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Exploration of Ticket/Label Based Representation by Social Re-Grading

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ABSTRACT

Social media sharing websites like flickr shares images using their respective tags. According to this tag, images can be retrieved and this process is known as tag-based image retrieval. However, making the tagged images as top ranked result relevant is challenging. In this paper, we propose a social re-grading system for tag-based image search with the consideration of image retrieval and diversity. Images are re-graded according to their visual information, semantic information, and social clues. The initial results include images contributed by different social users. Usually each user contributes multiple images by their views. First, we sort these images by inter- user re-grading and intra-user re-grading. Each user's contributed image come higher position and thus images are stored in social image dataset in the database to sort images and it is also re-graded by tag-based image search. Experimental results on a flickr dataset show that our social re-grading method is effective and efficient.
Keywords: Image Search, Re-Grading, Image Retrieval, Social Input, Social Media

I. INTRODUCTION

With the development of social media based on Web 2.0,amounts of images and videos resilience up everywhere on the Internet. This circumstance has brought great challenges to multimedia storage, indexing and retrieval. Generally speaking, tag-based image search is more frequently used in social media than content based image retrieval, sketch based image retrieval and context-and-content based image retrieval. In recent years, the re-ranking complication in the tag-based image retrieval (TBIR) has gained researchers' wide attention.

Nonetheless, the following challenges block the path for the evolution of re-ranking technologies in the TBIR.

1) Tag mismatch. Social tagging requires all the users in the social network to label their uploaded images with their individual keywords and share with others. Different from ontology based image illustration there is no predefined ontology or taxonomy in social image tagging. Every user has his individual habit to tag images. Even for the same image, tags afford by different users will be of great difference. Thus, the same image can be interpreted in multiple ways with several different tags according to the background behind the image. Thus, many seemingly trivial tags are introduced.

2) Query ambiguity. Users cannot literally describe their request with single words and tag resolution system always recommend words that are highly interact to the predefined tag set, thus add little information to a users' contribution. Besides, uncertainty and synonyms are the other causes of the query ambiguity.

Starting from this instinct and above analysis, we propose a social re-ranking algorithm which user information is firstly introduced into the conventional ranking method considering the denotation, social clues and visual data of images. The contributions of this paper can be illustrated as follows.

3) We propose a tag-based image search entrance with social re-ranking. We systematically dissolve the visual information, social user's information and image view

times to boost the assortment performance of the search result.

4) We propose the inter-user re-ranking method and intra-user re-ranking method to attain a good trade-off between the diversity and relevance performance. These methods not only assets the relevant images, but also adequately eliminate the similar images from the same user in the ranked results.

5) In the intra-user re-ranking process, we fuse the visual, semantic and illustrate information into a regularization framework to learn the relevance score of all images in each user's image set. To accelerate up the learning speed, we use the co-occurrence word set of the given query to measure the semantic relevance matrix.

II. METHODS AND MATERIAL

Social image websites such as Flickr, allow users to illustrate their images with a set of descriptors such as tags and was often employed in image tagging, video tagging and tag based image retrieval. Thus, the tag-based image search can be easily proficient by using the tags as query terms. However, the flimsy relevant tags, noisy tags and duplicated information make the search result deficient. Most of the literatures with reference to the re-ranking of the TBIR focus on tag processing, image relevance ranking and diversity enrichment of the retrieval results. The following parts present the predefined works related to the above three aspects respectively.

