A Survey On Re-Ranking of Images

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Abstract—**There is a huge amount of research work which gives information about image search re-ranking. The diverse work is need to be collected for getting more information in this area.**

This paper presents survey of various techniques which are used for image re-ranking. Firstly it introduces the object queries which gives result images specific to some kinds of objects and retrieval models. In next section, information about existing approaches towards the re-ranking techniques are discussed.

Index Terms— **Object queries, Re-ranking , Image Retrieval, Summarization.**

INTRODUCTION

While browsing on the search engine for query relevant images, sometimes the results which we are getting not that much satisfactory .Specially in case of object queries ,where object queries[1] are defined as a queries which are used to get some kinds of objects in the image. So here we expect that images which must contain objects in the result images. But existing approaches does not give that much efficient results. Using re-ranking of images we can achieve accurate results. Object retrieval model is observed to be better model for the images are re-ranking of relevant result images.

A. Retrieval models

A Retrieval model suggests how to compute the relevance of a image to a query. Retrieval models are consequently critical for the achievement of a search engine.

In the keyword-based image search approach, the fundamental retrieval models are adopted from the common text-document search. Such models are the most important topics of fundamental research in the information retrieval. The following are some retrieval models which are generally used for retrieval purpose.

i. tf-idf
ii. Okapi BM25
iii. Language models
iv. Learning-to-rank

i .tf-idf

Yu Suzuki et al [2] proposed many image retrieval systems such as vector space model for images. However, these systems are generally based on pattern recognition techniques. Therefore, the features of images are also based on these recognition techniques, like color histogram and shape of the object in images. Generally, these systems do not consider weight of features, which means how significant these features are, which are generally used in textual information retrieval systems. In this a proposed method considering weight, such as tf-idf, to identify the importance degree of features. Using this proposed method, the system can retrieve intuitively similar retrieval target images to user'squeryimages.

ii. Okapi BM25

Stephen E. Robertson, Karen Spärck Jones et al [3] proposed a Okapi BM25. It is based on the probabilistic retrieval framework. In information retrieval, Okapi BM25 (BM stands for Best Matching) is a ranking function used by search engines to rank identical documents according to their importance to a given search query. BM25 is a bag-of-words retrieval function. It ranks a set of documents based on the query terms appearing in each document, in spite of the inter-relationship between the query terms within a document.

iii .Language models

In the language model approach to information retrieval, it attempt to model the query generation process. Then it ranks documents by the probability that a query would be observed as a random example from the respective document model.

A statistical language model is a probability distribution over sequences of words. Language modeling is used in machine translation, part-of-speech tagging, parsing, handwriting recognition, speech recognition, information retrieval and other applications.

iv .Learning-to-rank

Tie-Yan Liu[4] proposed a Learning to Rank for Information Retrieval. In this list wise ranking is one of the approach in which instead of reducing ranking to regression or classification, perform learning directly on document list. It treats ranked lists as learning instances. There are two major types

- Directly optimize IR evaluation measures
- Define list wise loss functions

These methods are among the most well-known retrieval models that are very much influenced the progress of search engines over the earlier period.

In the example-based image search scenario, retrieval

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models are required to guess the importance of an image to the query image based on the match between the visual metadata and the features extracted from the query image. High competence and scalability of the BoW-based image representation has made it widely adopted as the basis for building a retrieval model.

B. Techniques for Re-Ranking

In this section we are going to review research work on different re-ranking techniques. The techniques are as follows

1.Multimedia Search with Pseudo-relevance Feedback
2.Object Retrieval Using Visual Query Context
3.Learning from Search Engine and Human Supervision for Web Image Search
4. Supervised Re-ranking for Web Image Search
5. Bayesian video search re-ranking
6. Visual Categorization with Bags of Key points.

I. Multimedia Search with Pseudo-relevance Feedback:

Rong Yan, Alexander Hauptmann et al [5] proposed a Multimedia Search with Pseudo-relevance Feedback. In this method an algorithm is used which is mainly focused on video retrieval that fuses the decisions of multiple retrieval agents in both text and image techniques. While the normalization and grouping of evidence is novel, this emphasizes the successful use of negative pseudo-relevance feedback to get better image retrieval performance. Although it does not work out all issues in video information retrieval, the results are hopeful, indicating that pseudo-relevance feedback shows great promise for multimedia retrieval with very diverse results.

Advantages: Pseudo-relevance Feedback is an interactive technique for query reformulation .It has been shown successfully used in Content Based Image Retrieval.

Limitations:

It Need user's involvement to provide relevance information. This impose a burden to users. Most of RF algorithms focus only on positive examples.

II. Object Retrieval Using Visual Query Context

Linjun Yang, Yang Cai,et al [6] proposed a object retrieval with visual query context .Object retrieval aims at retrieving images having objects similar to the query object identified in the region of interest (ROI) of the query image. a wide popularity of SIFT image features and bag-of-visual-words image representation is taking into consideration, so that object retrieval has progressed significantly. While existing object retrieval methods perform well in many cases, they may fail to return acceptable results if the ROI specified by the user is inaccurate.

