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An Efficient Image Re Ranking Based On Keyword Expansion Using Query Log

M.Jeyappratha MSc.[1], S.C.Punitha MSc, M.Phil,[2]

[1] *Mphil Research Scholar, Department of Computer Applications, PSGR Krishnammal College For Women,Coimbatore, Tamil nadu, India*

[2] *Head of the department, Department of Computer Science, PSGR Krishnammal College For Women,Coimbatore, Tamil nadu, India.*

Abstract— **Image re-ranking, as an efficient way to advance the results of web-based image search, has been implemented by present commercial search engines such as Bing and Google. For a given query keyword, a group of images is first retrieved based on textual information. From the group of images, the user selects the query image and the rest of images are re-ranked based on their visual similarities with the query image. A main dispute is that the similarities of visual features do not well correlate with semantic meanings of images which understand users' search purpose. This dispute is addressed by Keyword Query expansion an effective way to improve the performance of information retrieval systems by adding additional relevant keyword terms to the original queries. This paper presents a new method for keyword query expansion based on query logs mining. This method first calculates the ambiguity degree of the query by developing the user logs. The result measures the quality of the keyword query and decides the expanded length of the query. Next, the information of clicked images is used to create the correlations of the keyword queries, and the high-quality expanded keyword terms are selected from the past queries with the investigation of relation between queries and Images. This approach provides an effective way to avoid the problem of query drift by reducing the irrelevant expansion terms. The eexpanded keywords are used to widen the image pool to hold more relevant images. To further improve content-based image reranking, expanded keywords are used to enlarge the query image to multiple positive visual examples from which new query specific visual and textual similarity metrics are learned. Experimental result of the present work achieves better result when compare with the existing work.**

Keywords— **Image search, image reranking, Query log keyword expansion, adaptive similarity.**

I. INTRODUCTION

Web-scale image search engines mainly use keywords as queries and related by the nearby text to search images. It faces the challenge of the ambiguity of query keywords, because it is hard for users to accurately describe the visual content of target images only using keywords. Several industrial Internet scale image search engines use only keywords as queries. System users type query keywords in the expectation of discovering a certain type of images. The search engine precedes thousands of images ranked by the keywords taken out from the nearby text. It is well recognized that text-based image search endures from the uncertainty of query keywords. The keywords given by users likely to be short.

For example, the keyword of "apple" is used as a query keyword, the retrieved images go to various categories, such as "apple logo," "apple laptop." and "red apple," The uncertainty issue arises for various reasons. The meaning of query keywords might be more informative than users' expectations.This process is described in figure 1 is shown below. For instance, the significances of the word "apple" used in apple fruit, apple computer, and apple ipod. Second, the user might not have sufficient knowledge on the textual description of target images.

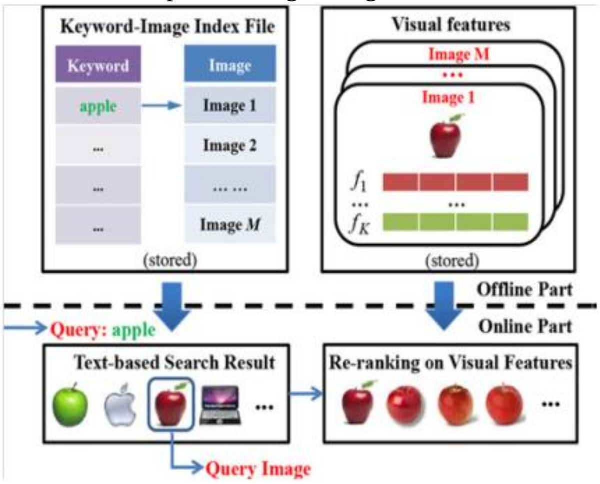

Figure 1: Trditional image-reranking architecture

In order to solve the uncertainty, supplementary information has to be used to confine users' search purpose. One way is text based keyword expansion, producing the textual description of the query added information. Existing linguistically-connected methods find either synonyms or other linguistic-connected words from thesaurus, or find words repeated co-occurrance with the keyword queries. For instance, Google image search provides the "Related Searches" feature to suggest likely keyword expansions. However, for the similar query keywords, the purpose of users can be extremely diverse and cannot be accurately captured by these expansions.

Another way is content-based image retrieval with relevance feedback [1]. Users label multiple positive and negative image instances. A visual similarity metric for query-specific is learnt from the selected instance and used to rank images. The necessity of more users' attempt makes it inappropriate for web-scale industrial schemes like Google image search and Bing image search in which users' feedback has to be reduced.

