# Web Image Search Re-ranking Dependent on Diversity

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***Abstract*- Social media sharing websites sanction users to annotate images with free tags, which significantly contribute to the development of the web image retrieval. Tag-predicated image search is a consequential method to find images shared by users in gregarious networks. However, how to make the top ranked result germane and with diversity is arduous. In this paper, we propose a topic diverse ranking approach for tag-predicated image retrieval with the consideration of promoting the topic coverage performance. First, we construct a tag graph predicated on the homogeneous attribute between each tag. Then community detection technique is led to mine the subject network of each tag. From that point forward, inter network and intra network positioning are acquainted with acquire the last recovered outcomes. In the inter-community ranking process, an adaptive desultory walk model is employed to rank the community predicated on the multi-information of each topic community. Besides, we build an inverted index structure for images to expedite the probing process. Experimental results on Flickr dataset and NUS-Wide datasets show the efficacy of the proposed approach.**

**Keyword – Image search, Re-ranking**

## **I.** INTRODUCTION

Web-scale image search engines mostly use keywords as queries and rely on circumventing text to probe images. It is prominent 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 and searching it has been shown the effective way to improving the image searching results. Real web picture web search tools have since embraced the re-ranking methodology. Given a query keyword input by a utilizer, according to a stored word-image index file, a pool of images pertinent to the query keyword are retrieved by the search engine. By asking a user to select 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 highlights of pictures are pre-processed disconnected and put away by the web crawler. The principle online computational expense of picture re-positioning is on contrasting visual highlights. In order to achieve high efficiency, the visual feature vectors need to be short and their matching needs to be expeditious. 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 offline image apperception and retrieval, there have been a number of studies to map visual features to a set of predefined concepts or attributes as semantic signature However, these approaches are only applicable to closed image sets of relatively small sizes. They are not congruous for online web-predicated image re-ranking. According to our empirical study, images retrieved by 120query keywords alone include more than 1500 concepts. Therefore, it is arduous and inefficient to design an immensely colossal concept dictionary to characterize highly diverse web images.

RELATED WORK : Social networks allow users to annotate their shared images with a set of descriptors such as tags. The tag-predicated image search can be facilely accomplished by utilizing the tags as query. However, the weakly relevant tags, noisy tags and duplicated information make the search results unsatisfactory. Most of the literature focuses on tag processing, image relevance ranking and diversity enhancement for the retrieval results. The following components present the subsisting works cognate to the above three aspects respectively.

### *A. Tag Processing Strategy*

It has been long acknowledged that tag ranking and refinement play a consequential role in the re-ranking of tag-predicated image retrieval, for they lay a firm foundation on the development of re-ranking in tag based image retrieval (TBIR). For example, Liu et al. [1] proposed a tag ranking method to rank the tags of a given image, in which probability density estimation is used to get the initial relevance scores and a random walk is proposed to refine these scores over a tag similarity graph. Similar to [1], and [26] sort the tag list by the tag relevance scores which are learned by counting votes from visually similar neighbors. The applications in tag-based image retrieval also have been conducted. Based on these initial efforts, Lee and Neve [66] proposed to learn the relevance of tag and image by visually weighted neighbor voting, a variant of the popular baseline neighbor voting algorithm. Agrawal and Chaudhary [17] proposed a relevance tag ranking algorithm, which can automatically rank tags according to their relevance with the constraint of image content. A modified probabilistic relevance estimation method is proposed by taking the size of object into account. Furthermore, random walk based refinement is utilized to improve final retrieval results. Li [24] presented a tag fusion method for tag relevance estimation to solve the limitations of a single measurement on tag relevance. Besides, early and tardy fusion schemes for a neighbor voting predicated tag pertinence estimator are conducted. Zhu et al. [34] proposed an adaptive teleportation random walk model on the voting graph which is constructed based on the images relationship to estimate the tag relevance. Moreover, many research efforts about the tag refinement emerged. Wu et al. [19] raised a tag completion algorithm to complete the missing tags and correct the erroneous tags for the given image. Qian et al. proposed a retagging approach to cover a wide range of semantics, in which both the relevance of a tag to image as well as its semantic compensations to the already determined tags are fused to determine the final tag list of the given image. Gu et al. [45] proposed an image tagging approach by latent community classification and multi-kernel learning. Yang et al. proposed a tag refinement module which leverages the abundant user-generated images and the associated tags as the "social assistance" to learn the classifiers to refine noisy tags of the web images directly. Qi et al. proposed a collective intelligence mining method to correct the erroneous tags [50].

### B. *Relevance Ranking Approach*

To directly rank the raw photos without undergoing any intermediate tag processing, Liu et al. [3] utilized an optimization framework to automatically rank images based on their relevance scores to a given tag. Visual consistency among pictures and semantic data of labels are both considered. Gao et al. [7] proposed a hypergraph learning approach, which aims to estimate the relevance of images. They investigate the bag-of-words and bag-of-visual words of images, which is extracted from both the visual and textual information of image. Chen et al. [21] proposed a support vector machine classifier per query to learn relevance scores of its associated photos. Wu et al. [15] proposed a two-step similarity ranking scheme that aims to preserve both visual and semantic resemblance in the similarity ranking. In order to achieve this, a self-tune manifold ranking solution that focuses on the visual-based similarity ranking and a semantic-oriented similarity re-ranking method are included. Hu et al. [27] proposed an image ranking method which represents image by sets of regions and apply these representations to the multiple-instance learning based on the max margin framework. Yu et al. [35] proposed a learning based ranking model, in which both the click and visual feature are adopted simultaneously in the learning process. Specially, Haruechaiyasak and Damrongrat [33] proposed a content-based image retrieval method to improve the search results returned by tag-based image retrieval. In order to give users a better visual enjoyment, Chen et al. [18] proposed relevance-quality re-ranking approach to boost the quality of the retrieval images.

