

RESEARCH ARTICLE



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WEB-IMAGE SEARCH BY RE-RANKING IMAGES BASED ON ATTRIBUTES USING HYPER GRAPH

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ABSTRACT

Image search re-ranking is an effective approach to refine the text-based image search result. Most existing re-ranking approaches are based on low-level visual features. 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 hyper graph is then used to model the relationship between images by integrating low-level visual features and attribute features. Hyper graph ranking is then performed to order the images. Its basic principle is that visually similar images should have similar ranking scores. In this paper, we propose a visual-attribute joint hyper graph learning approach to simultaneously explore two information sources. A hyper-graph is constructed to model the relationship of all images.

Keywords— Search, hypergraph, attribute-assisted

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INTRODUCTION

With the dramatic increase of online images, image retrieval has attracted significant attention in both academics and industry [7]. Many image search engines such as Google and Bing have relied on matching textual 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 re ranking has been proposed to refine text-based search results by exploiting the visual information contained in the images [1]. The existing visual re-ranking methods can be typically categorized into three categories as the clustering based, classification based and graph based methods.

LITERATURE SURVEY

Supervised re-ranking for web image search (2010)
Visual search re-ranking that aims to improve the text-based image search with the help from visual content analysis has rapidly grown into a hot research topic. The interestingness of the topic stems mainly from the fact that the search re-ranking is an unsupervised process and therefore has the potential to scale better than its main alternative, namely the search based on offline-learned semantic concepts. However, the unsupervised nature of the re-ranking paradigm also makes it suffer from problems, the main of which can be identified as the difficulty to optimally determine the role of visual modality over different application scenarios. Inspired by the success of the “learning-to-rank” idea proposed in the field of information retrieval, we propose in this paper the

“learning-to-rerank” paradigm, which derives the re-ranking function in a supervised fashion from the human-labeled training data. Although supervised learning is introduced, our approach does not suffer from scalability issues since a unified re-ranking model is learned that can be applied to all queries. In other words, a query-independent re-ranking model will be learned for all queries using query-dependent re-ranking features. The query-dependent re-ranking feature extraction is challenging since the textual query and the visual documents have different representation. In this paper, 11 lightweight re-ranking features are proposed by representing the textual query using visual context and pseudo relevant images from the initial search result. The experiments performed on two representative Web image datasets demonstrate that the proposed learning-to-rerank algorithm outperforms the state-of-the-art unsupervised re-ranking methods, which makes the learning-to-rerank paradigm a promising alternative for robust and reliable Web-scale image search.

Image ranking and retrieval based on multi-attribute queries (2011)

We propose a novel approach for ranking and retrieval of images based on multi-attribute queries. Existing image retrieval methods train separate classifiers for each word and heuristically combine their outputs for retrieving multiword queries. Moreover, these approaches also ignore the interdependencies among the query terms. In contrast, we propose a principled approach for multi-attribute retrieval that explicitly models the correlations that are present between the attributes. Given a multi-attribute query, we also utilize other attributes in the vocabulary which are not present in the query, for ranking/retrieval. Furthermore, we integrate ranking and retrieval within the same formulation, by posing them as structured prediction problems. Extensive experimental evaluation on the Labeled Faces in the Wild (LFW), Face Tracer and PASCAL VOC datasets show that our approach significantly outperforms several state of-the-art ranking and retrieval methods.

Describing objects by their attributes (2009)

About shift the goal of recognition from naming to describing. Doing so allows us not only to name familiar objects, but also: to report unusual aspects of a familiar object (“spotty dog”, not just “dog”); to say something about unfamiliar objects (“hairy and four-legged”, not just “unknown”); and to learn how to recognize new objects with few or no visual examples. Rather than focusing on identity assignment, we make inferring attributes the core problem of recognition. These attributes can be semantic (“spotty”) or discriminative (“dogs have it but sheep do not”). Learning attributes presents a major new challenge: generalization across object categories, not just across instances within a category. In this paper, we also introduce a novel feature selection method for learning attributes that generalize well across categories. We support our claims by thorough evaluation that provides insights into the limitations of the standard recognition paradigm of naming and demonstrates the new abilities provided by our attribute-based framework.