II. RELATED WORK

Various Internet scale image search methods [2], [3], [4] are text-based which are restricted by the statement that query keywords cannot explain image content precisely. Content-based image retrieval [5] uses visual features to assess image similarity. Numerous visual features [6], [7], [8] were extended for image search in recent years.

In [9] Yimeng Zhang et.al presented geometry preserving visual phases which considered the local and long range spatial layouts of visual words. This [9] work presents an method that can encode spatial information into BoV representation and that is proficient enough to be used to huge databases. This encodes additional spatial information through the geometry-preserving visual phrases (GVP). Still this method uses increased memory usage or computational time.

In [10] Jia Deng et.al presented visual similarities from a hierarchical structure described on semantic attributes of training images. As web images are extremely diversified, describing a set of attributes with sequential relationships for them is demanding. Generally, learning a common visual similarity metric for generic images is still an unlock problem to be solved.

In [11] Yuchi Huang et.al presented probabilistic hypergraph ranking in the semi-supervised learning structure. This used both labeled and unlabeled images in the learning system. Relevance feedback is essential for extra users' attempt. For a web-scale business system, users' feedback has to be restricted to the minimum, namely one-click feedback.

In [12] Shuang Liu et.al presented Thesaurus-based methods which lengthened query keywords with their linguistically connected words such as synonyms and hypernyms. This method made use of WordNet to differentiate word senses of query conditions. Every time the sense of a query term is decided, its synonyms, hyponyms, words from its definition and its compound words are measured for probable additions to the query.

In [13] Yossi Rubner et.al presented Online Algorithm for Scalable Image Similarity learning that discovers a bilinear similarity computation over sparse illustrations. It is an online dual method using the passive-aggressive group of learning algorithms with a great margin principle and a well-organized hinge loss cost. Conversely, this method is not supportive even for problems with a small hundreds of samples.

III. PROPOSED WORK

A. *Keyword Query Expansion Based On Query Logs*

This section describes the log-based Keyword query expansion. Initially, the test of assumption is made that the keyword used in queries and in Images are truly very different. This assumption has frequently been made, but certainly not tested by a quantitative estimation. The present work shows that there is certainly a large difference between the Keyword query terms and retrieved images. Consequently few methods are needed to bridge the gap, that is, to construct up the relationships between keyword query terms and retrieved images.

Each Image can be represented as vector { $W_1^{(I)}, W_2^{(I)} \dots \dots W_n^I$}in the retrieved image space, where $W_i^{(I)}$ is the weight of the *i^th^* term in a document and is defined by the traditional TF-IDF measure in (1)

$$\mathbf{W_i^{(I)}} = \frac{\ln\left(1+ tf_i^{(I)}\right)\times idf_i^{(I)}}{\sqrt{\sum ln^2\left(1+tf_i^{(I)}\right)\times\sum\left(idf_i^{(I)}\right)^2}} \rightarrow \mathbf{(1)}$$

$$idf_i^{(I)} = \ln\frac{N}{n_i}$$

where $\mathbf{tf_i^{(I)}}$s the frequency of the i^{th} term in the Image I , N is the total number of Image in the retrieved collection, and $\mathbf{n_i}$ the number of Images containing the i^{th} term of keyword. For each Image, construct a consequent Image in the query space by gathering all the queries for which the Images has been clicked on.

To evaluate the keyword query space and Image space, the similarity between the image vector and its corresponding query vector is need to be measured. Particularly, the similarity of each pair of vectors can be calculated by using the following Cosine similarity in (2):

$$\textbf{Similarity} = \frac{\sum_{i=1}^{n} W_i^{(q)} W_i^{(I)}}{\sqrt{\sum_{i=1}^{n} W_i^{2(q)}}\ \sqrt{\sum_{i=1}^{n} W_i^{2(I)}}} \rightarrow \mathbf{(2)}$$

1) *Correlation between Keyword Query Term and Images*

Queries in the query logs offer a likely way to bridge the gap between the query space and the Image space. Generally, the keyword terms in a query are correlated to the terms in the retrieved images that the user clicked on. If there is as a minimum one path between one query term and one image, a link is fashioned between them. In such a way a large numbers of such links are analysed and thus obtains a probabilistic measure for the correlations between the keyword terms in these two spaces.