A. Tag Processing Scenario

It has been long recognized that tag ranking and refinement play an important role in the re-ranking of TBIR, for they lay a firm foundation on the illustration of re-ranking in TBIR. For example, Liu *et al.* [1] proposed a tag ranking method to rank the tags of a defined image, in which probability density evaluation is used to get the initial relevance scores and a random walk is proposed to refine these scores over a tag correlation graph. Similar to [1], [2], and [14] sort the tag list by the tag concernment score which is learned by estimate votes from visually similar neighbors, and the applications in TBIR also have been regulated. Based on these fundamental efforts, Lee and Neve [12] proposed to learn the concernment of tags by visually weighted neighbor voting, a variant of the trendy baseline neighbor voting algorithm [2]. Agrawal and Chaudhary [9] proposed a concernment tag ranking algorithm, which can automatically rank tags according to their concernment with the image content. A modified probabilistic concernment estimation method is proposed by taking the size factor of objects into account and random walk based refinement is utilized. Li *et al.* [13] presented a tag fusion method for tag concernment estimation to solve the limitations of a single measurement on tag concernment. Besides, previous and late fusion schemes for a neighbor voting based tag concernment estimator are conducted. Zhu *et al.* [18] proposed an adaptive teleportation driftless walk model on the voting graph which is constructed based on the images relationship to estimate the tag concernment. Sun *et al.* [19] proposed a tag clarity score measurement approach to evaluate the precision of a tag in describing the visual content of its annotated images. The tag legibility score is measured by calculating the distance between the tag language model and the collection language model. Besides, many research intentions about the tag refinement emerged. Wu *et al.* [10] raised a tag completion algorithm to fill in the missed tags and correct the erroneous tags for the given image. Qian *et al.* [20] proposed a retagging evolution to cover a wide range of semantics, in which both the concernment of a tag to image as well as its semantic compensations to the existing determined tags are fused to determine the final tag list of the given image. Gu *et al.* proposed an image tagging approach by veiled community classification and multi-kernel learning [21].Yang *et al.* [11] proposed a tag refinement module which leverages the heavy user-generated images and the associated tags as the "social assistance" to learn the classifiers to refine noisy tags of the web images precisely. In [22], Qi *et al.* proposed a collective intelligence mining method to correct the erroneous tags in the Flickr scoopset.

B. Diversity Enrichment

The concernment based image retrieval approaches can boost the concernment performance; however the diversity attainment of searching are often ignored. Many researchers provide their extensive efforts to solve this problem. In [6], Cai *et al.* proposed a hierarchical clustering method to group the search results into different semantic clusters by using visual, textual and relative analysis. Similarly, in [7], Leuken *et al.* studied three prominently diverse ranking methods to re-rank the image search results based on the visual characteristics of these images. Different from clustering, Song *et al.* [8] proposed a re-ranking method to meet users' uncertain needs by analyzing the topic richness. Yang andWang *et al.* [3], [4] proposed a diverse relevance ranking algorithm to maximize moderate diverse precision in the optimization framework by mining the semantic affinity of social images based on their visual features and tags. Sun *et al.*[15] proposed a social image ranking scheme to retrieve the images which meet the concernment, typicality and diversity criteria by evaluate both semantic and visual information of images on the basis of [4]. Ksibi *et al.* [17] proposed to assign a irregularity trade-off between the relevance and diversity performance according to the ambiguity level of the given query. Based on [17], Ksibi *et al.* [5] proposed a query expansion approach to select the most clssical concept weight by aggregating the weights of concepts from different views, using a random threshold. Wang *et al.* [16] proposed a duplicate detection algorithm to perform images with hash code, so that large image database with related hash codes can be grouped quickly. Qian *et al.* proposed an approach for diversifying the landmark summarization from diverse viewpoints based on the similar viewpoint of each image. The similar viewpoint of each image is represented with a 4-dimensional viewpoint vector. However, most of the previous approaches highly rely on the visual and semantic information, and thus eliminate the social clues such as user and view information. User information is always exploited to do the final advertisement, travel recommendation, personalized service for endorsements and user communication based image re-ranking. However, user information is rarely used in retrieval work. In this paper, we propose a social re-ranking method which combine the user information into the traditional TBIR framework. We first get the initial conclusion by keyword matching process. Then the inter-user and intra-user re-ranking are imported to re-rank the initial results. Inter-user re-ranking algorithm is processed to rank users according to their contribution to the given query. After the inter-user re-ranking, we further introduce intra-user re-ranking to sequentially select the most applicable image from each image dataset of the ranked users. That's to say, the final retrieved images all have various user. The most relevant image uploaded by the highest donation user is the first in the retrieved results. Experimental results demonstrate that the prospective scheme is able to boost the diversity and relevance performance simultaneously.

