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RE-RANKING OF IMAGES USING KEYWORD EXPANSION BASED ON QUERY LOG & FUZZY C-MEAN CLUSTERING

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ABSTRACT: Image re-ranking, Image Search engines mostly use keywords and they rely on surrounding text for searching images. Ambiguity of query images is hard to describe accurately by using keywords. Eg: Apple is query keyword then categories can be “red apple”, “apple laptop” etc. In this paper, we have a tendency to propose a completely unique image re-ranking framework. Four steps: A query image is 1st classified into one in every of many predefined intention classes, and a particular similarity live is employed within every class to mix image options for re-ranking supported the query image. Query keywords are enlarged to capture user intention, through the visual content of the question image hand-picked by the user and the image agglomeration victimization fuzzy c mean algorithm, Image pool is enlarged to contain additional relevant pictures. The query image is additionally enlarged by victimization keyword growth. The Experimental analysis shows that our approach considerably improves the exactness of top-ranked pictures and conjointly the user expertise.

KEYWORDS: image reranking, keyword expansion, Keyword expansion based on query log, Fuzzy c- means algorithm, visual query expansion, and adaptive similarity.

1 INTRODUCTION

The Internet getting available to more and more people in the last decade and with the rapidly growing number of web pages, the Internet is a vast resource of information and images. How to find just the right bit of images that user need from the Internet is a big challenge in image retrieval. Even though there are a lot of well-known search engines like Google or Bing, still it is sometimes not easy to find the images one is interested in. One reason for this is that many users search the internet with keyword and with the huge amount of data on the internet, Almost all of these keywords will be ambiguous to a certain degree, e.g., someone searches for information about the Apple and queries a search engine with the keywords “Apple” he or she will get belonging to different categories, such as “red apple”, “apple logo”, and “apple laptop”. Within every main category, there can be several distinct sub classes’ images that are visually similar. Also, there are images that can be labeled as noise (irrelevant images) or neglect (hard to judge relevancy).

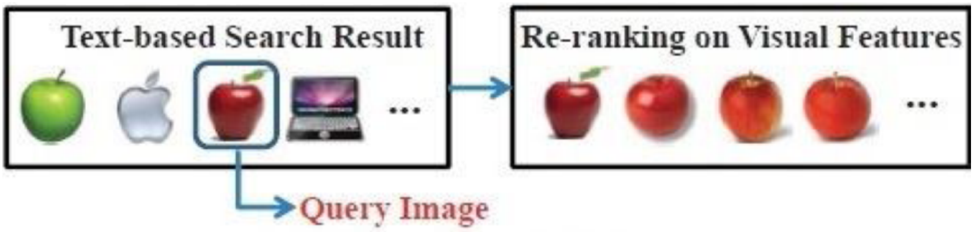

Fig. 1. Re-ranking of visual feature images

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-occurrence 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.

2 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. [11] Yuchi Huang et.al presented probabilistic hyper graph ranking in the semi-supervised learning structure. This used both labelled and unlabelled 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. [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

3 Proposed Work

3.1 Keyword Expansion

The keywords offered by users are usually shortened. They unable to explain the information of pictures correctly. The query keyword's meaning is sometimes richer when compared with users opinions. For example, the meanings of the term "apple" may include apple fruit, apple computer, and apple iPod. The user does not have sufficient understanding on the textual explain of target images in our technique, query keywords are enhanced to catch users browse objective, inferred from the visible information of search images that are not regarded in standard keyword expansion techniques. A phrase w is recommended as an extension of the search when a cluster of images are visually identical to the query image and also most consist of the similar phrase w. The extended keywords much better get users research purpose because the uniformity of both of those visual information and textual explain and also explanation is assured.

3.2 KEYWORD EXPANSION BASED ON QUERY LOG

This category explains the log-based keyword query expansion really, the test out of approach is created that the search term used for queries and in pictures are totally very different. This approach has made consistently been built, yet infrequently checked by a quantitative estimate. The present perform ensures that you can find a great variance between the keyword query words and also retrieved pictures. Subsequently few types are important to fill the gap, which is, to configure up the associations between keyword query search terms and also retrieved pictures.