Let us consider that how to establish the degrees of correlations between keyword terms. This section define degrees as the conditional probabilities between keyword terms i.e $P(w_j^{(I)}|w_i^{(q)})$. where $w_j^{(I)}$ and $w_i^{(q)}$ be an image and a query term, respectively. The probability $P(w_j^{(I)}|w_i^{(q)})$ is estimated as follows in (3):

$$\mathbf{P(w_j^{(I)}|w_i^{(q)})} = \frac{\mathbf{P(w_j^{(I)}|w_i^{(q)})}}{\mathbf{P(w_i^{(q)})}} \qquad \rightarrow \mathbf{(3)}$$

The proposed query expansion method is based on the probabilistic term correlations which are illustrated above. As soon as a new query is submitted, first, the keyword terms in the query are extracted. Subsequently for each keyword query term, all correlated Images are selected based on the conditional probability. By means of combining the probabilities of all keyword query terms, the following cohesion weight of a Image for the new keyword query Q is calculated in (4):

$$\text{CorrelatedWeight}_Q\left(\mathbf{w_j^{(I)}}\right) = \mathbf{\ln\left(\prod_{w_i^{(q)}\in Q}\left(P\left(w_j^{(I)}|w_i^{(q)}\right)+1\right)\right)} \rightarrow \mathbf{(4)}$$

Thus, for every query, a list of weighted Keyword expansion terms is obtained. The top-ranked terms of keyword can be chosen as expansion terms. The image which is chosen by the expanded keyword is divided into different clusters by using k-Means clustering. The number of clusters is experimentally set to be n/6, where n is the number of images to cluster.

B. Visual Query Expansion

The objective of visual query expansion is to attain multiple positive example images to learn a visual similarity metric which is stronger and more definite to the query image. Visual Query Expansion develops an image reranking method, which only needs one click on the query image and therefore positive examples have to be attained repeatedly. The chosen image cluster has the closest visual distance to the query instance and has reliable semantic meanings. Therefore, they are used as added positive instances for visual query expansion. Then one class SVM is adopted to improve the visual similarity. This takes the reranked image as input to the one-class SVM classifier and similarity to the query image is uses as output.

C. Image Pool Expansion

In Image pool expansion, the image pool retrieved by text-based search holds images with a large range of semantic meanings and the various images connected to the query image is small. In such cases reranking images in the pool is not very efficient. Therefore, more precise query by keywords is essential to fine the intent and retrieve more relevant images.

D. Combining Visual and Textual Similarities

In this section a query specific textual similarity metric is learnt from the positive examples obtained by visual query expansion and combined it with the query specific visual similarity metric.

For a selected query image, a keyword probability model is trained from positive examples and used to estimate the textual distance $dist_T$ for an image k its textual distance to the positive example is described by cross-entropy function in (5):

$$\mathbf{dist_T\ (k) = -\sum_w p(\,w|d_k\,)\log(\,w|\theta\,)} \quad \rightarrow(5)$$

Finally, the textual distance can be combined with the visual similarity sim_v to rerank images:

- $\alpha \cdot sim_v (k) + (1-\alpha).\ dist_T (k)$

α is a fixed parameter and set as 0.5

IV. Experimental Results

This section empirically evaluates the proposed system with the existing system. Performance metrics such as Accuracy, precision and recall is measured for image re-ranking with keyword expansion and image re-ranking with Query based log keyword expansion.

A. Accuracy

The Accuracy of the retrieval rate is measured with the values of the True Negative (TN), True Positive (TP), False Positive (FP), False negative (FN) of the actual class and predicted class results it is defined as follows

$$\mathbf{ACCURACY} = \frac{\mathbf{TP + TN}}{\mathbf{TP + TN + FP + FN}}$$

B. Precision

Precision value is calculated is based on the retrieval of information at true positive prediction, false positive. The data precision is calculated the percentage of positive results returned that are relevant.

$$\mathbf{Precision = TP/\ (TP+FP)}$$

C. Recall

Recall value is calculated is based on the retrieval of information at true positive prediction, false negative. Recall is calculated with the percentage of positive results returned that are Recall in this context is also referred to as the True Positive Rate. Recall is the fraction of relevant instances that are retrieved,

$$\mathbf{Recall = TP/(TP+FN)}$$

The comparison graph for the proposed and existing is shown in following graph:

