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VISUAL RE-RANKING FOR IMAGE RETRIEVAL SYSTEM

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ABSTRACT

The methods available now for image search re-ranking suffer from the unreliability of the assumptions under which the initial text-based images search result. The resulting images contain more irrelevant images. Hence the re ranking concept arises to re rank the retrieved images based on the text surrounding the image and metadata and visual feature. A number of methods are compared for this re-ranking. The top-ranked images are used as (noisy) training data and an SVM visual classifier is learned to improve the ranking further. The sensitivity of the cross-validation procedure is investigated to this noisy training data. The principal novelty of the overall method is in combining text/metadata and visual features in order to achieve a completely automatic ranking of the images. Human supervision is introduced to learn the model weights offline, prior to the online re-ranking process. While model learning requires manual labeling of the results for a few queries, the resulting model is query independent and therefore applicable to any other query .Examples are given for a selection of fruits , animals, vehicles, and other classes.

Keywords- Image Search Reranking, Metadata, Visual Classifier

I. INTRODUCTION

A person search images of apple using Google image search engine. The result is a number of images of fruit apple as well as digital products of company "Apple". The search requirement is either one of them. If user requirement is fruit-apple then all digital products of "Apple" are now irrelevant images in this caser. The popular search engines like Google, Yahoo are searching the images based on the textual information associated with it. And final result contains relevant as well as irrelevant images. Hence this gives very less probability of user search satisfaction.

Image search engines apparently provide an effortless route, but currently are limited by poor precision of the returned images and also restrictions on the total number of images provided. To handle this drawback one can't rely only on the textual information but the visual features of the image are to be considered.

Referencing the previous example if user requirement is fruit apple and clicking on it, further only images of apple fruit are to be displayed. Further categorization may be red and green apple. This defines the re-ranking method.

As drawback summary , the existing system I.e. the text based image contains relevant and irrelevant image results. As well as all of the existing re-ranking algorithms require a prior assumption regarding the relevance of the images in the initial, text-based search result. So to improve the precision of text based image search ranking ,visual re-ranking is applied to refine the search result by incorporating the knowledge like color, shape etc. Recently, many re-ranking methods have been proposed, including the classification-based , clustering- based and graph-based methods. All these require prior assumption regarding to relevance of images in initial text based search result. In all visual re-ranking methods, an essential problem is how to measure the visual similarity precisely.

In the proposed reranking method based on initial search result, visual prototype is generated. Each prototype is used to construct a meta re-ranker to produce a ranking a score for any other image from initial set. Finally all scores from all meta re-rankers are aggregated. For visual re-ranking it is proposed to use SVM (Support Vector Machine) algorithm.

Hence proposed system have objective of this work is to retrieve a large number of images for a specified object class from the browser. A multimodal approach employing text, metadata, and visual features is used to gather many high-quality images from the Web. Candidate images are obtained by a text-based Web search querying on the object identifier (e.g., the word penguin). The task is then to remove irrelevant images and re-rank the remainder. First, the images are re-ranked based on the text surrounding the image and metadata features. A number of methods are compared for this re-ranking. Second, the top-ranked images are used as (noisy) training data and an SVM visual classifier is learned to improve the ranking further. We investigate the sensitivity of the cross-validation procedure to this noisy training data. Based on the images in the initial result, visual prototypes are generated that visually represent the query.

Each of the prototypes is used to construct a Meta reranker to produce a re-ranking score for any other image from the initial list. Finally, the scores from all Meta reranker are considered for reranking..

II. LITERATURE SURVEY

Mario Fritz and Bernt Schiele[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 view points without labeling 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.

***Winston H. Hsu,Lyndon S. Kennedy,Shih-Fu Chang[3*]**,** have their work in video serach 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).

Li-Jia Li · Li Fei-Fei [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.

LinjunYang,AlanHanjalic[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.

R. Fergus, L. Fei-Fei, P. Perona, and A. Zisserman [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.

III. PROPOSED SYSTEM FRAMEWORK AND DESIGN

3.1 Problem Definition: Re-ranking

Problem is apply visual re-ranking on image retrieval system. Retrieve a large number of images for a specified object class from browser. Now assuming we have these N images ,retrieved from initial text-based search results . The re-ranking process is used to improve the search accuracy by reordering the images based on information extracted from the initial text based search results , the auxiliary knowledge and the example prototype. The auxiliary knowledge can be the extracted visual features from each image.

3.2 System Architecture

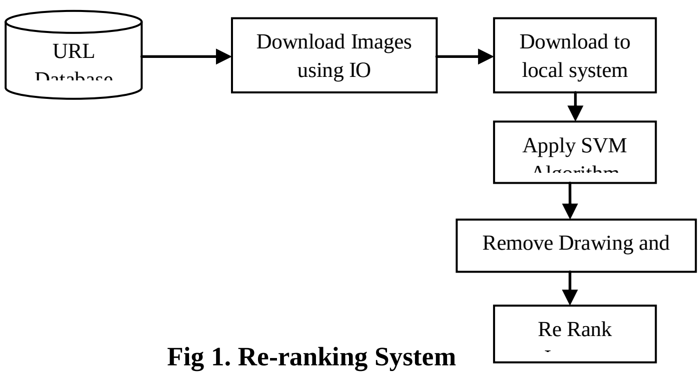

Fig 1. Re-ranking System

3.3 Modules in the System

The architecture is divided into following modules.

