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RERANK WEB SEARCH IMAGE USING HYPERGRAPH LEARNING

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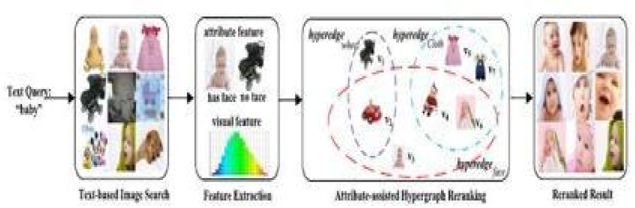
Abstract: Image search re-ranking results an effective approach to refine the text based search. In existing re-ranking models are only based on low level visual features. In proposed system implement to exploit semantic attributes for image search re-ranking. Based on the binary classifiers, the pre-defined attributes which are used to represent the images. A hyper-graph is used to model the relationship between images by integrating low-level visual features and attribute features and it re-rank the images. Its basic principle is that visually similar images should have similar ranking scores. Here we propose a visual-attribute joint hyper-graph learning approach. In this experiment, MSRA-MMV2.0 data set is used. This experiment results the effectiveness of our approach.

Index Terms-**Re-ranking, Visual-attributes, Data set.**

INTRODUCTION

With the increase of uploading and retrieval of images, has attracted all people. Many image search engines, Such as Google and Bing have matching textual Information of the images against queries. However, text-based image results essential problem that caused mainly by the incapability of the associated text to appropriately describe the image content. Recently, visual re-ranking has been proposed to find next level of text-based search results by exploiting the visual information restricted in the images. The existing visual re-ranking methods can be typically categorized into three, clustering based, classification based and graph based methods. The above three methods based on only low level visual features. The high level semantic concepts which are results clear image .Their attributes effectiveness is in face verification, other attributes verification for image re-ranking. The attributes like color, texture, size or object, such as circle, hand, green etc. Attribute based re-ranking is easy to compared full images e.g., baby.



In the figure we have to search baby image based on text. First related image are ranked. Attribute features and visual features are compare for each images. Using hyper-edge to group the images based on their attributes. After that baby images are re-ranked and getting result.

Web Image Search Re-ranking:

Web image search re-ranking is technique for retrieving the images. The basic function is to re-ranking the images based on text. Text based image search is result in relevant image are ranked in top level and less relevant images are in low rank. The most relevant images are top ranked. Based on visual attributes there are three methods clustering based, classification based, graph based methods.

Clustering-Based Method:

In clustering based method, some algorithm is used (e.g., mean shift, k-medodis, k-means) when image search that has group into several clusters. Then re-ranked result is created by using cluster conditional probability. When re-ranked result is crested then ordering the cluster based on cluster value. It is fast and accurate scheme, but it has not clear visual features. It is not guarantee.

Classification-Based Methods:

In the classification based methods, has overcome the binary classification problem. It has method for which quires independent with text based. Used pseudo-relevant feedback for image search results. The top ranked list are based on text based and related images are based on queries. Classification method based on visual features.

Graph-Based Methods:

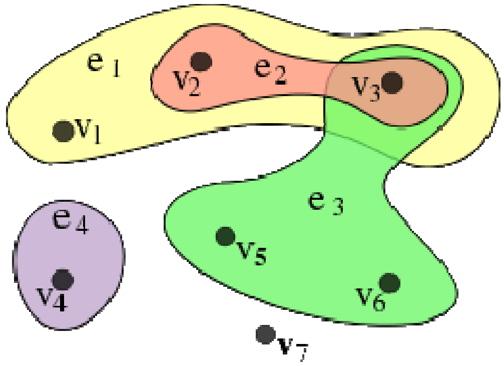
Graph based methods, is used frame work proposed by Jing and Baluja. In frame work re-rank the images based on visual features. The result is based on nodes and weights of graph. Energy minimization problem in the frame work that has formulate by Bayesian re-ranking proposed by Tian et ai. In, Tian et al. Graph based method has results top rank images. It has based on only visual features. Wang et al. proposed a semi-supervised to get clear image based on text.

Semantic Attributes:

Semantic attributes is different from low level visual features. It is easier to re-ranking the images. It is used for both multimedia and images. Thus, attributes are relationship between low level visual features and attributes by using attribute classifiers, Su *et al.* propose to the semantic gap between visual effectiveness and high level semantic attributes. Farhadi *et al has used* thousands of classifiers for chose as attributes (*e.g.*, attributes that "cat" and "dog"). Kumar *et al* define for face verification used binary attributes called similes. The attributes are detected for trained one specific feature (e.g., car's wheel). Recently, Parikh and Grauman propose new method that has related of two images. Binary classifiers are learned by ranking function. Its output is based on their relative attributes. The content based image retrieval is proposed by Zhang et al describe multiple factors and hybrid feedback results collection of images.

