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Image Re-Ranking based on Topic Diversity

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Abstract: *The growth of web image retrieval is significantly helped by the free tags users can add to photographs on social media sharing services. One crucial technique for locating photos that users have uploaded on social networks is tag-based image search. It can be difficult to make the top-ranked result diverse and meaningful, though. To improve the topic coverage performance, we present a topic diversity ranking method for tag-based image retrieval in this study. Based on how similar one tag is to the others, we first create a tag graph. The topic community of each tag is then mined using the community detection approach. The final recovered results are then obtained by introducing intra-community and inter-community.*

Based on the multi-information of each topic community, the community is ranked using an adaptive random walk model in the inter-community ranking process. Additionally, to speed up the search, we create an inverted index structure for photos..

Keywords: locating photos

I. INTRODUCTION

The variability of retrieval results has drawn increasing attention from scholars in recent years [7, 11, 15]. The authors of [25] first use graph clustering to group the photos into clusters, and then they use random walks to get the outcome. To achieve variety, the transition probability of two photos in distinct clusters is set greater than that of two images in the same cluster. According to Tian et al., the first list's topic structure is hierarchical [16].

Before using a greedy algorithm to get the highest topic cover score list, they first arrange the images according to various leaf topics. Then, they define the topic cover score based on the subject list. To create a topic tree, Dang-Nguyen et al. [17] first suggest a clustering approach. They then arrange subjects based on how many photos they contain. The user's uploaded image with the greatest visual score is chosen as the top-ranked image in each cluster. The image that is furthest distant from the first is the second one. The third image is chosen as the image with the largest distance to both the previous images, and so on. In our previous work [3],

Social user ranking is the basis for achieving diversity. To achieve diversity, we select one image from each cluster, which is uploaded by the same person. By using clustering on visual traits, the majority of articles take into account variety from a visual standpoint [4, 5–9]. Diversity is the main topic of this paper. Before assigning photos to distinct clusters, we first aggregate all of the tags in the original retrieval image list so that tags with similar semantics belong to the same cluster. Images that belong to the same cluster are thought to have comparable meanings. After ranking the clusters and images in each cluster, we select one image from each cluster to achieve our semantic diversity.

In this research, we propose to diversify the semantic information of the retrieval results by building the tag graph and mining the subject community. The following is a summary of this paper's contributions: 1) Taking into account the topic coverage of the collected photos, we suggest a topic-diverse ranking method. To attain a suitable balance between the performance of relevance and diversity, the intra-community and inter-community ranking systems are suggested.

2) To detect the subject community, we use a community mining approach and tag graph construction based on the word vector of each tag. Every subtopic under the specified query can be represented by the mined community. Additionally, we use the word2vec model to train the word vector of each tag based on the English Wikipedia corpus in order to better depict the relationships between tags.

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3) We assign a ranking to each mined community based on how relevant they are to the query. An adaptive random walk model is used in the inter-community ranking method to rank the communities according to their image number, pairwise similarity, and relevance to the query. The community with a higher confidence value and a higher semantic relevance value with the query will be ranked higher in the adaptive random walk model. Diversifying the top-rated retrieval results is the aim of both this research and our earlier work [1–3]. Nonetheless, they differ significantly, which might be summed up as follows: Initially, in [11–14],

By using social user-oriented re-ranking, we want to diversify the retrieval results. To achieve diversity, we include as many photographs from various users as feasible in the final result list. Diversifying the themes for the highest-ranking retrieval outcomes is our aim in this paper. To ensure that the final result list includes as many photos with varying semantics as possible, we use (topic) community detection. Second, this study computes the similarity between the tag community and query based on all of the community's tags, whereas [18-21] computes the similarity between the user-oriented picture set and query based on the co-occurrence tag technique. Third, since each image in the collection has a user ID, the grouping step is not necessary in [22–27].

However, a significant issue with this paper is the improper classification of photos into various topics.

