler’s latest finger painting.

Dis-advantages of Existing System

1. Most of the times, User can’t get the search images of his interest.
2. If user found some interesting Image and he wants to get more similar type of the images it is difficult to get it or it is not possible without providing correct keywords .

IV PROPOSED SYSTEM

The Project proposes novel image re-ranking framework , which automatically offline learns different semantic spaces for different query keywords. The visual features of images are projected into their related semantic spaces to get semantic signatures. At the online stage, images are re-ranked by comparing their semantic space specified by the query keyword. The Proposed System is shown in Fig 1.3.

For a query keyword(e.g.”apple”), a set of most relevant keyword expansions (such as “red apple “ and “apple macbook”) are automatically selected utilizing both textual and visual information. This set of keyword expansions defines the reference classes for the query keyword. In order to automatically obtain the training examples of a reference class, the keyword expansion (e.g. “red apple”) is used to retrieve images by the search engine based on textual information again. Images retrieved by the keyword expansion (“red apple”) are much less diverse than those retrieved by the original keyword(“apple”).after automatically removing outliers, the retrieved top images are used as the training examples of the reference class. Some reference classes (such as “apple laptop” and “ apple macbook”) have similar semantic meanings and their training sets are visually similar. In order to improve the efficiency of online image re-ranking, redundant reference classes are removed. To better measure the similarity of semantic signatures , the semantic correlation between reference class is estimated with a web-based kernel function.

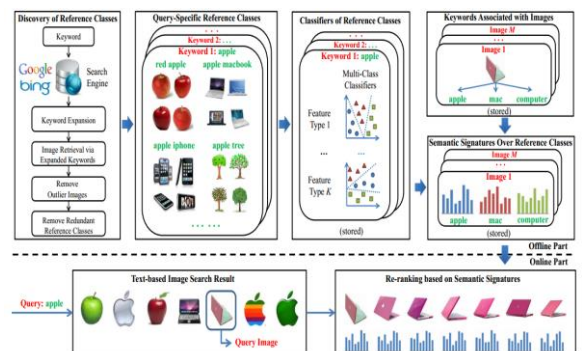


Figure 1.3 : Proposed System Architecture

VI CONCLUSION

Advantages of Proposed System

1. It learns query-specific semantic spaces to significantly improve the effectiveness and efficiency of online image re-ranking. The visual features of images are projected into their related semantic spaces automatically learned through keyword expansions offline.
2. This approach uses both text based keywords and Visual Feature extraction concept together and yield accurate result according to user interest.

V. EXPERIMENTAL RESULTS

The images for testing the performance of re-ranking and the images of reference classes can be collected at different time and from different search engines. Given a query keyword, 1000 images are retrieved from the whole web using certain search engine. we create three data sets to evaluate the performance of our approach in different scenarios. In data set I, 120; 000 testing images for re-ranking were collected from the Bing Image Search using 120 query keywords in July2010. These query keywords cover diverse topics including animal, plant, food, place, people, event, object, scene .etc. The images of reference classes were also collected from the Bing Image Search around the same time. Dataset II use the same testing images for re-ranking as in dataset I. However, its images of reference classes were collected from the Google Image Search also in July 2010. In data set III, both testing images and images of reference classes were collected from the Bing Image Search but at different time (eleven months apart)5. All testing images for re-ranking are manually label, while images of reference classes, whose number is much larger, are not labeled.

In this Paper, we propose a novel Internet image search approach which only requires one-click user feedback. Without supplementary human feedback ,textual and visual expansions are integrated to capture user intention.

Expanded keywords are used to extend positive example images and also enlarge the image group to include more appropriate images. This structure makes it possible for industrial scale image search by both text and visual content. The proposed new image re ranking structure consists of multiple steps, which can be enhanced separately or replaced by other techniques equivalently effective.

We believe that users will tolerate one-click interaction which has been used by many popular text-based search engines. For example, Google requires a user to choose a suggested textual query expansion by one-click to get additional results.

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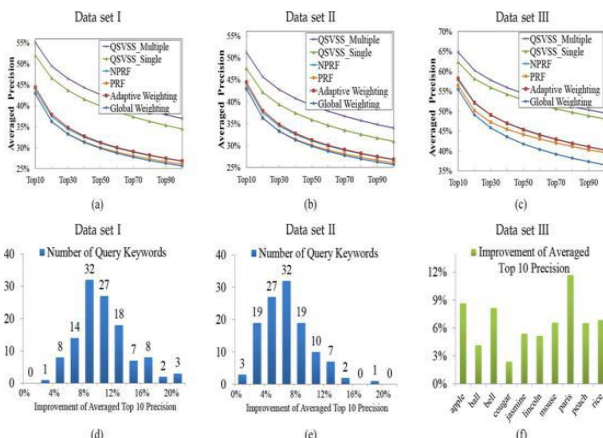


Figure 1.4: Incorporating semantic correlations among reference classes. (a)-(c):single visual semantic signatures with/without semantic correlation.(d)-(f): multiple visual & semantic correlation.