

# Web Image Re-ranking using Query Specific Semantic Signatures

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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. Given a query keyword, a pool of images are first retrieved by the search engine 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. This paper uses a novel image re-ranking framework, which automatically offline learns different visual semantic spaces for different query keywords through keyword expansions. The visual features of images are projected into their related visual semantic spaces to get semantic signatures. At the online stage, images are re-ranked by comparing their semantic signatures obtained from the visual semantic space specified by the query keyword.

## I. INTRODUCTION

Image re-ranking, as an effective way to improve the results of web-based image search, has been adopted by current commercial search engines. Given a query keyword, a pool of images are first retrieved by the search engine 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. On the other hand, learning a universal visual semantic space to characterize highly diverse images from the web is difficult and inefficient.

## II. OUR APPROACH

In Existing system, one way is text-based keyword expansion, making the textual description of the query more detailed. Existing linguistically-related methods find either synonyms or other linguistic-related words from thesaurus, or find words frequently co-occurring with the query keywords. In existing system low level visual features of images compared for re-ranking purpose. For comparing visual features of images it uses Global weighting and adaptive weighting approaches. For example, Google image search provides the "Related Searches" feature to suggest likely keyword expansions. However, even with the same query keywords, the intention of users can be highly diverse and cannot be accurately captured by these expansions.

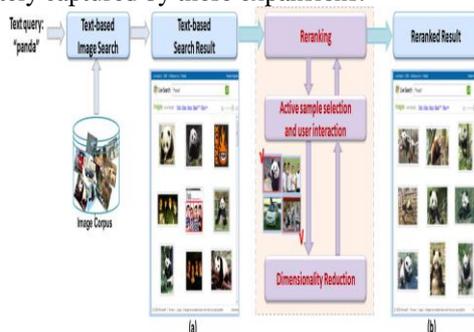


Figure 1. Proposed new image re-ranking framework.

For a query keyword (e.g. "apple"), a set of most relevant keyword expansions (such as "red apple", "apple macbook", and "apple iphone") are automatically selected considering both textual and visual information. This set of keyword expansions defines the reference classes for the query keyword. In order to automatically obtain the training examples of a reference class, the keyword expansion (e.g. "red apple") is used to retrieve images by the search engine.

## III. SYSTEM FEATURES MODULE

A. Label Information Collection: Text-Based image search is done. Results is displayed to the user according to ranking based on text matching

B. Active sample selection: For active sample selection we are using SINFO. SINFO – Structural Information based sample selection strategy. SINFO mainly consider two things for active sample selection, I. Ambiguity & II. Representativeness. In SINFO, the ambiguity of an image is measured by the entropy of the relevance probability distribution while the representativeness is measured by the density

C. Visual characteristic localization: To localize the visual characteristics of the user's intention, we propose a novel Local-Global Discriminative (LGD) dimension reduction algorithm. LGD considers both the local information contained in the labeled image and the global information of the whole image database simultaneously. We have three types of images in global database labeled relevant, labeled irrelevant, and unlabeled. Therefore, we build 3 types of patches, which are:

- 1) local patches for labeled relevant images to represent the local geometry of them and the discriminative information to separate relevant images from irrelevant ones
- 2) local patches for labeled irrelevant images to represent the discriminative information to separate irrelevant images from relevant ones

3) global patches for both labeled and unlabeled images for transferring both the local geometry and the discriminative information from all labeled images to the unlabeled ones. For convenience, we use superscript “+” to denote the labeled relevant images and “-” to denote the labeled irrelevant ones. If there is no superscript, it refers to an arbitrary image which may be labeled relevant, labeled irrelevant or unlabelled.

D. Re ranking implementation: Verify the effectiveness of the proposed active re-ranking method, we apply the SInfo active sample selection strategy and the LGD dimension reduction algorithm to re-ranking. In this paper, we take the Bayesian re-ranking as the basic re-ranking algorithm for illustration. When applying the Bayesian re-ranking for active re-ranking, modifications will be made to incorporate the new obtained information. The final re-ranking result is obtained by sorting the images according to in a descending

#### IV. KEYWORD EXPANSION

For a keyword  $q$ , we automatically define its reference classes through finding a set of keyword expansions  $E(q)$  most relevant to  $q$ . To achieve this, a set of images  $S(q)$  are retrieved by the search engine using  $q$  as query based on textual information. Keyword expansions are found from the words extracted from the images in  $S(q)$ .

