

# Attribute Based Image Search Reranking

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**Abstract** - Image search reranking is one of the effective approach to refine the text-based image search result. Text-based image retrieval suffers from essential problems that are lead to the incapability of the associated text to appropriately evoke the image content. In this paper, reranking methods are put forward to address this drawback in scalable fashion. Based on the classifiers for each and every predefined attributes, each and every image is represented by an attribute feature consisting of the responses from these classifiers. This hypergraph can be used to model the relationship between images by integration of low-level visual features and attribute features. Hypergraph ranking is then performed to order the images. Its basic principle is that visually close images should have identical ranking scores. It improves the performance over the text-based image search engine.

**Keywords** – Hypergraph, attribute-assisted, reranking

## 1. INTRODUCTION

The existing web image search engines, together with Bing, Google and Yahoo retrieve and rank images largely supported on the textual information incidental with the image in the hosting web pages, such as the title and the surrounding text. While text-based image ranking is usually effective to search for relevant images, the precision of the search result is largely bounded by the mismatch between the true relevance of an image and its relevance inferred from the associated textual descriptions. To improve the correctness of the text-based image search ranking, visual reranking has been put forward to refine the search result obtained from the text - based image search engine by incorporating the information bring by the visual modality. The existing visual Reranking methods can be roughly divided into three listing as the clustering based, classification based and graph based methods. Cluster analysis or clustering is that the quest of grouping a set of objects in such a way that objects within the same group (called as cluster) are more identical (in some sense or other) to each other than to those in other groups (clusters). Initial search results from text-based search can be classified by visual closeness.

In classification visual reranking is developed as binary classification drawback aiming to identify whether each search result is relevant or not. Graph based strategies have been put forward recently and received increasing attention as demonstrated to be effective. The multimedia entities in top ranks and their visual correlation can be represented as a collection of nodes and edges. The local patterns or salient features track down using graph analysis are very powerful to improve the effectiveness of rank lists. Semantic attributes may be shape, color, texture, material, or a part of objects, like “round,” “red,” “metal,” “wheel” and “leg” et cetera. This paper holds the attribute assisted reranking method based on hypergraph learning is introduced. First train some classifiers for all the pre-defined attributes and each image is represented by attribute feature consisting of the responses from these classifiers. Totally different from the existing methods, a hypergraph is then used to model the relationship between

images by integration of low-level features and attribute features. Finally, reranked list of the images acquired with respect to relevance scores in descending order.

## 2. RELATED WORK

This section consists of existing visual search reranking methods, explore the semantic attributes draw in from neoteric literature, and describe the hypergraph.

### 2.1 Visual Reranking Methods

On the report of statistical analysis model used, the existing reranking approach can roughly divided into three types inclusive of the clustering based, classification based and graph based methods.

#### Clustering-based methods:

Clustering analysis is very efficient approach to estimate the inter-entity similarity. The images in the initial results are primarily grouped automatically into a number of near duplicate media documents. However, for queries that return many and various results or without clear visual patterns, the output is not guaranteed. And also this method works when initial text based search should contain near duplicate images.

#### Classification-based methods:

In classification based methods visual reranking is formulated as binary classification problem line up to identify whether each search result is relevant or not. For an example, a classifier or a ranking model is learned with the pseudo relevance feedback. However, in many real situations, training examples obtained via PRF are very noisy and might not be enough for training effective classifier. To mark this issue, learned a query independent text based re-ranker. The top ranked results from the text based reranking are then picked as positive training examples. Negative training examples are picked randomly from the other queries. However PRF top N images are considered as positive sample but that top N images may contain irrelevant image that's why performance is not appropriate.

#### Graph-based methods:

Graph based methods have been proposed recently and meet with increased attention as demonstrated to be effective. In this method multimedia entities in top rank and their visual relationship is used as a graph but is purely based on low level visual features.

### 2.2 Semantic Attributes

Attributes are anticipated to narrow down the semantic gap between low-level visual features and high-level semantic meanings. Moreover, the type of the most effective features should vary across queries. For example, for queries that are correlated with color distribution, such as sunset, sunrise and beach, color features will be competent. For couple of queries like building and street, edge and texture features will be more effective. It can be acknowledged that semantic attribute would also be viewed as an interpretation or modality of image data. Using multimodal features can assure that the serviceable features for different queries are contained. Therefore, all these supremacy drive us to turn to good use of semantic attributes for image representation in the task of web image search reranking. Considering the classifiers for almost all the predefined attributes, each and every image is corresponded by an attribute feature formed by the responses from these classifiers.

### 2.3 Hypergraph

In a simple graph, images stand in for vertices and an edge links the two related vertices. This one noted that this simple graph cannot reflect high-level information. juxtaposed with the edge of a simple graph, a hyperedge in a hypergraph is competent to link the more than two vertices. Hypergraph is a simple graph which is used to find the relationship between images which gives the very appropriate results.

## 3. ATTRIBUTE BASED IMAGE SEARCH RERANKING

This section consists of Scale invariant feature transform (SIFT) and Hypergraph construction.

### 3.1. Scale Invariant Feature Transform (SIFT)

To extract attributes or key points from image scale invariant feature transform is used. First step in scale invariant feature transform is to give positive sample of each attribute. Then construct the scale space of image. Scale space means internal structure of image which makes easy in finding key points or attributes from image. In this Gaussian kernel is used as filter. Laplacian gives the second order derivative.

Value of second order derivative is very negligible in case of smooth surface and much higher in case of key points are there.

#### Algorithm

Step 1: Give training for each attribute.

Step 2: Construct scale space.

