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Query-Specific Semantic Signatures Used For Checking the Image Re-Ranking Controlled By Admin

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ABSTRACT: Image re-ranking, as an effective way to improve the results of web-based image search, has been adopted by current commercial search engines. Given a query keyword, a pool of images are first retrieved by the search engine based on textual information. On the other hand, learning a universal visual semantic space to characterize highly diverse images from the web is difficult and inefficient. In this paper, we propose a novel image re-ranking framework, which automatically offline learns different visual semantic spaces for different query keywords through keyword expansions. The visual features of images are projected into their related visual semantic spaces to get semantic signatures. At the online stage, images are re-ranked by comparing their semantic signatures obtained from the visual semantic space specified by the query keyword. The new approach significantly improves both the accuracy and efficiency of image re-ranking. The original visual features of thousands of dimensions can be projected to the semantic signatures as short as 25 dimensions. Experimental results show that 20% 35% relative improvement has been achieved on re-ranking precisions compared with the state of-the art methods.

KEYWORDS: Image Re-Ranking, Semantic spaces, Visualization.

I.INTRODUCTION

Web-scale image search engines mostly use keywords as queries and rely on surrounding text to search images. It is well known that they suffer from the ambiguity of query keywords. For example, using “apple” as query, the retrieved images belong to different categories, such as “red apple”, “apple logo”, and “apple laptop”. Online image re-ranking has been shown to be an effective way to improve the image search results .Major internet image search engines have since adopted the re ranking strategy . Its diagram is shown in Figure 1. Given a query keyword input by a user, according to a stored word-image index file, a pool of images relevant to the query keyword are retrieved by the search engine. By asking a user to select a query image, which reflects the user’s search intention, from the pool, the remaining images in the pool are re-ranked based on their visual similarities with the query image. The visual features of images are pre-computed off line and stored by the search engine. The main online computational cost of image re-ranking is on comparing visual features. In order to achieve high efficiency, the visual feature vectors need to be short and their matching needs to be fast. Another major challenge is that the similarities of low level visual features may not well correlate with images’ high-level semantic meanings which interpret users’ search intention. To narrow down this semantic gap, for off line image recognition and retrieval, there have been a number of studies to map visual features to a set of pre-defined concepts or attributes as semantic signature. However, these approaches are only applicable to closed image sets of relatively small sizes. They are not suitable for online web based image re-ranking. According to our empirical study, images retrieved by 120 query

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keywords alone include more than 1500 concepts. Therefore, it is difficult and inefficient to design a huge concept dictionary to characterize highly diverse web images.

II.RELATED WORK

Content-based image retrieval uses visual features to calculate image similarity. Relevance feedback was widely used to learn visual similarity metrics to capture users' search intention. However, it required more users' effort to select multiple relevant and irrelevant image examples and often needs online training. For a web-scale commercial system, users' feedback has to be limited to the minimum with no online training. Cui et al. proposed an image re-ranking approach which limited users' effort to just one-click feedback. Such simple image re-ranking approach has been adopted by popular web-scale image search engines such as Bing and Google recently, as the "find similar images" function. The key component of image re-ranking is to compute the visual similarities between images. Many image features have been developed in recent years. However, for different query images, low-level visual features that are effective for one image category may not work well for another. To address this, Cui et al. classified the query images into eight predefined intention categories and gave different feature weighting schemes to different types of query images.