II. LITERATURE SURVEY

"Boost Search Relevance For Tag-Based Social Image Retrieval," by D. Liu, X. Hua, M. Wang, and H. Zhang, 2009. To automatically rate photos based on their relevance to the query tag, the author of this study suggests a relevance-based ranking scheme for social image search. A single optimization framework incorporates both the semantic correlation between tags and the visual consistency between images. Relevance-based ranking can be achieved by using the authors' iterative approach to the optimization problem [12]."Social Image Search with Diverse Relevance Ranking," by K. Yang, M. Wang, X. Hua, and H. Zhang, 2010. The authors of this work suggest a social re-ranking approach for tag-based picture retrieval that takes into account the diversity and importance of the images. Our objective is to re-rank photos based on their visual, semantic, and social cues... Images supplied by various social users are included in the first result. Typically, multiple photos are contributed by one user. First, we employ user reranking to sort the photos. Higher-ranking users are those who have contributed more to the specified query. Only the most pertinent image from each user's image collection is chosen after we successively apply intra-user re-ranking to the rated user's image set. The final retrieved results are composed of these chosen photos. To speed up the search, the author creates an inverted index structure for the social image dataset [10].

"Towards relevant and diverse search of social images," by M. Wang, K. Yang, X. Hua, and H. Zhang, 2010. By examining the content of photos and the tags that go with them, the author of this paper offers a diversified relevance ranking system that simultaneously considers diversity and relevance. First, it uses both the visual information of the photos and the semantic information of the associated tags to estimate the relevance scores of the images to the query term. Based on their tags, the social photos' semantic similarity is then calculated. A greedy algorithm creates the ranking list based on the similarities and relevance scores.

ADP, a new metric that is an extension of the traditional Average Precision (AP), is optimized using an ordering algorithm [11].

"Hierarchical clustering of WWW image search results using visual, textual, and link information," by D. Cai, X. He, Z. Li, W. Ma, and J. Wen, 2004. The author of this research uses link, textual, and visual analysis to suggest a hierarchical clustering approach. A web page is divided into blocks using a vision-based page segmentation method, which allows for the precise extraction of an image's text and link information from the block that contains the image. Block-level link analysis techniques can be used to create an image graph. The images' Euclidean embedding that preserves the graph structure is then found using spectral techniques. We therefore have three different types of representations for every image [15].

System Study

The two main methods used to solve the diversity problem at the moment are image clustering and duplicate elimination. The promotion of semantic coverage is frequently overlooked, even though the majority of the literature

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views the diversity problem as one that aims to improve visual diversity performance. The topic community associated with each image should be taken into account to vary the top-ranked search results from the semantic component. To create a topic tree, Dang-Nguyen et al. first suggest a clustering approach. They then arrange subjects based on how many photos they contain. The top-ranked image in each cluster is determined by taking the user-uploaded image with the greatest visual score. The image that is furthest distant from the first is the second one. The image with the greatest distance from the first two is selected as the third image, and so on. The majority of publications use clustering on visual traits to account for variety from a visual perspective.

Drawbacks

- Tag mismatch
- Query ambiguity
- Most of the above literatures view the diversity problem as promoting the visual diversity but not the topic coverage.

III. PROPOSED SYSTEM

Diversity is the main topic of this paper. Before assigning photos to distinct clusters, we first aggregate all of the tags in the original retrieval image list so that tags with similar semantics belong to the same cluster. Images that belong to the same cluster are thought to have comparable meanings. We choose one image from each cluster to achieve our semantic diversity after ranking the clusters and the photos inside each cluster. In this research, we propose to diversify the semantic information of the retrieval results by building the tag graph and mining the subject community. The following is a summary of this paper's contributions: Taking into account the topic coverage of the retrieved photos, we suggest a topic diversity ranking method.

To attain a good balance between the performance of relevance and diversity, the intra-community and inter-community ranking systems are suggested. Our method for detecting topic communities uses a community mining methodology and tag graph generation based on the word vector of each tag. Every subtopic under the specified query can be represented by the mined community. Additionally, we use the word2vec model to train the word vector of each tag based on the English Wikipedia corpus to better depict the relationships between tags. Each mined community is ranked based on how relevant it is to the query. The adaptive random walk model is used in the inter-community ranking method to rank the communities according to their image number, pairwise similarity, and relevance to the query.