### C. *Diversity Enhancement*

The relevance based image retrieval approaches can boost the relevance performance, but the diversity performance of searching is also very important. Many researchers dedicated their extensive efforts to make the top ranked results diversified. Leuken et al. studied three visually diverse ranking methods to re-rank the search results [10]. Different from clustering, Song et al. [9] proposed a re-ranking method to meet users' ambiguous needs by analyzing the topic richness. A diverse relevance ranking algorithm to maximize average diverse precision in the optimization framework by mining the semantic similarities of social images based on their visual features and tags is proposed in [5]. Sun et al. [28] proposed a social image ranking scheme to retrieve the images to meet the relevance, typicality and diversity criteria. They explored both semantic and visual information of images on the basis of [5]. Ksibi et al. [31] proposed to assign a dynamic trade-off between the relevance and diversity performance according to the ambiguity level of the given query. Based on [31], they further proposed a query expansion approach [6] to select the most representative concept weight by aggregating the weights of concepts from different views. Wang et al. [29] proposed a duplicate detection algorithm to represent images with hash code, so that large image database with similar hash codes can be grouped quickly. Qian et al. [48] proposed an approach for diversifying the landmark summarization from diverse viewpoints based on the relative view point of each image. The relative viewpoint of each image is represented with a 4-dimensional viewpoint vector. They select the relevant images with large viewpoint variations as top ranked images. Tong et al. achieved the diversity by introducing a diversity term in their model whose function is to punish the visual similarity between images [61-62]. However, most of the above literatures view the diversity problem as to promote the visual diversity but not the topic coverage. As reported in [14], most people said they preferred the retrieval results with broad and interesting topics. So, many literatures about topic coverage are emerged [23, 30, 49, 54]. For instance, Agrawal et al. [23] classify the taxonomy over queries to represent the

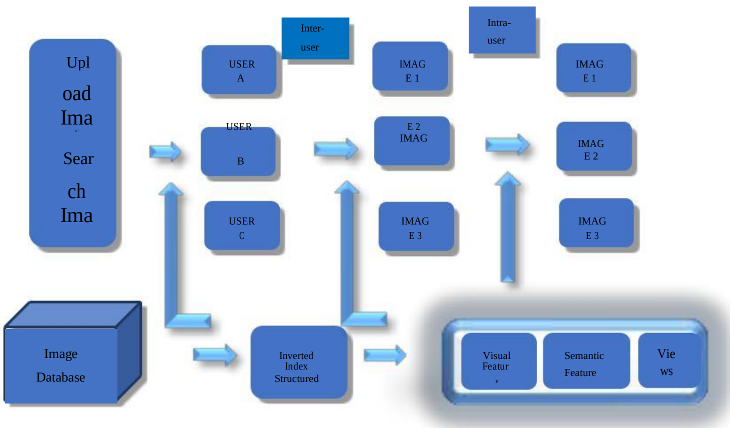
different aspects of query. This approach promotes documents that share a high number of classes with the query, while demoting those with classes already well represented in the ranking.

## II. SYSTEM OVERVIEW

Our system includes five main parts: 1) Tag graph construction based on the tag information of image dataset. Tag graph is constructed to mine the topic community. 2) Community detection. Affinity propagation clustering methods is employed to detect topic communities. 3) Image community mapping process. We assign each image to a single community according to the tag overlap ration between the topic community and image. 4) Inter- community ranking . we introduce the adaptive arbitrary walk model to rank topic communities according to the semantic pertinence between the community and query. 5) Intra community ranking. A regularization framework is proposed to determine the pertinence of each image to the query by fusing the visual, semantic and view information into a amalgamated system. We sequentially select the most relevant image in each ranked community as our final re- ranking results.

## III. PROPOSED SYSTEM

We propose a topic diverse ranking approach for tag –based image retrieval with the consideration of promoting the topic coverage performance. First we construct a tag graph predicated on the homogeneous attribute between each tag. The group strategy is directed to mine the point network of each tag. After that , inter-community and intra-community ranking are introduced to obtain the final retrieval results. We present a novel image search re-ranking, named spectral clustering re-ranking with click-based similarity and typicality. Which first use image click information to guide image similarity learning for multiple features, then conducts spectral clustering to group visually and semantically similar images into clusters. Determinately obtain the re-ranking results by calculating click-predicated clusters typicality and within-clusters click predicated image typicality in descending order. To the best of our knowledge, this is the attempt for cluster-based re-ranking using click-through data. The Proposed system Retrieve image results that are relevant and finding common features among images also interest points on the images are extracted. Similarity of each pair of images are computed by applying page ranking.

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