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 ith term in a document and is defined by the traditional TF-IDF measure in (1)

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

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

Where $tf_i^{(I)}$s the frequency of the ith 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 ith 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):

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

3.3 FUZZY C-MEANS CLUSTERING

The FCM algorithmic rule tries to partition a finite assortment of n parts $X = \{x_1, ..., x_n\}$ into a set of c fuzzy clusters with relevancy some given criterion. Given a finite set of information, the algorithmic rule returns an inventory of c cluster centers $C = \{c_1, ..., c_c\}$ and a partition matrix $W = w_{i,j} \in [0, 1],\ i = 1, ..., n,\ j = 1, ..., c$, wherever every element wij tells the degree to which element xi belongs to cluster cj . just like the k-means algorithmic rule, The FCM aims to reduce an objective perform the quality perform is:

$$w_k(x) = \frac{1}{\sum_j \left(\frac{d(\text{center}_k, x)}{d(\text{center}_j, x)} \right)^{2/(m-1)}}.$$

Which differs from the k-means objective perform by the addition of the membership values uij and the fuzzier m. The fuzzier m determines the amount of cluster indistinctness. an oversized m leads to smaller memberships wij and hence, fuzzier clusters. Within the limit m = one, converge to zero or one, which means a crisp partitioning. Within the absence of experimentation or domain information, m is often set to two. The fundamental FCM formula, given n knowledge points (x1, . . ., xn) to be clustered, variety of c clusters with (c1, . . ., cc) the middle of the clusters, and m the amount of cluster indistinctness with. In fuzzy cluster, each purpose encompasses a degree of happiness to clusters, as in formal logic, instead of happiness utterly to only one cluster. Thus, points on the sting of a cluster, could also be within the cluster to a lesser degree than points within the center of cluster. an summary and comparison of various fuzzy cluster algorithms is obtainable.[1]

Any purpose x encompasses a set of coefficients giving the degree of being within the k th cluster wk.(x). With fuzzy c-means, the center of mass of a cluster is that the mean of all points, weighted by their degree of happiness to the cluster

$$c_k = \frac{\sum_x w_k(x)^m x}{\sum_x w_k(x)^m}.$$

The degree of belonging, wk(x), is expounded reciprocally to the gap from x to the cluster center as calculated on the previous pass. It additionally depends on a parameter m that controls what quantity weight is given to the nearest center. The fuzzy c-means algorithmic program is incredibly the same as the k-means algorithmic program.

3.4 VISUAL QUERY EXPANSION

The objective of visual query enlargement is to achieve multiple positive example pictures to find out a visible similarity metric that is stronger and a lot of definite to the query image. Visual question enlargement develops a picture reranking technique, that solely desires one click on the question image and so positive examples got to be earned repeatedly. The chosen image cluster has the nearest visual distance to the query instance and has reliable linguistics meanings. Therefore, they're used as more positive instances for visual query enlargement. Then one category SVM is adopted to boost 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.

3.5 IMAGE POOL EXPANSION

In Image pool growth, the image pool retrieved by text-based search holds pictures with an outsized vary of linguistics meanings and therefore the numerous pictures connected to the query image is little. In such cases reranking pictures within the pool isn't terribly economical. Therefore, a lot of precise query by keywords is important to fine the intent and retrieve a lot of relevant pictures.

3.6 ADAPTIVE 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 distT for an image k its textual distance to the positive example is described by cross-entropy function in (5):

$$\text{distT}\ (k) = -\sum_{w} p(\,w|d_k\,) \log(\,w|\theta\,) \qquad \rightarrow(5)$$

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

$$-\alpha \,.\, \mathrm{sim}_v\,(k) + (1-\alpha\,).\ \text{distT}\ (k)$$

α is a fixed parameter and set as 0.5

4 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 Fuzzy c-means algorithm.

