Image Re-ranking based on Topic Diversity

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Abstract
Social media sharing websites allow users to annotate images with free tags, which significantly contribute to the development of the web image retrieval. Tag-based image search is an important method to find images shared by users in social networks. However, how to make the top ranked result relevant and with diversity is challenging. In this paper, 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 based on the similarity between each tag. Then community detection method is conducted to mine the topic community of each tag. After that, inter-community and intra-community ranking are introduced to obtain the final retrieved results. In the inter-community ranking process, an adaptive random walk model is employed to rank the community based on the multi-information of each topic community. Besides, we build an inverted index structure for images to accelerate the searching process. Experimental results on Flickr dataset and NUS-Wide datasets show the effectiveness of the proposed approach.

1. Introduction:

In recent years, more and more scholars pay attention to retrieval result's diversity [7, 11, 15]. In [25], the authors first apply graph clustering to assign the images to clusters, then utilize random walk to obtain the final result. The diversity is achieved by set the transition probability of two images in different clusters higher than that in the same cluster. Tian et al. think the topic structure in the initial list is hierarchical [16]. They first organize images to different leaf topic, then define the topic cover score based on topic list, and finally use a greedy algorithm to obtain the highest topic cover score list. Dang-Nguyen et al. [17] first propose a clustering algorithm to obtain a topic tree, and then sort topics according to the number of images in the topic. In each cluster, the image uploaded by the user who has highest visual score is selected as the top ranked image. The second image is the one which has the largest distance to the first image. The third image is chosen as the image with the largest distance to both two previous images, and so on. In our previous work [3], the diversity is achieved based on social user re-ranking. We regard the images uploaded by the same user as a cluster and we pick one image from each cluster to achieve the diversity. Most papers consider the diversity from visual perspective and achieve it by applying clustering on visual features [4, 5-9]. In this paper, we focus on the topic diversity. We first group all the tags in the initial retrieval image list to make the tags with similar semantic be the same cluster, then assign images into different clusters. The images within the same cluster are viewed as the ones with similar semantics. After ranking the clusters and images in each cluster, we select one image from each cluster to achieving our semantic diversity. In this paper, we propose to construct the tag graph and mine the topic community to diversify the semantic information of the retrieval results. The contributions of this paper are summarized as follows: 1) We propose a topic diverse ranking approach considering the topic coverage of the retrieved images. The intercommunity ranking method and intra-community ranking methods are proposed to achieve a good trade-off between the diversity and relevance performance. 2) The tag graph construction based on each tag's word vector and community mining approach are employed in our approach to detect topic community. The mined community can represent each sub-topic under the given query. Besides, in order to represent the relationship of tags better, we train the word vector of each tag based on the English Wikipedia corpus with the model word2vec. 3) We rank each mined community according to their relevance level to the query. In the inter-community ranking process, an adaptive random walk model is employed to accomplish the ranking based on the relevance of each community with respect to the query, pair-wise similarity between each community, and the image number in each community. With the adaptive random walk model, the community that possesses the bigger semantic relevance value with the query and larger confidence value will be ranked higher. Both the goals of this paper and our previous work [1-3] are to diversify the top ranked retrieval results. However they have considerable differences, which are summarized as follows: First, in [11-14], we aim at diversifying the retrieval results by social user oriented re-ranking. We make the final result list contain images from different users as many as possible to achieve the diversity. While in this paper, our goal is to diversify the topics for the top ranked retrieval results. We apply (topic) community detection to make the final result list contain images with different semantics as many as possible. Second, [18-21] computes the similarity between the user-oriented image set and query based on the co-occurrence tag mechanism, while this paper calculates the similarity between the tag community and query based on all of the tags in the community. Third, the grouping step is not required in [22-27], because in the dataset every image has a user-id. However, in this paper, grouping images into different topic properly is a major problem.

2. Literature Survey

D. Liu, X. Hua, M. Wang, and H. Zhang, "Boost Search Relevance For Tag-Based Social Image Retrieval", 2009. In this paper, Author proposes a relevance-based ranking scheme for social image search, aiming to automatically rank images according to their relevance to the query tag. It integrates both the visual consistency between images and the semantic correlation between tags in a unified optimization framework. Authors propose an iterative method to solve the optimization problem, and the relevance based ranking can thus be accomplished [12].