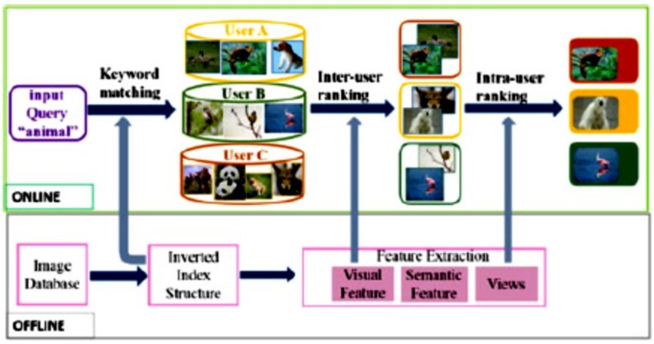

Figure 1. System framework of tag-based image retrieval with social re-ranking.

III. RESULTS AND DISCUSSION

In order to determine the effectiveness of the social re-ranking (denoted by SR) approach, we conduct experiments on our crawled Flickr images by utilizing the following 20 tags as queries: airplane, beach, Beijing, bird, blue, buildings, Christmas, cityscape, forest, reflection, garden, girl, honeybee, insect, lotus, ocean, orange, sea, sky, and zebra. We systematically make correlation for the following seven TBIR approaches:

1) VR: view-based re-ranking, a measure that rank the initial results by views in a downward order;

2) VUR: view and user based re-ranking. This model is based on VR, and the final re-ranked results are gained by removing the images which share the same user. That is to say, we only keep the image with the large number of views for a user in the top ranked results;

Figure 2. An exemplary image from Flickr and its associated information.

TABLE I
ILLUSTRATION OF IMAGE DATASET

		With tag	With views	With tags+ views
User	Number	7090	7241	7069
	Percentage	97.81%	99.48%	97.52%
Image	Number	5 325 265	6 593 090	5 318 503
	Percentage	80.69%	99.90%	85.58%

3) RR: relevance-based re-ranking , an optimization framework is adapted to automatically re-rank images based on visual and semantic information;

4) CRR: co-occurrence relevance re-ranking. In this algorithm we replace the semantic concernment score in with the semantic concernment score proposed in our paper. The semantic concernment score in takes all the tags of images into consideration. Our extensive approach only considers the co-occurrence tags;

5) DRR: diverse relevance re-ranking [4], which optimizes an ADP measure with the discussion of the semantic and visual information of images; and

6) SR: social re-ranking. Our evaluate approach dedicates to promote the concernment and diversity performance of our results. User information is apply to boost the diversity performance. A regularization

framework which fluxes the semantic, visual and views information is introduced to improve the concernment performance.

A. Scoopset

In order to extends the performance of our method, we dynamically crawled more than 6 million images together with their associated information from the image sharing websites Flickr.com through its public API. The initial data contains 6 600 034 images uploaded by 7249 users and their correlated files recoding the information of tags and views information. We have made a accomplishment about all the images and users in Table I. We not consider the images that have no views and no tags. Finally there will be 5 318 503 images and 7069 users left.

B. Performance Progression

The performance evaluation of our method is voted by five enlist who are invited to assign the relevance scores and diversity scores for the top n images of each query under different methods. The moderate relevance score is used to measure the relevance between the query and the retrieval results. And the moderate diversity score shows the diversity level of the retrieval results. Five enlist are asked to give the relevance score of each image among the top n results into the following four categories: 3-perfect, 2-good, 1-so so, 0-irrelevant, according to their judgment for the correlated re-ranking approaches. Then, the concernment score of the image i is obtained by averaging the assigned concernment values. Let *reli* denote the concernment value of image i. The five enlist are also asked to give the diversity score of the top n results into four categories: 3-excellent, 2-good, 1-so so, 0-similiar, according to their judgments for the correlated six re-ranking approaches. Similarly, the diversity score (denoted by div@n) is obtained by averaging the accepted diversity values. The larger of the div@n, the better diversity performance is achieved.