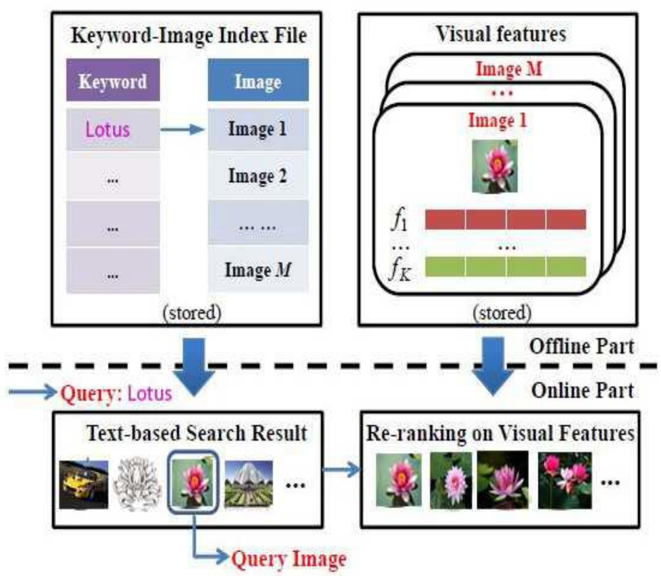

Fig:1 **The conventional image re-ranking framework**

However, it was difficult for only eight weighting schemes to cover the large diversity of all the web images. It was also likely for a query image to be classified to a wrong category. Recently, for general image recognition and matching, there have been a number of works on using predefined concepts or attributes as image signature. mapped visual features to a universal concept dictionary. used predefined attributes with semantic meanings to detect novel object classes. Some approaches transferred knowledge between object classes by measuring the similarities between novel object classes and known object classes All these concepts/attributes/reference-classes were universally applied to all the images and their training data was manually selected. They are more suitable for offline databases with lower diversity (such as animal databases and face databases such that object classes better share similarities. To model all the web images, a huge set of concepts or reference classes are required, which is impractical and ineffective for online image re-ranking.

This methodology is founded from the concepts of mining user questions by using Markov Chain model. The features of this method mark it also mostly valid in the framework of online image retrieval systems.

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This paper describes the augmentations done to the base project effort by containing LSI methodology to increase image retrieval accuracy and efficiency. Few difficulties of LSI can be overwhelmed by probabilistic latent semantic indexing (PLSI) and Markov Chain semantic indexing (MSI) methods. PLSI method is a way to précis the search results of entered query keyword. Due to the procedure of estimation results, our method achieves well in classifying search results and decreasing the redundancy among summaries. We introduced the Markovian Semantic Indexing (MSI), a new method for automatic annotation and image retrieval based on annotation. The necessity of returning to external taxonomy systems for allocating significance metrics among keywords, and, thus, face the problem of assessing the compatibility stuck between those methods and the semantics behind the actual users that are using the system is improved in MSI. This experiment have exposed that MSI achieves better retrieval results in sparsely annotated images from the large image database.

III.PROPOSED SYSTEM

We propose the semantic web based search engine which is also called as Intelligent Semantic Web Search Engines. We use the power of xml meta-tags deployed on the web page to search the queried information. The xml page will be consisted of built-in and user defined tags. Here propose the intelligent semantic web based search engine. We use the power of xml meta-tags deployed on the web page to search the queried information. The xml page will be consisted of built-in and user defined tags.

The metadata information of the pages is extracted from this xml into rdf. our practical results showing that proposed approach taking very less time to answer the queries while providing more accurate information.

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It was also likely for a query image to be classified to a wrong category. Recently, for general image recognition and matching, there have been a number of works on using predefined concepts or attributes as image signature. Mapped visual features to a universal concept dictionary. Used predefined attributes with semantic meanings to detect novel object classes. Some approaches transferred knowledge between object classes by measuring the similarities between novel object classes and known object classes All these concepts/attributes/reference-classes were universally applied to all the images and their training data was manually selected. They are more suitable for offline databases with lower diversity (such as animal databases and face databases such that object classes better share similarities. To model all the web images, a huge set of concepts or reference classes are required, which is impractical and ineffective for online image re-ranking.

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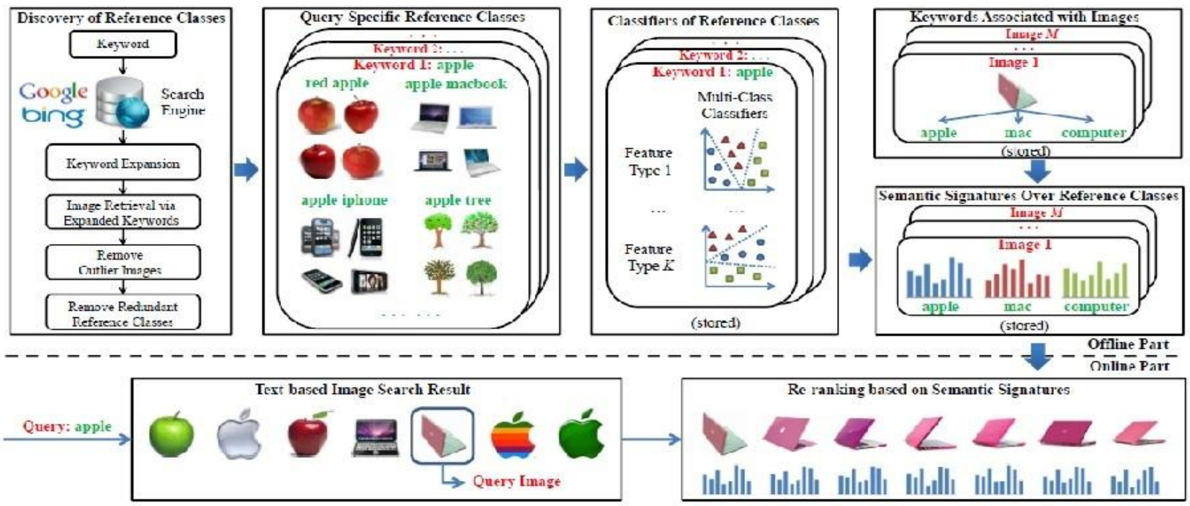