Hyper-graph Learning:

Hyper-graph is used for related the attributes features and low level visual features. It is a simple graph method. Hyper-graph used hyper-edge in graph method. It has related by vertices and edges. Hyper-edge has related to or more vertices.



A hyper-graph G= (V, E, W) V is vertex, E is edge, W is weight of the node. Edge has given by w (e). The hyper-graph *G* can be
Denoted by a | V | × | E | matrix **H** with entries
defined as:

$$h(vi, ej)=\begin{cases}1 & if\ vi \in ej\\ 0 & otherwise\end{cases} \quad (1)$$

For vertex $v \in V$, its vertex degree can be estimated by:

$$d(v)=\sum_{e\in E} w(e)h(v,e) \quad (2)$$

For a hyper-edge $e \in E$, its hyper-edge degree can be estimated by: $\delta(e) =\sum_{v\in V} h(v,e)$ (3)

We use *Dv* and *De*, *D* is denote as diagonal matrices containing the vertex and edge degrees, and let *W* denote the matrix weights of hyper-edges

$$W(i,j)=\begin{cases}w(i) & if\ i=1\\ 0 & otherwise\end{cases} \quad (4)$$

In a hyper-graph, machine learning task are performed, that is clustering based and classification based. Example taken in hyper-graph is binary classification. For hyper-graph Learning, the Normalized Laplacian method proposed in is employed, and it is formulated as regularization framework:

$$argmin_f\{\lambda R_{emp}(f) + \Omega(f)\} \quad (5)$$

Where f is the relevance score to be learned, $\Omega(f)$ is the normalized cost function, $R_{emp}(f)$ is empirical loss, and λ is a weight parameter. By minimize this cost function, vertices sharing many incidental hyper-edges are guaranteed to obtain similar relevance scores. The regularizer on the hyper-graph is defined as:

$$\Omega(f)=\frac{1}{2}\sum_{e\in E}\sum_{v\in e}\frac{w(e)h(u,e)h(v,e)}{\delta(e)}\left(\frac{f(u)}{\sqrt{d(v)}}-\frac{f(v)}{\sqrt{d(u)}}\right) \quad (6)$$

Let $\theta = D_V^{-\frac{1}{2}}$ HW$D_V^{-\frac{1}{2}}$,and $\Delta = 1-\theta$.Rewritten the normalized cost function:

$$\Omega(f)=f^T\Delta f \quad (7)$$

Where,Δ is a positive semi-definite matrix called hyper-graph laplacian.

ATTRIBUTE-ASSISTED IMAGE SEARCH RERANKING

The proposed attribute-assisted image search re-ranking framework. We elaborate image features in Section A, and then introduce the proposed attribute learning method in Section B. Finally, we describe our hyper-graph construction algorithm in Section C.

A. Image Features

Image used four types of features, color and texture, which are good for material attributes; edge, used for shape attributes; and scale-invariant feature change (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 text on filter banks. The texture descriptors of each image were then quantized into a 256-bin histogram. Edges were found using a average canny edge detector and their orientations were quantized into 8 unsigned bins. This gives rise to a 8-bin edge histogram for each image. SIFT descriptors were closely 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 characteristic. 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)1 classifier for each attribute. However, simply learning classifiers by fitting them to all visual features often fails to simplify 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 help 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 alleviate the effect of the *curse of dimensionality*. We here apply the feature selection method as described in. In particular, if we want to learn a "wheel" classifier, we select features that perform well at distinguishing the bike with indicator without indicator, we help the classifier avoid being confused about "metallic", as equally types of example for this "wheel" classifier have "metallic" surfaces. We select the features using an _1-regularized logistic failure trained for each attribute within each class, then group examples over all classes and train using the selected features. Such regression model is utilized as the preliminary classifiers to learn sparse parameters. The features are then selected by pooling the union of indices of the sparse non-zeros entries in those parameters. The regularization parameters of norm regression were set to 0.01 empirically and the parameters of SVM classifiers were resolute by fivefold cross validation. For example, we first select features that are good at individual cars with and without "wheel" by fitting an _1-regularized logistic regression to those examples. We then use the same method to select features that are good at unraveling motorbikes with and without wheels, buses with and lacking wheels, and trains with and without wheels. We then lake all those selected features and study the "wheel" classifier over all classes using those selected features. In this way, we select effective features for each attribute and the selected features are then used for learning the SVM classifier.

