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Survey On Intent Based Image Ranking For Web Search Re-ranking

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ABSTRACT

Web image search engines often use keywords as queries and also depend on metadata text to search images. These search engines have difficulties due to the ambiguity of query keywords, since it is hard for end users to correctly predict the visual content of targeted images by only using keywords. Image re-ranking is an effective way to efficient the results of web-based image search, has been implemented by various search engines such as Google and Bing. A main challenge in the research of image re-ranking is that the similarities of visual features do not perfectly associate with actual semantic meanings of images which intends users' search goal. This paper mainly focused on the survey of various methods used for image re-ranking techniques for different queries. Each method is differentiated with other surveyed method and comparative measures of methods are presented which provides the advantages and limitations of web image re-ranking techniques.

Keywords: **Re-ranking , Meta re-ranker, Prototype Based Re-ranking, Image search, noise, SVM, Supervised learning**

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I. INTRODUCTION

The search engines search images mostly by using the text associated with the images like title of the images. This is often good to search relevant images but the problem is that precision of search result is less .Methods like Clustering[7], topic modelling[6],[2], Support Vector machine (SVM)[8], graph learning[9],[10] have been investigated for visual re-ranking All these require prior assumption regarding the relevance of images in initial text based search result . Also Top N search results can also contain irrelevant images which introduce noise. here we propose a system To address a ranking problem in web image retrieval, System to re-rank images returned by image search engine, Re-ranking images by incorporating, Visual aspects, Visual similarity, To maximize relevancy of image results &To achieve diversity of image results. The goals of proposed system are Retrieve image results that are relevant and Finding common features among images. In this paper a quick review of the literature studied and existing and our proposed system is presented.

II. LITERATURE SURVEY

In [2], presented a novel method for the discovery and detection of visual object categories based on decompositions using topic models. The approach is capable of learning a compact and low dimensional representation for multiple visual categories from multiple viewpoints without labelling of the training instances. The learnt object components range from local structures over line segments to global silhouette-like descriptions. This representation can be used to discover object categories in a totally unsupervised fashion. Furthermore it employ the representation as the basis for building a supervised multi-category detection system making efficient use of training examples and outperforming pure features-based representations.

In [3], have their work in video search re-ranking. Multimedia search over distributed sources often result in recurrent images or videos which are manifested beyond the textual modality. To exploit such contextual patterns and keep the simplicity of the keyword-based search, they proposed novel re-ranking methods to leverage the recurrent patterns to improve the initial text search results. The approach, context re-ranking, is formulated as a random walk problem along the context graph, where video stories are nodes and the edges between them are weighted by multimodal con- textual similarities. When evaluated on TRECVID 2005 video benchmark, the pro-posed approach improve retrieval on the average up to 32% relative to the baseline text search method in terms of story-level Mean Average Precision. In the people-related queries, which usually have recurrent coverage across news sources, we can have up to 40% relative improvement. Most of all, the proposed method does not require any additional input from users (e.g., example images), or complex search models for special queries (e.g., named person search).

In [4], proposed automatic online picture collection via incremental model learning. The explosion of the Internet provides us with a tremendous resource of images shared online. It also confront vision researchers the problem of finding effective methods to navigate the vast amount of visual information. Semantic image understanding plays a vital role towards solving this problem. One important task in image understanding is object recognition, in particular, generic object categorization. Critical to this problem are the issues of learning and dataset. Abundant data helps to train a robust recognition system, while a good object classifier can help to collect a large amount of images. This paper presents a novel object recognition algorithm that performs automatic dataset collecting and incremental model learning simultaneously. The goal of this work is to use the tremendous resources of the web to learn robust object category models for detecting and searching for objects in real-world cluttered scenes.

In [5], proposed supervised re-ranking for web image search. Visual search re-ranking that aims to improve the text-based image search with the help from visual content analysis has rapidly grown into a hot research topic. The interestingness of the topic stems mainly from the fact that the search re-ranking is an unsupervised process and therefore has the potential to scale better than its main alternative, namely the search based on offline-learned semantic concepts. However, the unsupervised nature of the re-ranking paradigm also makes it suffer from problems, the main of which can be identified as the difficulty to optimally determine the role of visual modality over different application scenarios.

In [6], have proposed the idea of training using just the objects name by bootstrapping with an image search engine. The training sets are extremely noisy yet, for the most part, the results are competitive (or close to) existing methods requiring hand gathered collections of images.

In [7], have proposed a novel and generic video/image re-ranking algorithm, IB re-ranking, which reorders results from text-only searches by discovering the salient visual patterns of relevant and irrelevant shots from the approximate relevance provided by text results. The IB re-ranking method, based on a rigorous Information Bottleneck (IB) principle, finds the optimal clustering of images that preserves the maxi- mal mutual information between the search relevance and the high dimensional low-level visual features of the images in the text search results.

In [8], present an algorithm for video retrieval that fuses the decisions of multiple retrieval agents in both text and image modalities. While the normalization and combination of evidence is novel, they emphasizes the successful use of negative pseudo-relevance feedback to improve image retrieval performance.