Fig2:Re-Ranking Process Implementation

In this system, when user enter the query keyword and click on the search button then this system searches the set of images as per the given query keyword and display the relevant images. The numbers of images are displayed on the basis of maximum count selected by the user. When user clicks on one particular image from the retrieved images then he/she can view the visually similar images as per the selected image as shown in fig.2.In fig. 3,displayed the resultant images as per the given query keyword with their title and description from both Google and local database. On the basis of displayed images title and description match found are displayed for each image as per the given query keyword. **Insider Access** Data processed or stored outside the confines of an organization, its firewall, and other security controls bring with it an inherent level of risk. The insider security threat is a well-known issue for most organizations and, despite the name, applies as well to outsourced cloud services. Insider threats go beyond those posed by current or former employees to include organizational affiliates, contractors, and other parties that have received access to an organization‘s networks, systems, and data to carry out or facilitate operations [36]. Incidents may involve various types of fraud, sabotage of information resources, and theft of information. Incidents may also be caused unintentionally. Moving data and applications to an external cloud computing environment expands the insider security risk not only to the service provider‘s staff, but also potentially among other customers using the service.

. Query-specific visual semantic space using multiple signatures. For an image, multiple semantic signatures are computed from multiple SVM classifiers, each of which is trained on one type of visual features separately. Some parameters used in our approach as mentioned in Sections 3 and 4 are tuned in a small separate data set and they are fixed in all the experiments. The averaged top m precisions on data sets. Our approach significantly outperforms Global Weighting and Adaptive Weighting, which directly compare visual features. On data set I, our approach enhances the averaged top 10 precision from 44:41% (Adaptive Weighting) to 55:12% (QSVSS Multiple). 24:1% relative improvement has been achieved. the histograms of improvements of averaged top 10 precision of the 120 query keywords on data set I and II by comparing QSVSS Multiple with Adaptive Weighting. Figure 4 (f) shows the improvements of averaged top 10 precision of the 10 query keywords on data set III. In our approach, computing multiple semantic signatures from separate visual features has higher precisions than computing a single semantic signature from combined features. However, it costs more online computation since the dimensionality of multiple semantic signatures is higherif the testing images for re-ranking and images of reference classes are collected from different search engines, the performance is slightly lower than the case

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when they are collected from the same search engine. However, it is still much higher than directly comparing visual features. This indicates that we can
utilize images from various sources to learn query-specific semantic spaces. As shown in Figure 4 (c), even if the testing images and images of reference classes are collected at different times (eleven months apart), query specific semantic spaces still can effectively improve re-ranking. Compared with Adaptive Weighting, the averaged top 10 precision has been improved by 6:6% and the averaged top 100 precision has been improved by 9:3%. This indicates that once the query-specific semantic spaces are learned, they can remain effective for a long time and do not have to be updated frequently.

MODULES
User

Registration:
User management can maintain this registration to register the new users
It maintain user information for login to the system.
Image Search:
This Module can be describe about image information. A registered user can search an image by using text-key words, it gives related information
Search Rank:
The registered user can get information about image and then find the rank of that object. By using the Search Rank to get better images for right information.

Admin
User Details:
Admin can maintain all registered users information. To provide better information for every user, provide security to the user information.
Image Upload:
Admin can maintain as much as possible updated information about all images.
All updated information is uploaded by admin only, No one is not possible to modified this information.