C. Attribute-Assisted Hyper-graph Construction

In attribute assisted hyper graph learning is to reorder the images which are ranked when uploading based on the text-based. Hyper-graph different form not only the vertex on hyper-graph and also a specific e. Hyper-graph learning is improve their performance of re-ranked images.
Images in hyper-graph has based on graph G= (V,E,ω). Assume that data set has n images and hyper-graph has n digit of vertices, Let V={$v1, v2, \ldots.vn$}where n is vertices and E={$e1, e2, \ldots\ldots.em$} where is hyper-edges. Same attribute has shared by many images are connect by one hyper-edge. Different hyper-edges are weight vector w={$w1, w2, \ldots\ldots\ldots wm$} in hyper-graph where $\sum_{i=1}^{m} w_i$=1. The incidences matrix is given by:

$$h(v_i,e_j)=\begin{cases}s_{v_i} & if\ v_i \in e_j\\ 0 & otherwise\end{cases} \quad (8)$$

where s_{v_i}represent j-attributes classifier score of images v_i for vertex v$\in V$ degree of vertex is d$(v)=\sum_{e\in E} w(e), h(v,e)$. Hyper-edge e$\in E$ and its degree is $\delta(e)=\sum_{v\in V} h(v,e)$.
The similarities matrix A between two images is given by:

$$A(i,j)=\gamma_1 A_{attributes}+\gamma 2A_{local}+\gamma 3A_{global}$$
$$=\gamma_1 exp\left(-\frac{D_i s_{attributes}(i,j)}{D_{attributes}}\right)+\gamma 2exp\left(-\frac{D_i s_{local}(i,j)}{D_{local}}\right)+$$
$$\gamma 3\exp\left(-\left(\sum_{i=1}^{3}\frac{D_i s_{gk}(i,j)}{D_{gk}}\right)\right) \quad (9)$$

Where $D_i s_j(i,j), D_i s_{local}, D_i s_{attributes}$ is the distance between v_i, v_j. $D_i s_{attributes}(i,j)$ is denoted as:

$$D_i s_{attributes}(i,j)=i_a-j_{a_2^1}=\sqrt{(i_a-j_a)^T(i_a-j_a)} \quad (10)$$

i_a and j_a attribute features of two images.

D. Utilization of Text-Based Search Prior

Since in re-ranking, the text-based search provides original ranking lists instead of quantized scores, a necessary step is to turn the ranking positions into scores. Details about the queries and the dataset will be introduced in Section IV. However, the average relevance score curve with respect to the ranking position is not smooth enough even after using more than 1,000 queries. A prior knowledge can be that the expected relevance score should be decreasing with respect to ranking position. Therefore, we further smooth the curve with a parametric approach.

EXPERIMENTS

Describe the experimental dataset that we used to evaluate our proposed approach. Then we present the results of evaluation at different levels and verify the effectiveness of our method.

A. Dataset

We use the MSRA-MM V2. 0 dataset as our experimental data. This dataset consists of about 1 million images from 1,097 various yet representative queries collected from the query log of Bing. We choose this dataset to evaluate our approach for the following reasons: (1) it is a real-world web image dataset; (2) it contains the original ranking information of a popular search engine, and thus we can easily evaluate whether our approach can improve the performance of the search engine; (3) it is publicly available. There are roughly 900 images for each query. For each image, its relevance to the matching query is labeled with three levels: very relevant, relevant and irrelevant. These three levels are indicated by scores 2, 1 and 0, respectively. The number of queries at various categories and some instance images of different significance levels. The queries are used for re-ranking performance evaluation. We first randomly select 40 queries from two categories animal and object .All the very related images within these queries are kept for attribute classifiers training. We defined 108 attributes by referring to the attributes in as scheduled, such as the ground truth of attributes are manually annotated. As aforementioned in Section III-A, there are four types of features extracted including color, texture, edge and SIFT descriptor. We adopt a bag-of-words style for each of these four features and obtained 9,744-dimensional feature for each image.

B. Evaluation Measure

We assume Normalized Discounted Cumulative Gain (NDCG), which is a standard evaluation in information recovery when there are more than two significance levels, to measure the performance. To evaluate the overall performance, we average the NDCGs over all queries to obtain the Mean NDCG.

C. Experimental Results and Analysis

We first evaluate the effectiveness of our attribute classifiers on the 1,097 testing queries. Regarding the outputs of each attribute classifier on all the images, we use both binary classification decision and continuous confidence scores. The binary outputs are used to evaluate the classifier performance and the confidence score are used to calculate probabilistic hyper-edge. Due to the high cost of manual labeling, we only label the 108 attributes on the top 10 images from initial text search for each query. We adopt the widely used metric AUC (area under ROC curve) value for evaluate the accuracies of attribute classifiers. The experimental results demonstrate that semantic description of each image as the attribute features are formed by prediction of several classifiers.