K. Yang, M. Wang, X. Hua, and H. Zhang, "Social Image Search with Diverse Relevance Ranking", 2010. In this paper, Author propose a social re-ranking system for tag based image retrieval with the consideration of image's relevance and diversity. We aim at re- ranking images according to their visual information, semantic information and social clues. The initial results include images contributed by different social users. Usually each user contributes several images. First we sort has images by inter-user re-ranking. Users that have higher contribution to the given query rank higher. Then we sequentially implement intra-user re-ranking on the ranked user's image set, and only the most relevant image from each user's image set is selected. These selected images compose the final retrieved results. Author builds an inverted index structure for the social image dataset to accelerate the searching process [10].

M. Wang, K. Yang, X. Hua, and H. Zhang, "Towards relevant and diverse search of social images", 2010. In This Paper, Author presents a diverse relevance ranking scheme which simultaneously takes relevance and diversity into account by exploring the content of images and their associated tags. First, it estimates the relevance scores of images with respect to the query term based on both visual information of images and semantic information of associated tags. Then semantic similarities of social images are estimated based on their tags. Based on the relevance scores and the similarities, the ranking list is generated by a greedy ordering algorithm which optimizes Average Diverse Precision (ADP), a novel measure that is extended from the conventional Average Precision (AP)[11].

D. Cai, X. He, Z. Li, W. Ma, and J. Wen, "Hierarchical clustering of WWW image search results using visual, textual and link information", 2004. In this paper, Author proposes a hierarchical clustering method using visual, textual and link analysis. By using a vision-based page segmentation algorithm, a web page is partitioned into blocks, and the textual and link information of an image can be accurately extracted from the block containing that image. By using block-level link analysis techniques, an image graph can be constructed. We then apply spectral techniques to find a Euclidean embedding of the images which respects the graph structure. Thus for each image, we have three kinds of representations, [15].

3. System Study

Currently, image clustering and duplicate removal are the major approaches in settling the diversity problem. However, most of the literature regards the diversity problem as to promote the visual diversity performance, but the promotion of the semantic coverage is often ignored.To diversify the top ranked search results from the semantic aspect, the topic community belongs to each image should be considered.Dang-Nguyen et al. first propose a clustering algorithm to obtain a topic tree, and then sort topics according to the number of images in the topic. In each cluster, the image uploaded by the user who has highest visual score is selected as the top ranked image. The second image is the one which has the largest distance to the first image. The third image is chosen as the image with the largest distance to both two previous images, and so on.Most papers consider the diversity from visual perspective and achieve it by applying clustering on visual features

Drawbacks

- Tag mismatch

- Query ambiguity
- Most of the above literatures view the diversity problem as to promote the visual diversity but not the topic coverage.

Proposed System:

In this paper, we focus on the topic diversity. We first group all the tags in the initial retrieval image list to make the tags with similar semantic be the same cluster, then assign images into different clusters. The images within the same cluster are viewed as the ones with similar semantics. After ranking the clusters and images in each cluster, we select one image from each cluster to achieving our semantic diversity.In this paper, we propose to construct the tag graph and mine the topic community to diversify the semantic information of the retrieval results. The contributions of this paper are summarized as follows:We propose a topic diverse ranking approach considering the topic coverage of the retrieved images. The inter-community ranking method and intra-community ranking methods are proposed to achieve a good trade-off between the diversity and relevance performance.The tag graph construction based on each tag's word vector and community mining approach are employed in our approach to detect topic community. The mined community can represent each sub-topic under the given query. Besides, in order to represent the relationship of tags better, we train the word vector of each tag based on the English Wikipedia corpus with the model word2vec.We rank each mined community according to their relevance level to the query. In the inter-community ranking process, an adaptive random walk model is employed to accomplish the ranking based on the relevance of each community with respect to the query, pair-wise similarity between each community, and the image number in each community.