METHODOLOGY

A. Latent Semantic Indexing

Latent Semantic Indexing method is used to perform re-ranking of retrieved images. LSI method applies synonymy concept to given query keyword and then compares it with title and description of images to produce resultant similarity value in fraction (percentage). By using this similarity co-efficient image is re-ranked.
Example: Steps
a. Search query : „Water"
b. Get all synonyms of query „water" from dictionary and store it in array. Like,
c. Synonym Query[H2O, body of water, irrigate, watery, ….]
d. Compare these synonyms with array of title plus description of retrieved images.
e. Retrieved Images [title1, title2, title3,….,desc1, desc2, desc3,….]
f. Count ++

$$LSI = \frac{\text{WORDS LENGTH}}{\text{COUNTER}} * 10$$

Where, words length = total length of word for comparison and Counter = total match found

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B. Marrkovian Semantic Indexing:

On the other hand Markovain Semantic Indexing method obtains synonyms of image title and description and then compares it with the query keyword to retrieve similarity co-efficient for retrieved images and using these similarity co-efficient images are re-ranked.
Example: Steps
a. Search query : „Water‟
b. Get all synonyms of title plus description of retrieved images from dictionary and store it in array. Like,
c. Synonym Retrieved Images [a, b, c…]
d. Compare these synonyms with given search query „water‟.
e. Count ++

$$MSI = \frac{COUNTER}{WORDS\ LENGTH} * 100$$

Where, words length = total length of word for comparison
Counter = total match found

C. Probabilistic Latent Semantic Indexing:

Probabilistic Latent Semantic Indexing method is used to perform the re-ranking on the retrieved images. PLSI method is used to compute the synonyms of query keywords as well as synonyms of title and description of images and then perform the comparison and display the result in between 0 to 1. As per the resultant value this system performs the re-ranking on images.
Example: Steps
a. Search query : „Water‟
b. Get all synonyms of query „water‟ from dictionary and store it in array. Like,
c. Syn_Query[H2O, body of water, irrigate, watery, ….]
d. Get all synonyms of title plus description of retrieved images from dictionary and store it in array. Like,
e. Syn_Images [a, b, c…]
f. Compare Syn_Query with Syn_Images.
g. Count ++

$$PLSI = \frac{WORD\ LENGTH}{COUNTER} * 1$$

Where, words length = total length of word for comparison
Counter = total match found

VI.CONCLUSION AND FUTURE WORK

We propose a novel image re-ranking framework, which learns query-specific semantic spaces to significantly improve the effectiveness and efficiency of online image re-ranking. The visual features of images are projected into their related visual semantic spaces automatically learned through keyword expansions at the offline stage. The extracted semantic signatures can be 70 times shorter than the original visual feature on average, while achieve 20%35% relative improvement on re-ranking precisions over state-of the-art methods. This system have reviewed a novel image re-ranking framework by learning the query-specific semantic spaces it helps to significantly expand both the efficiency and effectiveness of online image re-ranking. Through keyword expansions the visual features of images are estimated into their related visual semantic spaces automatically, at offline stage. This project introduced a system using which user is able to retrieve images

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based on query keyword from Google using web service and from local image database. This system also provided functionality where user can view the ranking provided to the image result set based on Latent Semantic Indexing (LSI), Probabilistic Latent Semantic Indexing (PLSI) and Markovian Semantic Indexing (MSI) methods. This system also provided precision and recall (P&R) graph where user can compare the performance of these ranking methods.Currently this system does not use image clustering of retrieved images based on image similarity in terms of family of images, size, shape and colours, etc. I would like to address this functionality development on local image database in future work.

REFERENCES

1 Berners-Lee, T., Hendler, J. and Lassila, O. “The Semantic Web”, Scientific American, May 2001.
2 Deborah L. McGuinness. “Ontologies Come of Age”. In Dieter Fensel, J im Hendler, Henry Lieberman, and Wolfgang Wahlster, editors. Spinning the Semantic Web: Bringing the World Wide Web to Its Full Potential. MIT Press, 2002.
3 Ramprakash et al “Role of Search Engines in Intelligent Information Retrieval on Web”, Proceedings of the 2nd National Conference; INDIACom-2008.
4 R. Bekkerman and A. McCallum, “Disambiguating Web Appearances of People in a Social Network,” Proc. Int‟l World Wide Web Conf. (WWW ‟05), pp. 463-470, 2005.
5 G. Salton and M. McGill, Introduction to Modern Information Retreival. McGraw-Hill Inc., 1986.
6 M. Mitra, A. Singhal, and C. Buckley, “Improving Automatic Query Expansion,” Proc. SIGIR ‟98, pp. 206-214, 1998.
7 F. Manola, E. Miller, and B. McBride, RDF primer. *W3C recommendation*, Vol. 10, No., 2004
8 T. Hofmann, “Unsupervised Learning by Probabilistic Latent Semantic Analysis,” Machine Learning, vol. 42, no. 1/2, pp. 177- 196, 2001.
9 B. Luo, X. Wang, and X. Tang. A world wide web based image search engine using text and image content features. In Proceedings of the SPIE Electronic Imaging, 2003.

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