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Image Search in Web Using Attribute Assisted Reranking

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Abstract— Image search reranking is an effective approach to refine the text-based image search result. Most existing reranking approaches are based on low-level visual features. In this paper, we propose to exploit semantic attributes for image search reranking. Based on the classifiers for all the predefined attributes, each image is represented by an attribute feature consisting of the responses from these classifiers. A hypergraph is then used to model the relationship between images by integrating low-level visual features and attribute features. Hypergraph ranking is then performed to order the images. Its basic principle is that visually similar images should have similar ranking scores. In this work, we propose a visual-attribute joint hypergraph learning approach to simultaneously explore two information sources. A hypergraph is constructed to model the relationship of all images. We conduct experiments on more than 1,000 queries in MSRA-MM V2.0 dataset. The experimental results demonstrate the effectiveness of our approach.

I. I NTRODUCTION

With the dramatic increase of online images, image re- trieval has attracted significant attention in both academia and industry. Many image search engines such as Google and Bing have relied on matching textual

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information of the images against queries given by users. However, text- based image retrieval suffers from essential difficulties that are caused mainly by the incapability of the associated text to appropriately describe the image content. Recently, visual reranking has been proposed to refine text-based search results by exploiting the visual information contained in the images .The existing visual reranking methods can be typically categorized into three categories as the clustering based, classification based and graph based methods. The clustering based reranking methods stem from the key observation that a wealth of visual characteristics can be shared by relevant images. With intelligent clustering algorithms(e.g., mean-shift, K -means, and K -medoids), initial search results from text-based retrieval can be grouped by visual closeness. However, for queries that return highly diverse results or without clear visual patterns, the performance of the clustering-based methods is not guaranteed. In the classification based methods, visual reranking is formulated as binary classification problem aiming to identify whether each search result is relevant or not. Pseudo Relevance Feedback(PRF) is applied to select training images to learn a classifier or a ranking model. However, in many real scenarios, representative examples obtained via PRF for the training dataset are very noisy and might not be adequate for constructing effective classifiers. Graph based methods have been proposed recently and received increasing attention as demonstrated to be effective. The multimedia entities in top ranks and their visual relationship can be represented as a collection of nodes and edges. The local patterns or salient features discovered using graph analysis are very powerful
to improve the effectiveness of rank lists. Nevertheless, the reranking algorithms mentioned above are purely based on low-level visual features while generally do not consider any semantic relationship among initial ranked list. The high level semantic concepts which are crucial to capture property of images could deliver more clear semantic messages between various nodes in the graph. Thus, in this paper, we propose to exploit stronger semantic relationship in the graph for image search reranking.

II. RELATED WORK

In this section, we provide a brief description of the existing visual search reranking approaches, review the semantic attributes exploited in recent literature, and describe the hy- pergraph learning theory.

Web Image Search Reranking

Web image search reranking is emerging as one of the promising techniques for automative boosting of retrieval precision[2, 17]. The basic functionality is to reorder the retrieved multimedia entities to achieve the optimal rank list by exploiting visual content in a second step. In particular, given a textual query, an initial list of multimedia entities is returned using the text-based retrieval scheme. Subsequently, the most relevant results are moved to the top of the result list while the less relevant ones are reordered to the lower ranks. As such, the overall search precision at the top ranks can be enhanced dramatically. According to the statistical analysis model used, the existing reranking approaches can roughly be categorized into three categories including the clustering based, classification based and graph based methods.

III. ATTRIBUTE ASSISTED IMAGE SEARCH RERANKING

In this section, we elaborate the proposed attribute-assisted image search reranking framework. We elaborate image features, and then introduce the proposed at tribute learning method in. Finally, we describe our hypergraph construction algorithm.

A. Image Features

We used four types of features, including color and texture, which are good for material attributes; edge, which is useful for shape attributes; and scale-invariant feature transform (SIFT) descriptor, which is useful for part attributes. We used a bag-of-words style feature for each of these four feature types. Color descriptors were densely extracted for each pixel as the 3-channel LAB values. We performed K-means clustering with 128 clusters. The color descriptors of each image were then quantized into a 128-bin histogram. Texture descriptors were computed for each pixel as the 48-dimensional responses of texton filter banks. The texture descriptors of each image were then quantized into a 256-bin histogram. Edges were found using a standard canny edge detector and their orienta- tions were quantized into 8 unsigned bins. This gives rise to a 8-bin edge histogram for each image. SIFT descriptors were densely extracted from the 8 ×8 neighboring block of each pixel with 4 pixel step size. The descriptors were quantized into a 1,000-dimensional bag-of-words feature. Since semantic attributes usually appear in one or more certain regions in an image, we further split each image into 2 × 3 grids and extracted the above four kinds of features from each grid respectively. Finally, we obtained a 9,744-dimensional feature for each image, consisting of a 1,392 ×6- dimensional feature from the grids and a 1,392-dimensional feature from the image. This feature was then used for learning attribute classifiers.

B. Attribute Learning

We learn a Support Vector Machine (SVM) classifier for each attribute. However, simply learning classifiers by fitting them to all visual features often fails to generalize the semantics of the attributes correctly. For each attribute, we need to select the features that are most effective in modeling this attribute. It is necessary to conduct this selection based on the following two observations:

1) such a wealth of low level features are extracted by region or interest point detector, which means these extraction may not aim to depict the specific attribute and include redundant information. Hence we need select representative and discriminative features which are in favor to describe current semantic attributes.

2) the process of selecting a subset of relevant features has been playing an important role in speeding up the learning process and alleviating the effect of the curse of dimensionality

C. Attribute-assisted Hypergraph Construction

We propose an attribute-assisted hypergraph learning method to reorder the ranked images which returned from search engine based on textual query. Different from the typical hypergraph [10], it presents not only whether a vertex v belongs to a hyperedge e , but also the prediction score that v is affiliated to a specific e . The weight is incorporated into graph construction as tradeoff parameters among various features. Our modified hypergraph is thus able to improve reranking performance by mining visual feature as well as attribute information

IV CONCLUSIONS

Image search reranking has been studied for several years and various approaches have been developed recently to boost the performance of text-based image search engine for general queries. This paper serves as a first attempt to include the attributes in reranking framework. We observe that semantic attributes are expected to narrow down the semantic gap between low-level visual features and high-level semantic meanings. Motivated by that, we propose a novel attribute- assisted retrieval model for reranking images. Based on the classifiers for all the predefined attributes, each image is represented by an attribute feature consisting of the responses from these classifiers. A hypergraph is then used to model the relationship between images by integrating low-level visual features and semantic attribute features. We perform hypergraph ranking to re-order the images, which is also constructed to model the relationship of all images. Its basic principle is that visually similar images should have similar ranking scores and a visual-attribute joint hypergraph learning approach has been proposed to simultaneously explore two information sources. We conduct extensive experiments on 1000 queries in MSRA-MM V2.0 dataset. The experimental results demonstrate the effectiveness of our proposed attribute assisted Web image search reranking method.

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