1) Performance Comparison Among Cluster-Based, Classification-Based, Graph-Based:

To verify the effectiveness of the proposed attribute-assisted re-ranking method, we compare the following approach for performance evaluation: Information Bottle. The re-ranking approach apply information bottleneck clustering over visual features with the help of a smoothed initial ranking. The method is denoted as cluster-based Pseudo Relevance Feedback .To specified a query, we use top 100 search results in the original ranking list as positive samples, and randomly collect 100 images from the whole dataset and use them as negative samples. We adopt RBF kernel based on these samples and learn SVM classifier to re-rank the search results. The approach is denoted as "PRF-SVM". Bayesian Re-ranking. Since the Local-Pair variant of Bayesian re-ranking performs the best among the six Bayesian variants re-ranking approaches, we will use it as the representative of Bayesian re-ranking methods. The method is denoted as "Pair-Local". Specifically, our method obtain 7.3% and 3.9% relative improvements on MNDCG@100 compared with the Bayesian re-ranking. In addition, for attributed assisted Pair-Local method, it has relatively improved 1.8% on MNDCG@40 in comparison with original re-ranking approach. The main reason is that our method involves beneficial attribute features throughout the re-ranking framework. Additionally, we also explore and create visual neighborhood relationship for each hyper-edge instead of isolated visual similarity mainly used in the Bayesian re-ranking.

2) Performance Comparison for Hyper-graph Re-ranking:

In the above, we have verified that our proposed hyper-graph Re-ranking approach performs the best in comparison with the conventional re-ranking strategies. In this section, we will further confirm the superiority of joint hyper-graph learning approach by adding a robust regularized on hyper-edge weights. We denote the method published in preliminary work as "Hyper-graph Re-ranking", where we concatenate all features into a long vector and construct hyper-graph based on their visual similarity. The performance in terms of MNDCG of the two re-ranking methods. We can see that the presented hyper-graph learning approach assisted with regularized performs better than Hyper-graph Re-ranking. It achieves around 3. 8% improvements at MNDCG@20. Moreover, to demonstrate the robustness of the proposed regularize. From the experimental comparison, we could see that our approach is more favorable in the task of Web image search re-ranking, which improves the baseline steadily and outperforms the other re-ranking strategies. The good performance of the novel approach for Web image search re-ranking could be attributed to the following appealing properties: (1) since attribute features are formed by prediction of several classifiers, semantic attributes description might be noisy and only limited semantic attributes could be distributed in a single image. Such implicit attribute selection could make hyper-graph based approach much more robust to improve the re-ranking performance, as inaccurate attributes could be removed and informative ones have been selected for image representation. our proposed iterative regularization frame could further explore the semantic similarity between images by aggregating their local, global similarities instead of simple fusion with concatenation. As the hyper-edges in the graph are formed by K images sharing the common semantic attribute, we perform evaluation on re-ranking performance with various sizes of hyper-edge K.

For each K value plotted, we perform the re-ranking comparison with attribute feature and without its help. It achieves the best performance when we set K as 40 among all selected values. It seems that larger or smaller size of hyper-edge may result in lower re-ranking performance in terms of involving more harmful or less useful attributes. We could also see that our proposed re-ranking approach with local and global feature is boosted by mining attribute information in the experiment.

3) Performance Evaluation for Selected Semantic Attributes:

To further illustrate the importance role of semantic attributes on the re-ranking framework, we conduct experimental evaluation on the hyper-edges that have the highest weights. In Table III, it has been pointed out that the top 20 attributes with higher weights in the proposed approach and such semantic attributes are highlighted in italic blues . We also illustrate the semantic attributes that have top 5 highest weights on some images. We could see that beneficial attributes are distributed in exemplar image which preserve the stronger semantic similarity and thus facilitate ranking performance. Moreover,
it is also observed that the semantic attributes with a lower classification score might give a low or high weight in the hyper-graph, in regardless to attributes. Hence, the experimental results show the robustness of our proposed approach. Hyper-graph Re-ranking in comparison to Bayesian Re-ranking and Cluster-based approach on MSRA-MM dataset. It is obvious that that our proposed approach considerably outperforms the baselines methods.

V. CONCLUSION

Image search re-ranking has been calculated for several years and various approaches have been developed recently to be performance of text-based image search engine for general queries. We introduced the first attributes are re-ranking framework. We observe that semantic attributes are expected . Motivated by a novel attribute-assisted retrieval model for re-ranking images. base on the classifiers for all the predefined attribute for image represented by an attribute . A hyper-graph is used to model the related images for low-level visual features and semantic attributes. We perform hyper-graph ranking to reuse the images orderly and also constructed to model the relationship of all images. Its basic principle is visually similar images should be related ranking scores and a visual-attribute joint hyper-graph learning approach has been proposed to simultaneously explore two information sources. We conduct extensive experiments queries in dataset. The experimental results demonstrate the effectiveness of attribute-assisted Web image search re-ranking method.

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