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$$

Where,

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-((x*x)+(y*y))/2\sigma^2}$$

Step 3: Take difference of Gaussians.

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma) \end{aligned}$$

This gives the key points or Attributes from image.

Step 4: Distance Calculation: Brute Force Matcher is used.

Brute Force Matcher is used to match those points which are obtained from previous step.

It has two parameters;

[I] norm Type

[II] boolean variable

Formula,

float nndrRatio = 0.5

if(D1.distance <= D2.distance \* nndrRatio)

```
{
    Add to good match list
}
```

Step 5: Create array list for each matched attribute.

### 3.2. Hypergraph Construction

Hypergraph is a simple graph which is used to find the relationship between images which gives the very appropriate results.

#### Algorithm

Input: The image set for re-ranking.

$$\mathcal{X} = (x_1, x_2, \dots, x_n)$$

Output: Re-ranking result.

Step 1: Generate id for each image in the image set  $\mathcal{X} = (x_1, x_2, \dots, x_n)$  as a vertex in the hypergraph.

Step 2: Add each image as vertex in the set  $\mathcal{X} = (x_1, x_2, \dots, x_n)$

Step 3: Initialize +1 weight to each edge in hypergraph.

Step 4: Reranking.

Step 5: show result.

### 4. EXPERIMENTS

To evaluate our system Normalized Discounted Cumulative Gain (NDCG) is used. Which is standard evaluation measure in information retrieval.

$$NDCG@n = \frac{1}{Z_n} \sum_{j=1}^n \frac{2^{r(j)} - 1}{\log(1+j)}$$

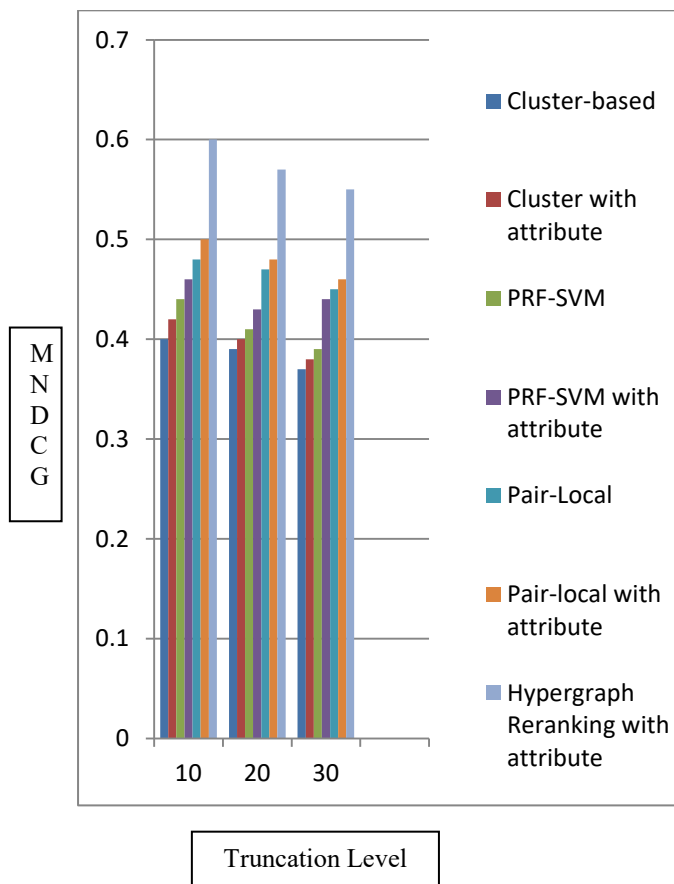
Values obtained using above formula are as below;

Query	Evaluation Measure Value		
	NDCG@10	NDCG@20	NDCG@30
Baby	1.1	1.06	1
Eagle	0.8	0.75	0.7
Rock	0.7	0.62	0.6
Sphinx	0.9	0.82	0.8
Mustang	0.7	0.62	0.6
Mouse	1.1	1.04	1
Keyboard	0.6	0.52	0.5
Joystick	0.4	0.32	0.3

Below table shows the comparison between proposed and existing system;

Mean of NDCG	Mean evaluation value of proposed system	Mean evaluation value of existing system
MNDCG@10	0.6	0.58
MNDCG@20	0.57	0.55
MNDCG@30	0.55	0.53

Performance comparison between our method and conventional methods is as below:



### 5. CONCLUSIONS

This servers as first attempt to include attributes and hypergraph in reranking framework. It is observe that semantic attributes are expected to narrow down the semantic gap in the middle of low-level visual features and highlevel semantic meanings. A hypergraph can be the effective approach to model the relationship between images by integrating low-level visual features moreover semantic attribute features.

### REFERENCES

- [1] L Yang and A. Hanjalic. Supervised reranking for web image search. In Proceeding of ACM Conference on Multimedia, 2010.
- [2] X. Tian, L. Yang, J. Wang, Y. Yang, X. Wu and X-S. Hua. Bayesian video search reranking. Transction on Mmultimedia , vol.14, no. 7, pp. 131-140, 2012.
- [3] F. Shroff, A. Criminisi and A. Zisserman. Harvesting image databases from the web. In proceedings of the IEEE International Conference on Computer Vision, 2007.
- [4] B. Siddiquie , R.S.Feris and L.Davis. Image ranking and retrieval based on multi-attribute queries. In proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2011.
- [5] A. Farhadi, I. Endres, D. Hoiem and D. Forsyth. Describing objects by their attributes.
- [6] N. Kumar, A. C. Berg, P. N. Belhumeur and S. K. Nayar. Attribute and simile classifiers for face verification.