(a)

(b)

(c)

(d)

(e)

(f)

Figure 3. Top 10 ranking results of different methods for query *honeybee.* (a) Search results using VR. (b) Searching results using VUR. (c) Searching results using RR. (d) Searching results using CRR. (e) Searching results using DRR. (f) Searching results using SR.

1) Criteria of Performance Interpretation: We use the NDCG [21] and average precision under depth n (denoted as *AP@n*) as the concernment performance evaluation measure which are expressed as follows:

$$\mathrm{NDCG}@n = \frac{1}{W}\sum_{i=1}^{n}\frac{2^{\mathrm{lev}(i)}-1}{\log(1+i)}$$

$$\mathrm{AP}@n = \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{i}\frac{\mathrm{rel}_j}{i}\right)$$

where W is a normalization consistent that is chosen so that the optimal ranking's NDCG score is 1.

Moreover, we can get the moderate diverse precision under depth n (denoted as ADP@n) as follows:

$$\mathrm{ADP}@n = \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{i}\frac{\mathrm{rel}_j}{i}\right)*\mathrm{norm\_div}@n$$

where norm div@n is the assign diversity value under depth n, which is represented as follows:

$$\mathrm{norm\_div}@n = \frac{\mathrm{div}@n}{3}.$$

2) Epitome Search Results: The top 10 results of exemplar queries: honeybee, and zebra on Flickr database under six different ranking algorithms are shown in Figs. 3 and 4 respectively. The images marked by the red borders are random with the query. Besides, we mark the correlated images from the same user with the same color.

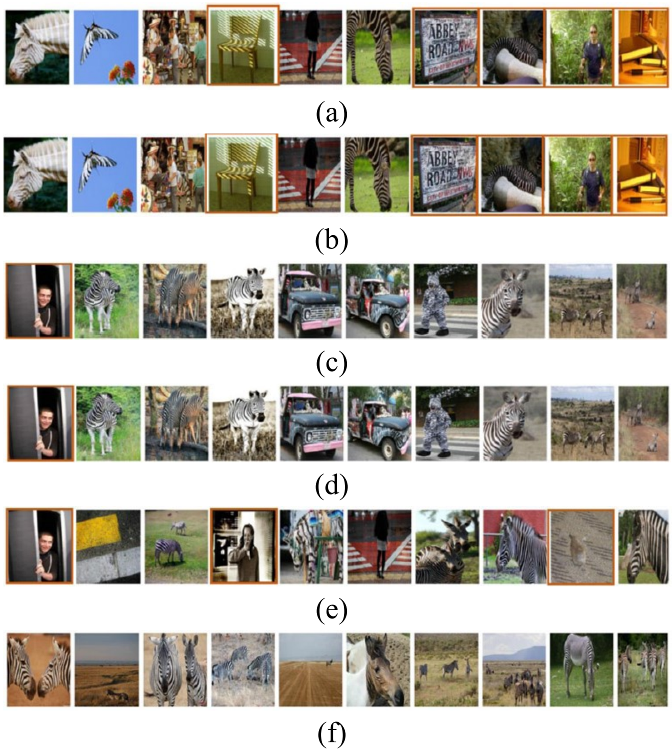

Figure 4. Top 10 ranking results of different methods for query *zebra*. (a) Searching results using VR. (b) Searching results using VUR. (c) Searching results using RR. (d) Searching results using CRR. (e) Searching results using DRR. (f) Searching results using SR.