In order to improve the object retrieval performance also in these difficult cases, an object retrieval method is used that manipulates the information about the visual perspective of the query object and employ it to compensate for possible uncertainty in feature-based query object representation. In this, the ROI as an uncertain observation of the latent search intent and the saliency map identified for the query image as a prior. Then a language modeling approach is employed to devise contextual object retrieval (COR) model. The relevance score is determined based on the search intent scores that are inferred from the uncertain ROI.

Advantages:

It improve the object retrieval performance when the query object is specified by a rectangular bounding box in the query image.

Limitations:

It considers the ROI as an uncertain observation of the latent search objective and the saliency map detected for the query image as a prior. So if ROI is wrong then results are not that much satisfactory.

III. Learning from Search Engine and Human Supervision for Web Image Search

Alan Hanjalic et al. [7] proposed a Learning from Search Engine and Human Supervision for Web Image Search method. In this method it combines two learning approaches for deriving the re-ranking model, learning from search engine and learning from human supervision. The first approach learns the re-ranking model in a pseudo-supervised fashion by interpreting parts of the first text-based search result as pseudo-relevant. The second approach involves manual relevance labeling of the text-based search results derived for a restricted number of representative queries.

It gives a two-stage learning approach to visual re-ranking, where in the online stage multiple query-relative meta re-rankers are learned in a pseudo-supervised way from the search results and in the offline stage human supervision is used to get the final re-ranking function based on these meta re-rankers.

Advantages:

While learning from search engine it is query dependent and can therefore give better to individual queries, it is essentially unsupervised and noisy. While human supervision can better speak about the search results to true relevance criteria, it needs to be deployed in a way to keep the re-ranking scalable.

Limitations:

This method can be said to generalize better since the knowledge
about the image search is discovered automatically.

IV. Supervised Re-ranking for Web Image Search

Linjun Yang et al. [8] proposed a supervised Re-ranking for Web Image search. In this method the learning-to-re rank model is used, which shows the

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re-ranking function in a supervised way from the human-labeled training data. Although supervised learning is introduced, this approach does not go through scalability problems because a unified re-ranking model is learned that can be applied to all queries. In other words, a query-independent re-ranking model will be learned for all queries using query-dependent re-ranking features. The query-dependent re-ranking feature extraction is difficult because the textual query and the visual documents have different representation.

Advantages:

The re-ranking performance of individual query is related to the characteristics of the initial text-based search result. The queries for which the relevant images in the initial result are semantically or visually coherent, will benefit more from re-ranking.

Limitations:

The performance is even degraded in some cases. Since the result diversity is also an important objective so that more informative search result can be provided to users, It does not consider the diversity of results.

V. Visual Categorization with Bags of Key points

Gabriella Csurka et al. [9], present a novel method for generic visual categorization. In this the problem of identifying the object content of natural images while generalizing across variations inherent to the object class. This bag of key points approach is based on vector quantization of affine invariant descriptors of image patches. It compares two alternative implementations using various classifiers: Nave Bayes and SVM. The main advantages of the method are that it is simple, intrinsically invariant and computationally efficient. It present results for simultaneously classifying seven semantic visual categories.

These results demonstrate that the method is robust to background clutter and produces good categorization precision even without exploiting geometric information.

Advantages:

The Bag of Key points is computationnelle efficient and simple. It is Invariant to affine transformations, occlusions, lighting, intra-class variations.

Limitations:

If visual categories are extended, the discriminative power of the appearance of unordered image patches will not suffice and need to extend the categorizer to incorporate geometric information.

VI. Bayesian video search re-ranking

Xinmei Tian, Linjun Yang et al. [10] Proposed a Bayesian video search re-ranking. Content-based video search re-ranking can be regarded as a process that uses visual content to recover the true ranking list from the noisy one generated based on textual information.

The Bayesian framework solves the problem, i.e., maximizing the ranking score consistency among visually similar video shots while minimizing the ranking distance, which represents the dissimilarity between the objective ranking list and the initial text based. Different from existing point-wise ranking distance measures, which compute the distance in terms of the individual scores, two new methods are used to measure the ranking distance based on the disagreement in terms of pair-wise orders. Specifically, hinge distance penalizes the pairs with reversed order according to the degree of the reverse, while preference strength distance further considers the preference degree. By incorporating the proposed distances into the optimization objective, two re-ranking methods are developed which are solved using quadratic programming and matrix computation respectively.

Advantages:

It examine the re-ranking problem from the probabilistic perspective and derive an optimal re-ranking function based on Bayesian analysis.

Limitations:

There are some limitations of this method. The first one is to speed-up the computation of hinge re-ranking via working set selection approach. To better represent the visual consistency, the semantic similarity which can be learned using distance metric learning will be incorporated into the re-ranking objective function.

CONCLUSION

The present survey presents various methods used for image retrieval models and re-ranking techniques of web images. Each method is significantly efficient in image retrieval process and ranking of images. In re-ranking techniques, Pseudo-relevance Feedback is an interactive technique for query reformulation . Object Retrieval Using Visual Query Context technique improve the object retrieval performance and The Bag of Key points is simple and Computationally efficient.

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