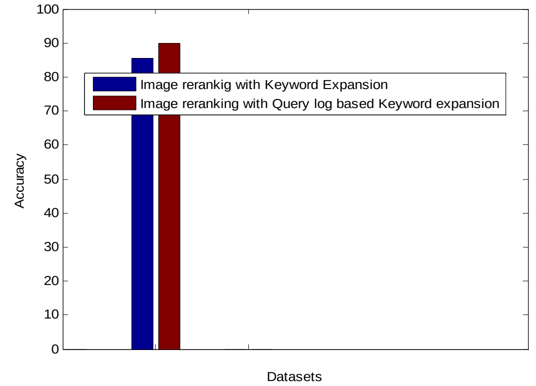

Figure 1. Accuracy comparison graph

The above graph in Figure 1shows that the accuracy comparison of the methods namely image re-ranking with keyword expansion and image re-ranking with Query based log keyword expansion. The accuracy is measured in % at Y-axis as algorithm and considered the datasets in the X-axis. The Accuracy of the re-ranking rate is measured with the values of the True Negative, True Positive, False Positive, False negative. True positive defines a positive test result that accurately reflects the tested-for an activity is analyzed. True negative measures the incorrect data in training and testing, true negative rate is accomplished. False positive result that indicates for a given condition is present when it is not. False negative results indicate that the result appears negative when it should not. From this result re-ranking accuracy is measured with the values of the True Negative, True Positive, False Positive, and False negative with the actual and predicted classes. As a result, the accuracy value of the proposed image re-ranking with Query based log keyword expansion is higher than image re-ranking with keyword expansion.

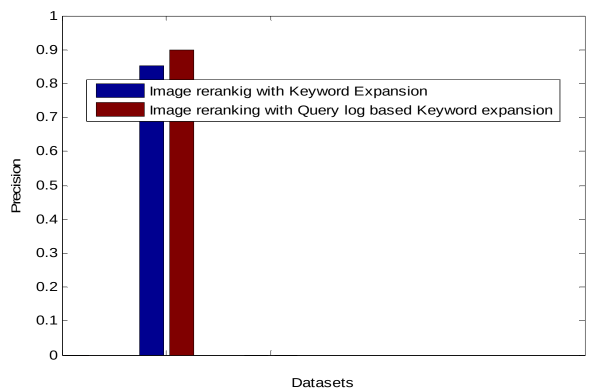

Figure 2: Precision comparison graph

The above graph in Figure 2 shows that the Precision comparison of the methods namely image re-ranking with keyword expansion and image re-ranking with Query based log keyword expansion. The Precision can be measured at Y-axis as algorithm and considered datasets in the X-axis. Precision value is calculated is based on the retrieval of images at true positive prediction, false positive. In the dataset the value is calculated for these datas provides positive result and those result has been considered as relevant. As a result, the Precision value of the image re-ranking with Query based log keyword expansion is higher than image re-ranking with keyword expansion.

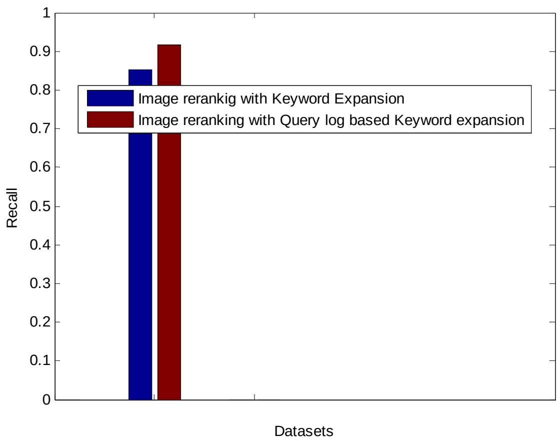

Figure 3.Recall comparison graph

The above graph in Figure 3 shows that the Recall comparison of the methods namely image re-ranking with keyword expansion and image re-ranking with Query based log keyword expansion. The Recall can be measured at Y-axis as algorithm and considered datasets in the X-axis. Recall value is calculated is based on the retrieval of information at true positive prediction, false negative. In the dataset recall is calculated the percentage of positive results returned that are Recall in this context is also referred to as the True Positive Rate. Recall is the fraction of relevant instances that are retrieved. As a result, the Recall value of the image re-ranking with Query based log keyword expansion is higher than image re-ranking with keyword expansion.

V. CONCLUSION

The present work proposes keyword query expansion based on query logs mining. The image search only requires one-click user feedback. Query expansion provides an effective way to improve the performance of information retrieval systems by adding additional relevant terms to the original queries. The present work estimates the ambiguity degree of the query by exploiting the user logs. The result estimates the quality of the keyword query and decides the expanded length of the keyword query. Efficient analysis of the keyword query and retrieved images are obtained by using correlations of the queries. Expanded keywords enlarge the image pool to incorporate more relevant images. This proposed phase makes it possible for large scale image search by both text and visual content. Thus the experimental analysis of proposed system achieves better result in terms of accuracy, precision and recall metrics.

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