We find that the same user's images about a same topic are repeatedly taken in the same spot at a specific time. So these images have a higher probability to share the same visual appearance, tags and related views. Therefore, the top ranked images decisive by VR, RR, and CRR, are all languish from the lack of diversity. We find that many of the related images obtained through them are from the same user. For example, in the search results of VR as shown in Fig. 3(a), the second and the ninth one are from the exact user. For results of RR as shown in Fig. 3(c), the second and the forth, and the fifth and the eighth are from the exact user. For results of CRR as shown in Fig. 3(d), the first and the third, and the fourth, the fifth and the ninth are from the exact user. However, SR moves these related images successfully. By correlate the experimental results, we find that the results of VUR and SR which suggest the social user factors and select only one representative image from exact user's image set are more diverse. Additionally, from Fig. 4(a), we can also find that large views images are not all related with the query q, beautiful images and images of hot topics all have a more views. The DRR introduces the semantic correlated restriction to enhance the diversity performance which brings about the elevation of the diversity performance and declines of their concernment performance, just as the result of DRR on query zebra have shown. From Fig. 4(a)–(e), we find that there are some unrelated images in the top ranked results, just as the images with the red border shown. From the examples as shown in Figs. 3 and 4, we can acknowledge that our method takes the above deficiencies into consideration and makes a greater trade-off between the diversity and concernment performance.

3) Performance Scrutiny: To make impartial comparisons for the methods VR, VUR, RR, CRR, DRR and SR, the parameters α is all set to be 10, and β is all set to be 1. The discussions on α and β are illuminated in Section VI-D. Let MAP@nandMADP@ndenote the mean values ofAP@n and ADP@n for all the 20 query tags. The NDCG@n, MAP@n and MADP@n with n = 1,5,10,15, and 20 are shown in Figs. 5, 6 and 7 respectively. For example, the MAP@20 of VR, VUR, RR, CRR, DRR, and SR are 2.52, 2.50, 2.71, 2.77, 2.64, and 2.80 respectively, while theirMADP@20 values are 1.16, 1.667, 1.08, 1.07,1.814, and 2.148 respectively. We can see that the VR achieves a little bit higher NDCG, MAP much lower MADP than the VUR. From this, we can understand that user information contributes to the promotion of the diversity performance. However, without the collaboration of the appropriate intra-user re-ranking, the improvement of the diversity performance is at the cost of the reduction of the concernment performance, just as Figs. 5 and 6 shown. When the intra-user re-ranking and inter-user re-ranking are joined, SR get higher NDCG, MAP than the VR and higher MADP than VUR. Besides, the RR has a little bit lower NDCG@20, MAP@20 values and a little bigger MADP@20 value than the CRR method. But, using RR is relatively time intense. For the RR method takes the all tags of images into deliberation, CRR only accept the co-occurrence tags. Time is one of the key role in the image retrieval system except the performance. So, the CRR is more convinient for the retrieval of the large database.

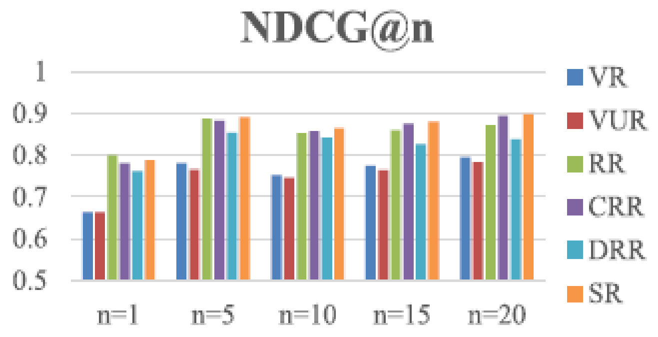

Figure 5. NDCG of all six ranking methods under different depths.

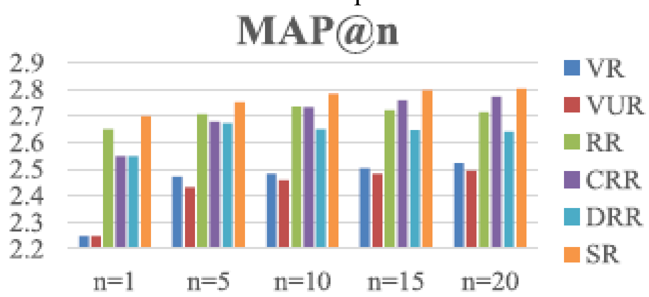

Figure 6. MAP of all six ranking methods under different depths.