4.1 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

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

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

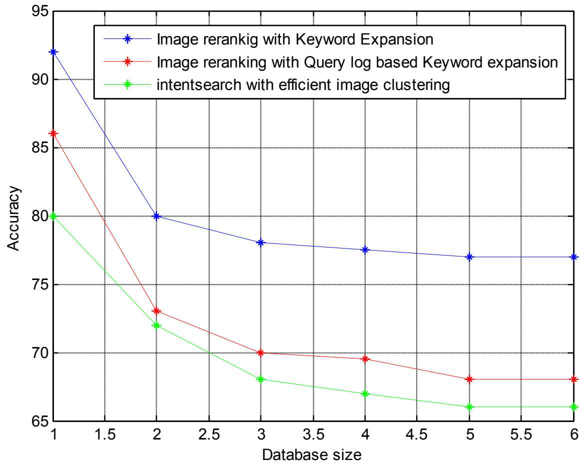

Figure 1. Accuracy comparison graph

The above graph in Figure 1shows that the accuracy comparison of the methods namely image re-ranking with K-Means keyword expansion and image re-ranking with Fuzzy C-Means 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 Fuzzy C-Means keyword expansion is higher than image re-ranking with k-Means keyword expansion.

4.2 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.

PRECISION =TP/ (TP+FP)

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

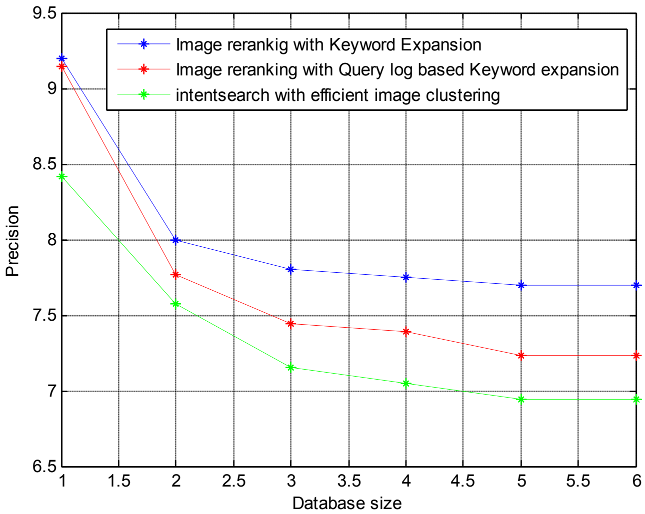

Figure 2: Precision comparison graph

The above graph in Figure 2 shows that the Precision comparison of the methods namely image re-ranking with K-Means keyword expansion and image re-ranking with Fuzzy C-Means 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 data's provides positive result and those result has been considered as relevant. As a result, the Precision value of the image re-ranking with Fuzzy C-Means keyword expansion is higher than image re-ranking with K-Means keyword expansion.

4.3 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,

RECALL =TP/(TP+FN)

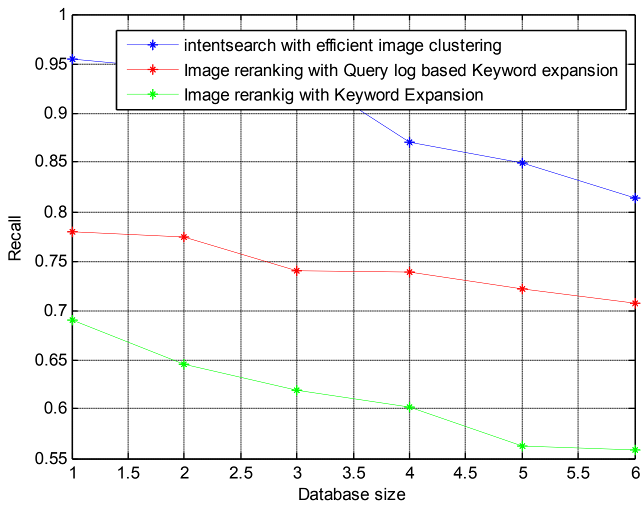

Figure 3.Recall comparison graph

The above graph in Figure 3 shows that the Recall comparison of the methods namely image re-ranking with K-Means keyword expansion and image re-ranking with Fuzzy C-Means 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 Fuzzy C-Means keyword expansion is higher than image re-ranking with K-Means keyword expansion

5 CONCLUSION

The present work proposes keyword query expansion based on Fuzzy logic approach. 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 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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