A keyword expansion  $e$  belongs to  $E(q)$  is expected to frequently appear in  $S(q)$ . In order for reference classes to well capture the visual content of images, we require that there is a subset of images which all contain  $e$  and have similar visual content.

Based on these considerations, keyword expansions are found in a search-and-rank way as follows. For each image  $I$  belongs to  $S(q)$ , all the images in  $S(q)$  are re-ranked according to their visual similarities to  $I$ . The  $T$  most frequent words  $W_I = \{w_{1I}; w_{2I}; \dots; w_{TI}\}$  among top  $D$  re-ranked images are found. If a word  $w$  is among the top ranked image, it has a ranking score  $r_I(w)$  according to its ranking order;

$$\begin{aligned} &\text{otherwise } r_I(w) = 0, \\ r_I(w) &= T - j \quad w = w_{jI} \\ r_I(w) &= 0 \quad w \text{ not belongs to } W_I \dots \dots \dots \end{aligned} \quad (1)$$

The overall score of a word  $w$  is its accumulated ranking scores over all the images,

$$r(w) = \text{summation of } (I \times S) \quad r_I(w) \dots \dots \dots \quad (2)$$

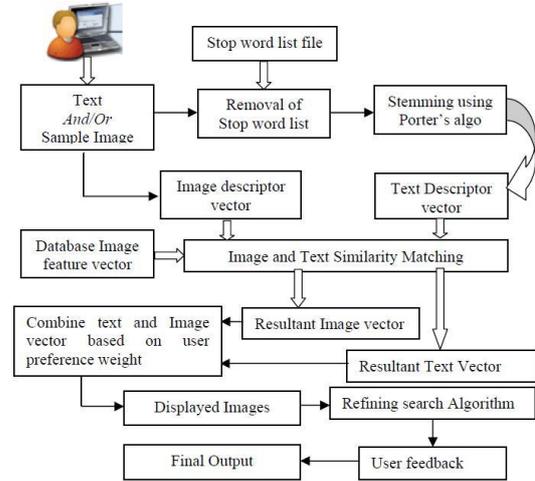
The  $P$  words with highest scores are selected and combined with the original keyword  $q$  to form keyword expansions, which define the reference classes.

#### V. SEMANTIC SIGNATURES

Given  $M$  reference classes for keyword  $q$  and their training images automatically retrieved, 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. Then  $p$  is used as semantic signature of  $I$ . The distance between

two images  $I_a$  and  $I_b$  are measured as the L1-distance between their semantic signatures  $p_a$  and  $p_b$ ,  $d(I_a; I_b) = \|p_a - p_b\|_1$ .

### VI. METHODOLOGY



### VII. EXPECTED RESULT

System will re-rank the images on the basis of semantic signatures to give required result related to query image. System will form and store the semantic signatures offline, at online stage it will compare only semantic signatures and result given to user. System will improve the re-ranking precisions up to 20% to 35% related to existing system as well as it will improve efficiency. The new approach will improve both the accuracy and efficiency of image re-ranking.

### VIII. CONCLUSIONS

We propose a novel image re-ranking framework, which learns query-specific semantic spaces to significantly improve the effectiveness and efficiency of online image re-ranking. The visual features of images are projected into their related visual semantic spaces automatically learned through keyword expansions at the offline stage. The extracted semantic signatures can be 70 times shorter than the original visual feature on average, while achieve 20% to 35% relative improvement on re-ranking precisions over state-of-the-art methods.

A unique re-ranking framework is proposed for image search on internet in which only one-click is used feedback by user. Specific intention weight schema is used proposed to combine visual features and visual similarities which are adaptive to query image are used. The feedback of humans is reduced by integrating visual and textual similarities which are compared for more efficient image re-ranking. User has only to do one click on image, based on which re-ranking is done.

Also duplication of images is detected and removed by comparing hash codes. Image content can be compactly represented in form of hash code. Specific query semantic spaces are used to get more improvised re-ranking of image.

### **IX. ACKNOWLEDGEMENT**

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