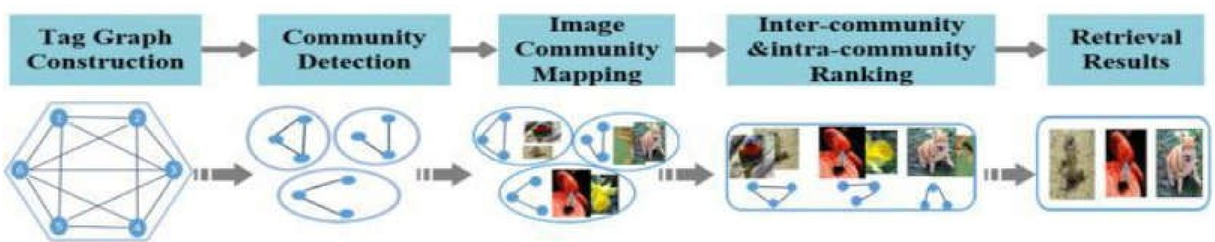

Fig.1. The framework of our proposed method

Advantages

- Good trade-off between the diversity and relevance performance.
- With the adaptive random walk model, the community that possesses the bigger semantic relevance value with the query and larger confidence value will be ranked higher.
- To diversify the top ranked retrieval results
- Computes the similarity between the user-oriented image set and query based on the co-occurrence tag mechanism.
- We sort the communities based on relevance scores obtained by random walk.

4. Implementation

- Admin
- Request & Response
- User

Admin

In this module, the Admin has to login by using valid user name and password. After login successful he can do some operations such as search history, view users, request & response and view the image, View all user image tag and top ranking image and inter-intra community user activity etc.

Request & Response

In this module, the admin can view the all the friend request and response. Here all the request and response will be stored with their tags such as Id, requested user photo, requested user name, user name request to, status and time & date. If the user accepts the request then status is accepted or else the status is waiting.

User

In this module, there are n numbers of users are present. User should register before doing some operations. And register user details are stored in user module. After registration successful he has to login by using authorized user name and password. Login successful he will do some operations like view or search users, send friend request, view messages, send messages, search photo and view and like etc.

5. Experiments

In order to demonstrate the effectiveness of the proposed topic diverse ranking (denoted by TDR) based image retrieval approach, we conduct experiments on our crawled Flickr images [3,7] and NUS-wide. We will give the detailed descriptions of our dataset in next subsection. In order to evaluate the performance of different methods, we utilize following 20 tags as query: airplane, beach, bird, blue, buildings, Christmas, forest, reflection, garden, girl, ocean, orange, sea, sky, animal, and etc. We systematically make comparisons for the following five tag-based image retrieval approaches: 1) RR: Relevance-based ranking [3], an optimization framework is applied to automatically re-rank images based on visual and semantic information. 2) DRR: Diverse relevance ranking [5], which optimizes an ADP measure with the consideration of the semantic and visual information of images. 3) DR: Diverse ranking [24]. First, the topic coverage of each image is calculated. Then, PageRank model based on the topic coverage is utilized to re-rank the initial retrieval results. 4) SR: Social ranking [23,28]. User information is utilized to boost the diversity performance. A regularization framework which fuses the semantic, visual and views information is introduced to improve the relevance. 5) TDR: Topic

Diverse Ranking. Tag graph and community detection method are utilized to boost the diversity performance. A regularization framework which fuses the semantic, visual and view information is introduced to improve the relevance performance. In order to train the word vector of each tag, Word2vec model is conducted to train each tag's word vector

6. Conclusions

In this paper, we propose a topic diverse re-ranking method for tag-based image retrieval. In this topic diverse re-ranking method, inter-community ranking and intra-community ranking are carried out to get satisfactory retrieved results. Tag graph construction and community detection are two effective ways to enhance the diversity. Besides, each tag's word vector is trained by using the Word2vec model based on the English Wikipedia corpus to enhance the relevance performance of the retrieved results. However, we consider the community similarity in the intercommunity ranking process while the topic similarity of representative images is ignored. In addition, much information in social media image set, such as Flickr dataset are still unutilized, such as title, time stamp and so on. For future work, we will investigate the similarity among representative images. Besides, we may fuse these relationships to enhance the diversity performance of image ranking system.

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