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A Novel Image Re-Ranking Framework for Query-Specific Semantic Spaces

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ABSTRACT

Image re-ranking, as an effective way to improve the results of web-based image search has been adopted by current commercial search engines. A query keyword, a pool of images are first retrieved by the search engine based on textual information. Asking the user to select a query image from the set the minus images are reranked based on their visual similarities with the query image. Query and Image based recommendation sorted by the method of re-ranking provides an accurate output of images based on the visual semantic signatures of the query image .In query based recommendation, keyword expansions help provide better results whereas in image recommendation, re-ranking based on priority of images accessed by other users provides more accurate results. At the online stage, images are re-ranked by comparing their semantic signatures obtained from the visual semantic space specified by the query keyword.

IndexTerms—Imagesearch, image re-ranking, semanticspace, semanticsignature, keyword expansion

INTRODUCTION

The primary objective of this paper is to provide accurate search results based on keyword expansion as well as comparing the semantic signatures of images to provide re-ranked images for the users. The application will feature a search box for typing queries as well as have an option to browse and open the image which the user requires to search for in the web. There are two stages: offline stage and online stage. Semantic signatures of any image queried by the user is calculated and stored in database at the offline stage. Most of the work is done at the offline stage. At the online stage, the user receives re-ranked images those are calculated using semantic signatures at the offline stage.A novel framework is proposed for web image re-ranking. Instead of developing a universal concept dictionary it learns different visual semantic spaces for different query keywords individually and automatically.

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”. They 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 found into their related visual semantic spaces to get semantic signatures. 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 re ranking 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

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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.

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 queryspecific 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 reranked by comparing their semantic signatures obtained from the visual semantic space of the query keyword. 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 re ranking 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.

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 precisions with much faster speed by our approach, compared with the state-of-the-art methods.

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

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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.

EXISTING SYSTEM

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 this paper), such as "red apple," "apple logo," and "apple laptop."

This is the most common form of text search on the Web. Most search engines do their text query and retrieval using keywords. The keywords based searches theyusually provide results from blogs or other discussion boards. The user cannot have a satisfaction with these results due to lack of trusts on blogs etc. low precision and highrecall rate. In early search engine that offered disambiguation to search terms. User intention identification plays an important role in the intelligent semantic search engine.

Disadvantages:

* 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.

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. 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.

We propose the semantic web based search engine which is also called as Intelligent Semantic Web Search Engines. We use the power of xml meta-tags deployed on the web page to search the queried information. The xml page will be consisted of built-in and user defined tags. Here propose the intelligent semantic web based search engine. We use the power of xml meta-tags deployed on the web page to search the queried information. The xml page will be consisted of built-in and user defined tags. The metadata information of the pages is extracted from this xml into rdf. our practical results showing that proposed approach taking veryless time to answer the queries while providing more accurate information.

Advantages:

- The visual features of images are projected into their related semantic spaces automatically learned through keyword expansions offline.
- Our experiments show that the semantic space of a query keyword can be described by just 20-30 concepts (also referred as “reference classes”). Therefore 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.

SYSTEM ARCHITECTURE

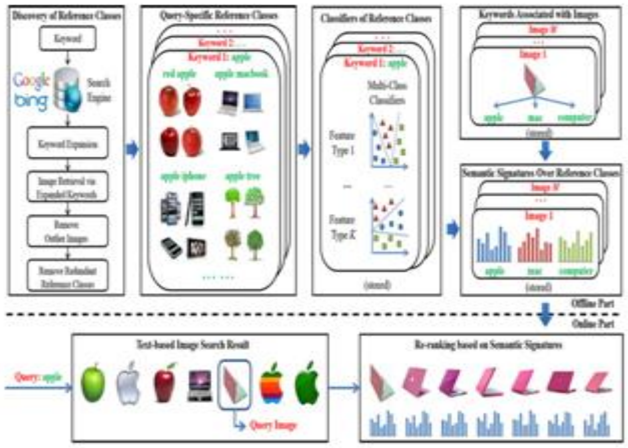

Fig:- Diagram of our new image re-ranking framework.