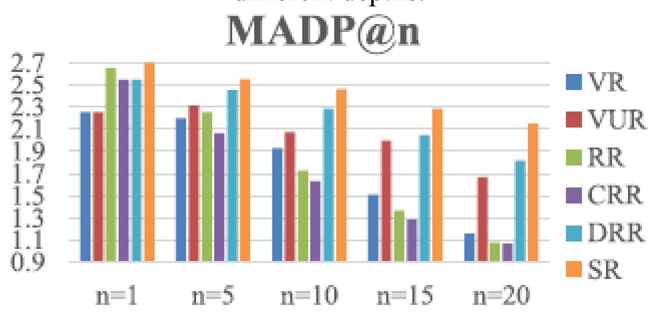

Figure 7. MADP of all six ranking methods under different depths.

From the tentative results, we can find that the DRR and SR both get greater diversity performance as shown in Fig. 7. However, the semantic prototype which DRR proposed to enhance the diversity performance weakens their concernment performance as shown in Fig. 5. SR makes a better trade-off between the concernment and diversity performance by considering the social user's information.

4) Scrutiny About Image Features: Recently, using deep learning visage for image classification and recognition is very popular [23]. In order to determine the efficient performance of our method, we add an experiment which replaces the color and texture visage with the AlexNet feature [23], we denote this experiment as the SR-AlexNet.

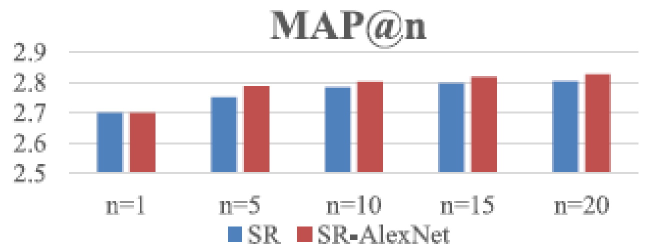

Figure 8. MAP of SR and SR-AlexNet under different depths.

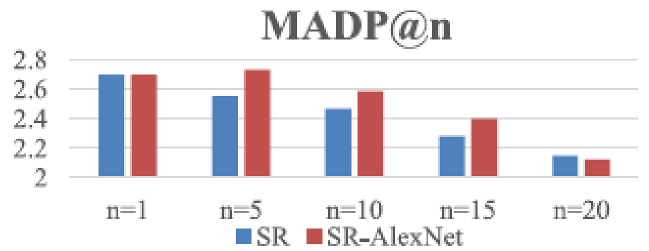

Figure 9. MADP of SR and SR-AlexNet under different depths.

The performance comparisons are illustrated in Figs. 8 and 9. Form the Figs. 8 and 9, we can see that using AlexNet feature can make the concernment performance better, and also retrieve some diversity improvement for the top 15 ranked results. However, the 4096-dim AlexNet provides much more complexity than our 215-dim color and texture feature, so we prefer the 215-dim color and texture feature for a quality user experience.

IV. CONCLUSION

In this paper, we are to propose a social re-ranking method for TBIR. In this social re-ranking method, inter-user re-ranking and intra-user re-ranking are carried out to gain the retrieved results. In order to enrichment the diversity performance, user information is initially introduced into our proposed approach and obtains satisfactory results. Besides, views of social image are also firstly fused into a traditional regularization framework to enhance the concernment performance of retrieved results. Discussions and experiments have established that our proposed method is efficient and time-saving. However, in the inter-user ranking process only user's contribution is considered and the correlation among users is ignored.

In addition to this, many information in Flickr dataset are still avoid, such as title information, time stamp and so on. For future work, we will research the similarity among user groups in Flickr dataset. Therefore, we can fuse these relationships to enrich the diversity performance of image ranking system.

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