Image retrieval via probabilistic hypergraph ranking (2010)

In this approach, a new learning framework for image retrieval, in which images are taken as vertices in a weighted hypergraph and the task of image search is formulated as the problem of hypergraph ranking is made. Based on the similarity matrix computed from various feature descriptors, we take each image as a ‘centroid’ vertex and form a hyper-edge by a centroid and its k -nearest neighbors. To further exploit the correlation information among images, we propose a probabilistic hypergraph, which assigns each vertex v_i to a hyper-edge e_j in a probabilistic way. In the incidence structure of a probabilistic hypergraph, we describe both the higher order grouping information and the affinity relationship between vertices within each hyper-edge. After feedback images are provided, our retrieval system ranks image labels by an inference approach, which tends to assign the same label to vertices that share many incidental hyper edges, with the constraints that predicted labels of feedback images should be similar to their initial labels.

PROPOSED WORK

Web image search re-ranking is emerging as one of the promising techniques for automotive boosting of retrieval image. It is a fast and accurate scheme proposed for grouping precision. Graph based methods have been proposed recently and received increased attention as demonstrated to be effective. An attribute-assisted hyper graph learning method is used to reorder the ranked images which returned from search engine based on textual query. Hyper graph is thus able to improve re-ranking performance by mining visual feature as well as attribute information. The hyper graph model has been widely used to exploit the correlation information among images.

Methodologies

- I. Web Image Search Re-ranking
- II. Semantic Attributes
- III. Hyper graph Learning
- IV. Image Features Attribute Learning
- V. Attribute-Assisted Hyper graph Construction

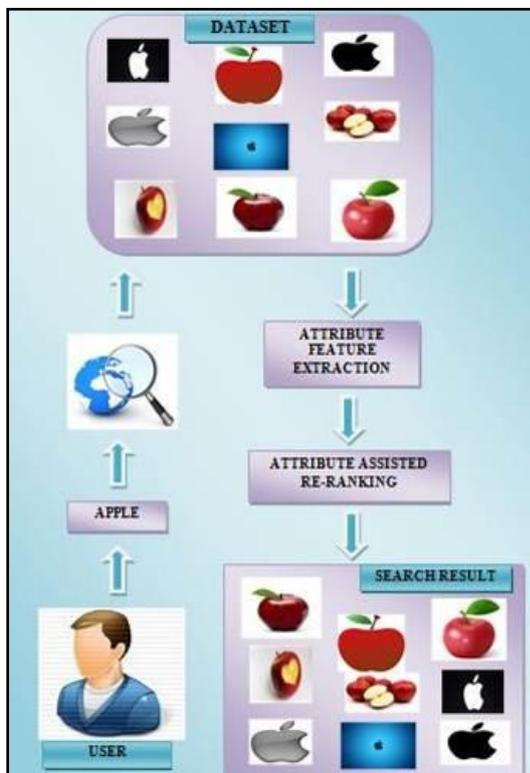


Figure 1: Architecture of proposed system

A. Web Image Search Re-Ranking

Web image search re-ranking is emerging as one of the most promising techniques for automotive boosting of retrieval precision [2]. 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 re-ranking approaches can roughly be categorized into three categories including the clustering based, classification based and graph based methods.

B. Semantic Attributes

Semantic attributes can be regarded as a set of mid-level semantic preserving concepts. Different from low-level visual features, each attribute has an explicit semantic meaning, e.g., "animals". Attribute concepts also differ from specific semantics since they are relatively more general and easier to model, e.g., attributes "animal" and "car" are easier to model and distinguish than the concrete semantic concepts "Husky" and "Gray Wolves". Due to the advantages of being semantic-aware and easier to model, attributes have been studied recently and are revealing their power in various applications such as object recognition [3], [4] and image/video search [6]. Thus, attributes are expected to narrow down the semantic gap between low-level visual features and high-level semantic meanings.

C. Hyper graph Learning

In a simple graph, samples are represented by vertices and an edge links the two related vertices. Learning tasks can be performed on a simple graph. Assuming that samples are represented by feature vectors in a feature space, an undirected graph can be constructed by using their pair wise distances, and graph-based semi-supervised learning approaches can be performed on this graph to categorize objects. It is noted that this simple graph cannot reflect higher-order

information. Compared with the edge of a simple graph, a hyper edge in a hyper graph is able to link more than two vertices.

D. Image Features Attribute Learning

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 are involved. A bag-of-words style feature for each of these four feature types is taken. Color descriptors can be densely extracted for each pixel as the 3-channel LAB values. K-means clustering with 128 clusters is made. The color descriptors of each image are then quantized into a 128-bin histogram. Texture descriptors are computed for each pixel as the 48-dimensional responses of text on filter banks. The texture descriptors of each image are then quantized into a 256-bin histogram. Edges are found using a standard canny edge detector and their orientations are quantized into 8 unsigned bins. This gives rise to an 8-bin edge histogram for each image. SIFT descriptors are densely extracted from the 8×8 neighboring block of each pixel with 4 pixel step size.