IMPLEMENTATION

Image Search:-

Many Internet scale image search methods are text-based and are limited by the fact that query keywords cannot describe image content accurately. Content-based image retrieval uses visual features to evaluate image similarity. One of the major challenges of content-based image retrieval is to learn the visual similarities which will reflect the semantic relevance of images. Image similarities can be learned from a large training set where the relevance of pairs of images.

Query Categorization:-

The query categories we considered are: General Object, Object with Simple Background, Scenery Images, Portrait, and People. We use 500 manually labeled images, 100 for each category, to train a C4.5 decision tree for query categorization. The features we used for query categorization are: existence of faces, the number of faces in the image, the percentage of the image frame taken up by the face region, the coordinate of the face center relative to the center of the image.

Visual Query Expansion:-

The goal of visual query expansion is to obtain multiple positive example images to learn a visual similarity metric which is more robust and more specific to the query image. The query keyword is "Paris" and the query image is an image of "eiffel tower". The image re-ranking result based on visual similarities without visual expansion. And there are many irrelevant images among the top-ranked images. This is because the visual similarity metric learned from one query example image is not robust enough. By adding more positive examples to learn a more robust similarity metric, such irrelevant images can be filtered out. In a traditional way, adding additional positive examples was typically done through relevance feedback, which required more users' labeling burden. We aim at developing an image re-ranking method which only requires one-click on the query image and thus positive examples have to be obtained automatically.

Images Retrieved by Expanded Keywords:-

considering efficiency, image search engines, such as Bing image search, only re-rank the top N images of the text-based image search result. If the query keywords do not capture the user's search intention accurately, there are only a small number of relevant images with the same semantic meanings as the query image in the image pool. Visual query expansion and combining it with the query specific visual similarity metric can further improve the performance of image re ranking.

Re-ranking precisions:-

We invited five labelers to manually label testing imagesunder each query keywords into different categories accordingto their semantic meanings. Image categories were carefullydefined by the five labelers through inspecting all thetesting images under a query keyword. Each image was labeledby at least three labelers and its label was decided byvoting. A small portion of the images are labeled as outliersand not assigned to any category (e.g., some imagesare irrelevant to the query keywords).Averaged top m precision is used as the evaluation criterion.

Top m precision is defined as the proportion of relevantimages among top m re-ranked images. Relevant imagesare those in the same category as the query image. Averagedtop m precision is obtained by averaging top m precisionfor every query image (excluding outliers). We adoptthis criterion instead of the precision-recall curve since inimage re-ranking, the users are more concerned about thequalities of top retrieved images instead of number of relevantimages returned in the whole result set.We compare with two benchmark image re-ranking approaches. They directly compare visual features.

(1)Global Weighting: Predefined fixed weights are adopted to fuse the distances of different low-level visual features.

(2) Adaptive Weighting: proposed adaptiveweights for query images to fuse the distances of differentlow-level visual features. It is adopted by Bing ImageSearch.

For our new approaches, two different ways of computing semantic signatures as discussed are compared.

a) Query-specific visual semantic space using single signatures (QSVSS Single). For an image, a single semantic signature is computed from one SVM classifier trained by combining all types of visual features.
b) Query-specific visual semantic space using multiple signatures (QSVSS Multiple). For an image, multiple semantic signatures are computed from multiple SVM classifiers, each of which is trained on one type of visual features separately.

CONCLUSION & FUTURE WORK

A unique re-ranking framework is proposed for image search on internet in which only one-click as feedback by user. Specific intention weight schema is used proposed to combine visual features and visual similarities which are adaptive to query image are used. The feedback of humans is reduced by integrating visual and textual similarities which are compared for more efficient image re-ranking. User has only to do one click on image, based on which re-ranking is done. Also duplication of images is detected and removed by comparing hash codes. Image content can be compactly represented in form of hash code. Specific query semantic spaces are used to get more improvised re-ranking of image. Features are projected into semantic spaces which are learned by expansion of keywords.

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