In [9], present the image-ranking problem into the task of identifying “authority” nodes on an inferred visual similarity graph and propose VisualRank to analyze the visual link structures among images. The images found to be “authorities” are chosen as those that answer the image-queries well. To understand the performance of such an approach in a real system, they conducted a series of large-scale experiments based on the task of retrieving images for 2,000 of the most popular products queries. Their experimental results show significant improvement, in terms of user satisfaction and relevancy, in comparison to the most recent Google Image Search results. Maintaining modest computational cost is vital to ensuring that this procedure can be used in practice; they describe the techniques required to make this system practical for large-scale deployment in commercial search engines

In [10], They formulates the image re-ranking problem in the Bayesian framework, i.e. maximizing the ranking score consistency among visually similar video shots while mini-mizing the ranking distance, which represents the disagree-ment 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 indi-vidual scores, two new methods are proposed by them to measure the ranking distance based on the disagreement in terms of pair-wise orders. Specifically, hinge distance pe-nalizes the pairs with revers ed order according to the de-gree of the reverse, while preference strength distance further considers the preference degree.

III.EXISTING SYSTEM

Existing Types Of Re-ranking:

1. Random Walk Re-ranking:

This method perform re-ranking as a random walk over document level context graph. Context graph is a graph with nodes represents documents and edges between them represents the multimodal contextual likeness between two credentials. Assume that we have N nodes which represent the video stories. The N nodes are the N credentials obtained in the initial search results. The traversing of graph is initialized from one node and based on the multimodal similarity connecting the credentials and the original text scores in the initial search result, it traverse to the next node.

2. Minimum Incremental Information Loss (Mill) :

This video search re-ranking involves two parts- Learning and Re-ranking. In the knowledge process several query examples are provided for each textual query. This is the first pair wise approach for visual search re-ranking. The example images are paired with samples randomly selected from most important search result. The purpose of learning is to find out the relevant and unrelated information. Concept uncovering is processed on this example pairs to form the relevant and unrelated information.

3. Pairoff Wise Re-ranking:

Two methods are used by pair wise re-ranking named as example re-ranking and crowd re-ranking. Like MIIL re-ranking it also has two parts learning and Re-ranking. First feed the textual query and get the primary ranked list then this query is feed into the web search engine to acquire a situate of image search result.

4. Bag Based Image Re-Ranking

Clustering means grouping similar images together and comparing or matching among clusters instead of individual images. This will reduce the concerned time complexity to a great extent. cluster of similar images containing most of the relevant images is called positive bag and the bag containing least relevant images related to query is labelled as negative bag. This way of clustering is derived from the theory of Generalized Multi called as bag based image re-ranking. Diverse clustering algorithms are available with varying degree of success based on domain requirement.

5. Active Re-Ranking

Active re-ranking is the re-ranking with user interactions. The flow of active re ranking technique for the query is it involves active sample selection in which user labels the images as relevant or irrelevant. The images seen in the user labelled relevant images. This step is followed by dimension reduction which localizes visual features. Iterative applications of above steps leads to proper result. The above explained techniques use single feature for re-ranking, but the type of most effective features vary across queries, as elaborated above under the topic extraction of visual features. Thus, employing multimodal features (colour, texture, and edge) will be solution.

6. IB-Re-ranking:

Re-ranking Based On Recurrent Frequency In image/video search systems, we're given a query or a statement of information need, and must estimate the relevance R(x) of each image or video shot in the search set, X, and order them by relevance scores. Researchers have tested many approaches in recent years from simply associating video shots with text search scores to fusing multiple modalities. Some approaches rely on user-provided query images as positive examples to train a supervised classifier to approximate the posterior probability P(Y|X), where Y is a random variable representing search relevance. They then use the posterior probability for R(x) in visual ranking.

7. Context Re-ranking:

Story Re-ranking Based On Multimodal Similarity Context-re-ranking method uses the multimodal similarity between video stories to improve the initial text query results. An initial text query retrieves video stories with the keywords. However, it doesn't retrieve certain relevant stories because of the lack of keyword annotations associated with such videos. We can use contextual links (such as visual duplicates and text) to link such missing stories to the initial text queries and further improve the search accuracy.

IV. DRAWBACKS OF EXISTING SYSTEM

The random walk method has some major disadvantages. First, it does not exactly conserve the mean position of the vorticity in free space. Next, the computed solutions are noisy due to the statistical errors. In flow control studies, the statistical errors could mask the effects of varying the control parameters. The statistical errors can also cause symmetric flows to turn asymmetric erroneously. To reduce the statistical errors requires a very large number of vortices. As in MILL, there are N! possible re-ranked lists for the given initial search results with the size of N. Therefore, it is impractical to compare with each other when N is extremely large. Pairoff method suffers from either limited applicability to the specific queries, the desire of the specific user interfaces, or the limited detection performance.
One major problem impacting performance is the mismatches between the actual content of image and the textual data on the web page. The problem with these methods is the reliability of the obtained pseudo-positive and pseudo-negative images is not guaranteed.

V. CONCLUSION

Here by studying various papers and re-ranking methods we should propose a re-ranking framework, which constructs meta re-rankers corresponding to visual prototypes representing the textual query and learns the weights of a linear re-ranking model to combine the results of individual meta re-rankers and produce the re-ranking score of a given image taken from the initial text-based search result. The induced re-ranking model is learned in a query-independent way requiring only a limited labelling effort and being able to scale up to a broad range of queries. A new algorithm should be proposed which overcomes the drawback of existing system which improves the performance over the text-based search result by combining prototypes and textual ranking features.

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