IMPROVE THE EFFECTIVENESS AND EFFICIENCY OF ONLINE IMAGE RE-RANKING

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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 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 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 paper, I 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 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. 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 percent relative improvement has been achieved on re-ranking precisions compared with the state-of-the-art methods.

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

1.INTRODUCTION

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them.

It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too.

2. 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 they usually 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 high recall rate. In early search engine that offered disambiguation to search terms. User intention identification plays an important role in the intelligent semantic search engine.

3. PROPOSED SYSTEM

In this project, 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. I 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. I 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 very less time to answer the queries while providing more accurate information.

4. LITERATURE REVIEW

4.1 IMAGE RETRIEVAL: IDEAS, INFLUENCES, AND TRENDS OF THE NEW AGE

We have witnessed great interest and a wealth of promise in content-based image retrieval as an emerging technology. While the last decade laid foundation to such promise, it also paved the way for a large number of new techniques and

4.2 CONTENT-BASED IMAGE RETRIEVAL

Traditional methods of image retrieval require that meta-data is associated with the image, commonly known as keywords. These methods power many World Wide Web search engines and accomplish reasonable amounts of search accuracy.

Though some content based image retrieval (CBIR) systems use both semantic and primitive attributes to match search criteria, history has proven that it is difficult to extract linguistic information from a 2D image.

In this research, activity theory is used as a base to demonstrate how semantic information can be retrieved from objects identified in an image. Using an image segmentation technique by The Berkeley Digital Library Project (Blobworld), and combining it with object-to-community relationships, a high-level understanding of the image can be demonstrated.

4.3 RELEVANCE FEEDBACK: A POWER TOOL FOR INTER ACTIVE CONTENT-BASED IMAGE RETRIEVAL

Content-Based Image Retrieval #CBIR# has become one of the most active research areas in the past few years. Many visual feature representations have been explored and many systems built. While these research e#orts establish the basis of CBIR, the usefulness of the proposed approaches is limited.

Speci#cally, these e#orts have relatively ignored two distinct characteristics of CBIR systems: #1# the gap between high level concepts and low level features; #2# subjectivityofhuman perception of visual content. This paper proposes a relevance feedback based interactive retrieval approach, which e#ectively takes into account the abovetwocharacteristics in CBIR.

During the retrieval process, the user's high level query and perception subjectivity are captured by dynamically updated weights based on the user's feedback. The experimental results over more than 70,000 images show that the proposed approach greatly reduces the user's e#ort of composing a query and captures the user's information

4.4 ASYMMETRIC BAGGING AND RANDOM SUBSPACE FOR SUPPORT VECTOR MACHINES-BASERELEVANCE FEEDBACK IN IMAGE RETRIEVAL

Relevance feedback schemes based on support vector machines (SVM) have been widely used in content-based image retrieval (CBIR). However, the performance of SVM-based relevance feedback is often poor when the number of labeled positive feedback samples is small.

This is mainly due to three reasons: 1) an SVM classifier is unstable on a small-sized training set, 2) SVM's optimal hyperplane may be biased when the positive feedback samples are much less than the negative feedback samples, and 3) overfitting happens because the number of feature dimensions is much higher than the size of the training set. In this paper, I develop a mechanism to overcome these problems. To address the first two problems, I propose an asymmetric bagging-based SVM (AB-SVM).

For the third problem, I combine the random subspace method and SVM for relevance feedback, which is named random subspace SVM (RS-SVM). Finally, by integrating AB-SVM and RS-SVM, an asymmetric bagging and random subspace SVM (ABRS-SVM) is built to solve these three problems and further improve the relevance feedback performance .

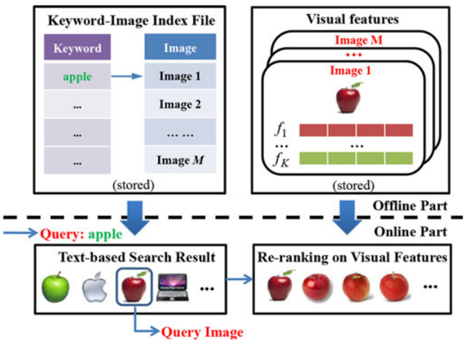
4.5 IMPROVING WEB IMAGE SEARCH RESULTS USING QUERY-RELATIVE CLASSIFIERS

Web image search using text queries has received considerable attention. However, current state-of-the-art approaches require training models for every new query, and are therefore unsuitable for real-world web search applications. The key contribution of this paper is to introduce generic classifiers that are based on query-relative features which can be used for new queries without additional training.