E. Attribute-Assisted Hyper graph Construction

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 that 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 to 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.

EXPERIMENTAL RESULTS

We have considered a set of data for analysis in this section. The data considered involves

several images belonging to categories like “babies”, “human”, “vehicle”, “objects”, “toys”, etc. These data are then processed based on our assumptions. The image attributes like “eye”, “cheeks”, “feet”, “face”, etc. are considered for categorical data like humans. Similarly, attributes like “size”, “color”, “shape”, etc. are considered for objects. Figure 2 shows the various images taken into consideration for experimental purposes.



Figure 2: A part of the data considered for analysis

The images are uploaded and then retrieved on request. These retrieved images are re-ranked based on the user’s requirement. Re-ranking the images brings the more relevant images to the top and lesser relevant images to the bottom. Once the images are re-ranked, the updating takes place in the database. The further results for the queries are more relevant than the previous attempts.



Figure 3: Re-ranking images

The image details are updated if the user feels that the retrieved image results are not “relevant” or “most relevant”. Less relevant results leads to inefficiency and so these image details are further updated.

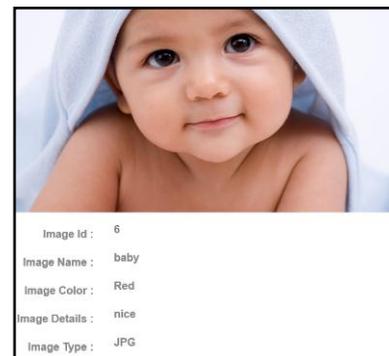


Figure 4: Image details

Figure 5 gives the search results for the keyword "smile". The images that are in one or more ways related to the keyword "smile" (either by name or attribute) are retrieved. Few other keywords like "baby", "boy", "girl", "kid", "cute", "eyes", etc. can also be used.



Figure 5: Search results for the keyword "smile"

Searches vary from one user to another. Various users give requests based on their necessities. Figure 6 shows the pie chart representing the frequently requested type of images. Semantic attributes like "Face", "Arm", "Leg", "Hand", "Tail", "Beak", "Wheel", "Cloth", "Furry", "Nose", "Wing", "Wood", "Rock", "Leaf", "Headlight", "Feather", "Flower", "Vehicle Part", "Dotted", "Smooth", etc. are used for different images. The frequent requests from users are mined and the pie diagram is generated.

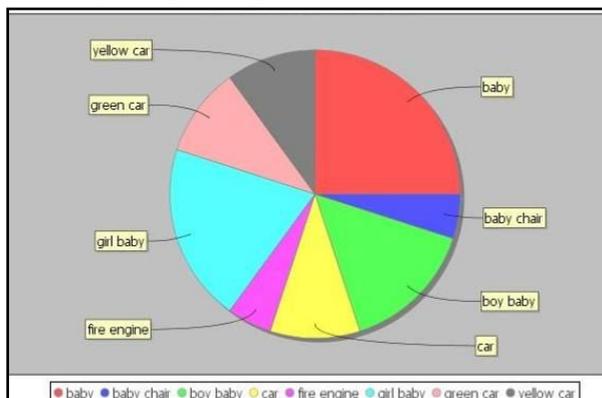


Figure 6: Pie chart for frequent user search based on the image name

FUTURE WORK

We see several possibilities to further explore and extend the learning-to-rerank paradigm. The existing unsupervised re-ranking methods can be employed to construct re-ranking features in the learning-to-rerank method. The advantage of the proposed re-ranking feature lies in the lightweight computational cost. However, in cases that the response time is not critical, we can fuse multiple unsupervised re-ranking methods for a better ranking.

The proposed learning-to-rerank method as well as the existing unsupervised re-ranking methods takes only the relevance into consideration. However, the result diversity is also an important objective so that more informative search results can be provided to users. The learning-to-rerank framework makes it easy to take the result diversity into consideration by designing diversity aware re-ranking features or a diversity-aware learning objective [5]. As the experimental result suggests, the re-ranking feature selection can further improve the performance of the learned re-ranking model.

CONCLUSION

Image search re-ranking 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 is an attempt to include the attributes in re-ranking 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, a novel attribute-assisted retrieval model for re-ranking images is proposed.

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 hyper graph is then used to model the relationship between images by integrating low-level visual features and semantic attribute features. Hyper graph ranking to re-order the images, which is also constructed to model the relationship of all the images are used. Its basic principle is that visually similar images should have similar ranking scores and a visual-attribute joint hyper graph learning approach has been proposed to simultaneously explore two information sources.

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