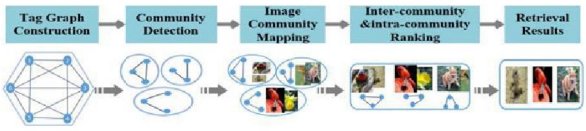

Fig.1. The framework of our proposed method

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 a 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 a random walk.

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IV. IMPLEMENTATION

- Admin
- Request & Response
- User

Admin

The administrator must use a working username and password to log in to this module. He can browse users, request and respond, search history, and view images after successfully logging in. See every user picture tag, the image with the highest ranking, user activity within the intracommunity, etc.

Request & Response

The administrator can see every friend request and response in this module. Id requested user photo, requested user name, user name requested to, status, time, and date are among the tags that will be used to store each request and answer. The state is either accepted or waiting, depending on whether the user accepts the request.

User

A total of n users are present in this module. Before beginning any operations, the user should register. Additionally, the user module contains the registered user's details. Following a successful registration, he must use his password and permitted user name to log in. After successfully logging in, he will be able to see or search users, send friend requests, view and send messages, search for photos, view and like, and more.

V. EXPERIMENTS

We do trials on our crawled Flickr photos [3,7] and NUS-wide to show the efficacy of the suggested topic diverse ranking (denoted by TDR) based image retrieval approach. In the following subsection, we will provide comprehensive descriptions of our dataset. We use the following 20 tags as queries to assess the effectiveness of various approaches: airplane, beach, bird, blue, buildings, Christmas, forest, reflection, garden, girl, ocean, orange, sea, sky, animal, and so on.

We systematically make comparisons for the following five tag-based image retrieval approaches:

1) RR: Relevance-based ranking [3], which automatically re-ranks images according to visual and semantic information using an optimization framework.

2) Diverse relevance ranking, or DRR [5], optimizes an ADP measure while taking into account the visual and semantic information of images.

Diverse ranking (DR) [24]. Each image's topic coverage is first determined. The initial retrieval results are then re-ranked using the PageRank model, which is based on the topic coverage.

Social rating (SR) [23, 28]. The diversity performance is improved by using user information. To increase relevance, a regularization approach that integrates semantic, visual, and view information is presented.

5) Topic Diverse Ranking, or TDR. To improve diversity performance, tag graphs community detection techniques are used. To enhance the relevance performance, a regularization approach that integrates semantic, visual, and view information is presented. The Word2vec model is used to train the word vector of every tag.

VI. CONCLUSION

We present a topic-diversified re-ranking technique for tag-based picture retrieval in this study. To provide satisfactory recovered results, the topic's diversified re-ranking approach uses both intra-community and inter-community ranking. Two efficient methods to increase diversity are tag graph generation and community discovery.

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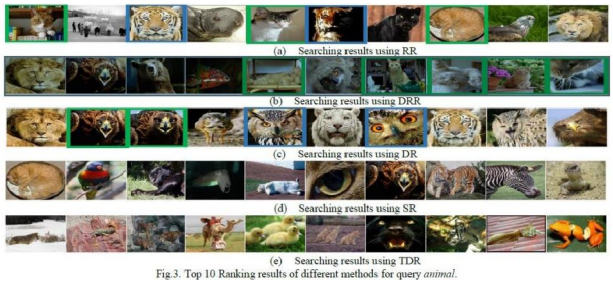

Fig.3. Top 10 Ranking results of different methods for query *animal*.

Additionally, to improve the relevance performance of the retrieved results, the Word2vec model, which is based on the English Wikipedia corpus, is used to train the word vector for each tag. However, we disregard the topic similarity of representative photos and take community similarity into account in the intercommunity rating method. Additionally, a lot of information, including the title and time stamp, is currently unused in social media image collections like the Flickr dataset. In further research, we will examine the degree of resemblance between representative photos. Additionally, we could combine these connections to improve the image rating system's diversity performance.

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