3.3.1. Query Image

When an image search in search engines, that corresponding images are loaded in that time, meanwhile among them there is a uncategorized images are also spotted. However, producing such databases containing a large number of images and with high precision is still an arduous manual task.

Generally Image search engines apparently provide an effortless route. For this type of obtaining images can be filter and arrange.

The results of the applicable images are assembled and our objective in this work is to re rank a large number of images of a particular class automatically, and to achieve this with high precision.

Image clusters for each topic are formed by selecting images where nearby text is top ranked by the topic. A user then partitions the clusters into positive and negative for the class. Second, images and the associated text from these clusters are used as exemplars to train a classifier based on voting on visual (shape, color, and texture) and text features

3.3.2. Download Associate Images

We compare three different approaches to downloading images from the Web.

The first approach, named Web Search, submits the query word to Google Web search and all images that are linked within the returned Web pages are downloaded. Google limits the number of returned Web pages to 1,000, but many of the Web pages contain multiple images, so in this manner, thousands of images are obtained.

The second approach, Image Search, starts from Google image search (rather than Web search). Google image search limits the number of returned images to 1,000, but here, each of the returned images is treated as a "seed"—further images are downloaded from the Webpage where the seed image originated.

The third approach, Google Images, includes only the images directly returned by Google image search (a subset of those returned by Image Search). The query can consist of a single word or more specific descriptions such as "penguin animal" or "penguin OR penguins." Images smaller than 120 _ 120 are discarded. In addition to the images, text surrounding the image HTML tag is downloaded, together with other metadata such as the image filename.

3.3.3 URL Parsing

Image Search gives a very low precision (only about 4 percent) and is not used for the harvesting experiments. This low precision is probably due to the fact that Google selects many images from Web gallery pages which contain images of all sorts. Google is able to select the in-class images from those pages, e.g., the ones with the object-class in the filename; however, if we use those Web pages as seeds, the overall precision greatly decreases. Therefore, we only use Web Search and Google Images, which are merged into one data set per object class. Table 2 lists the 18 categories downloaded and the corresponding statistics for in-class and non-class images. The overall precision of the images downloaded for all 18 classes is about 29 percent.

3.4 Apply Re-Ranking Algorithm

Now describe the re ranking of the returned images based on text and metadata alone. Here, we follow and extend the method proposed by using a set of textual attributes whose presence is a strong indication of the image content.

The goal is to re rank the retrieved images. Each feature is treated as binary: "True" if
it contains the query word (e.g., penguin) and "False" otherwise. To rerank images for one particular class (e.g., penguin), we do not employ the whole images for that class. Instead, we train the classifier using all available annotations except the class we want to rerank.

3.4.1 SVM Implementation

Support vector machine used to form the cluster of similar images. This technique will filter PNG or GIF format images. Based on threshold value the re ranking process will be done.

3.4.2 Filtering Process

The text reranker performs well, on average, and significantly improves the precision up to quite a high recall level. To re-ranking the filtered images, we applied the text+vision system to all images downloaded for one specific class, i.e., the drawings and symbolic images were included.

It is interesting to note that the performance is comparable to the case of filtered images. This means that the learned visual model is strong enough to remove the drawings and symbolic images during the ranking process. Thus, the filtering is only necessary to train the visual classifier and is not required to rank new images,
, using unfiltered images during training decreases the performance significantly, the main exception here is the airplane class, where training with filtered images is a lot worse than with unfiltered images. In the case of i.e., airplane, the filtering removed 91 good images and the overall precision of the filtered images is quite low, 38.67 percent, which makes the whole process relatively unstable, and therefore can explain the difference.
In short the process can be redefined sequentially in following algorithm.

3.5 Algorithm

1**:** start
2: User requests an image to Search Engine.
3: Search Engine collects images and stores in the database.
4: Filter images by removing symbols and drawings from the collected images.
5: Rerank filtered images using metadata.
6: Rerank images using SVM algorithm.
7: Get the SVM re-ranking result which is more relevant to the image requested by user.
8**:** Render the relevant images to the user.
9: Stop

3.6 Requirements

Software Requirement

- Language : JAVA
- Front End : JSP, Servlet
- Back End : My SQL
- Web server : :Apache Tomcat 5.5

Hardware Requirement

- Processor : Above 2 GHZ
- Hard disc : 80 GB
- RAM : 1GB

IV CONCLUSION

Here the proposed visual re-ranking framework, which constructs meta rerankers 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 rerankers 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 labeling effort and being able to scale up to a broad range of queries. It improves the performance over the text-based search result by combining prototypes and textual ranking features. Finally we conclude that ,the accuracy of the image search be achieved. And the system should be robust and performance of the proposed method is more compared with existing methods.

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