They combine textual features, based on the occurrence of query terms in web pages and image meta-data, and visual histogram representations of images. The second contribution of the paper is a new database for the evaluation of web image search algorithms. It includes 71478 images returned by a web search engine for 353 different search queries, along with their meta-data and ground-truth annotations.

Using this data set, I compared the image ranking performance of our model with that of the search engine, and with an approach that learns a separate classifier for each query. Our generic models that use query-relative features improve significantly over the raw search engine ranking, and also outperform the query-specific models.

5 THE CONVENTIONAL IMAGE RE-RANKING FRAME WORK



Our approach

Related work

Related Work

The key component of image re-ranking is to computevisual similarities reflecting semantic relevance of images.Many visual features [36], [37], [38], [39], [40] have beendeveloped in recent years. However, for different queryimages, theeffective low-level visual features are different.Therefore, Cui et al. [6], [7] classified query images intoeight predefined intention categories and gave different featureweighting schemes to different types of query images.But it was difficult for the eight weighting schemes to coverthe large diversity of all the web images. It was also likely for a query image to be classified to a wrong category. Inorder toreduce the semantic gap, query-specific semanticsignature was first proposed in [41]. Kuo et al. [42] recentlyaugmented eachimage with relevant semantic featuresthrough propagation over a visual graph and a textualgraph which were correlated.

Another way of learning visual similarities without addingusers' burden is pseudo relevance feedback [43], [44],[45]. It takes the top N images most visually similar to thequery image as expanded positive examples to learn a similaritymetric. 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. In object retrieval, in order to purify the expanded positive examples, the spatial configurations of local visual features are verified [46], [47], [48]. But it is not applicable to general web image search, where relevant images may not contain the same objects. There is a lot of work [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32] on using visual features to re-rank images retrieved by initial text-only search, however, without requiring users to select query images. Tian et al. [24] formulated image reranking with a Bayesian framework. Hsu et al. [15] used the Information Bottleneck (IB) principle to maximize the mutual information between search relevance and visual features. Krapac et al. [26] introduced generic classifiers based on query-relative features which could be used for new query keywords without additional training. Jing and Baluja [21] proposed VisualRank to analyze the visual link structures of images and to find the visual themes for reranking. Lu et al. [31] proposed the deep context to refine search results. Cai et al. [32] re-ranked images with attributes which were manually defined and learned from manually labeled 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. In Section 7, we show that the proposed 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. Without query images selected by users, these approaches cannot accurately capture users' search intention. Recently, for general image recognition and matching, there have been a number 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. [9] mapped visual features to a universal concept dictionary for image retrieval. Attributes [49] with semantic meanings were used for object detection [10], [50], [51], object recognition [52], [53], [54], [55], [56], [57], [58], [59], [60], face recognition [58], [61], [62], image search [60], [63], [64], [65], [66], [67], action recognition [68], and 3D object retrieval [69]. Lampert et al. [10] predefined a set of attributes on an animal database and detected target objects based on a combination ofm human-specified attributes instead of training images. Sharmanska et al. [50] augmented this representation with additional dimensions and allowed a smooth transition between zero-shot learning, unsupervised training and supervised training. Parikh and Grauman [58] proposed relative attributes to indicate the strength of an attribute in an image with respect to other images. Parkash and Parikh [60] 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. [51] learned part and attribute detectors which were shared across categories and modeled the correlation among attributes. Some approaches [11], [54], [70], [71] transferred knowledge between object classes by measuring the similarities between novel object classes and known object classes (called reference classes). For example, Torresani et al. [71] 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

6 . SEMANTIC SIGNATURES

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 signature of I. The distance between two images Ia and Ib are measured as the L1-distance between their semantic signatures p^a and p^b,

$$d\,(I^a, I^b) = \| p^a - p^b \|_1$$

7. CONCLUSIONS

We propose a novel framework, which learns query-specifics 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. The extracted semantic signatures can be 70 times shorter than the original visual features, while achieve 25-40 percent 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 features. 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 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.

8. REFERENCES

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