TAG TREE CREATION OF SOCIAL IMAGE FOR PERSONALIZED RECOMMENDATION

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ABSTRACT

The tags are usually tagged by different users in social image sharing websites, which can indicate image semantic information and imply user's preference. Therefore, the tags can contribute to personalized recommendation of social image. However, the present social image tags models only consider single tag, resulting in the relationships among tags are ignored. In this paper, we propose a novel method to create tag tree of social image for personalized recommendation. Firstly, the tag ranking is realized to remove noisy tags. Then, the first layer tags are selected from re-ranked tags lists. To sufficiently express tag's significances, the tag subtrees can be created based on different image categories and combined with first layer tags to create tag tree. Finally, the personalized recommendation of social image is achieved by using tag tree. Experimental results show that our tag tree can effectively express the relationships among tags as well as obtain satisfactory results in personalized recommendation of social image.

Index Terms**—**Social image, tag tree, personalized recommendation, tag ranking, co-occurrence

1. INTRODUCTION

With the rapid evolution of multimedia technology, social media has been widely used in web-based services, such as Flickr. For large-scale image resources in social image sharing websites, it has become a development trend that the images satisfying personalized preference are accurately recommended to users [1-2]. The users are allowed to upload social images and to tag them with tags [3]. Due to the diversities of user's preference, the different tags may be tagged by different users in an image. Tag as important semantic information not only represents the image content, but also expresses user's preference, which can provide new solution for personalized recommendation of social image.

Reference [4] utilized the tags to recommend images in personalized by constructing the user-image-tag (UIT) model, which can achieve the better recommendation results. However, the UIT model only considers the single tag and ignores the context relationships among tags, which limits the expression of tags information. Heymann *et al*. [5] proposed a hierarchical social tag model in tagging system which can effectively reflect the semantic relationships among tags by organizing the tags in hierarchical structure. In the structure, the nodes represent the tags and the lines between nodes express the tags' relationships. The present hierarchical tag methods can be divided into two categories: 1) the method based on similarity relationships [5-6]. Firstly, the tag's popularity can be calculated according to the tagged frequency. The tags are ranked in descending order based on popularity. Then, the tags are inserted in a reasonable location of hierarchical structure based on the similarity relationships among tags. The method can quickly and accurately create the hierarchical structure. However, each tag only appears once in the hierarchical structure, in which the method cannot apply to social image tags. For example, the image tags "dog" and "cat" should include the tag "black" respectively; 2) the method based on subsumption relationships. The co-occurrence graph is constructed based on subsumption relationships. And then, the co-occurrence graph is trimmed to achieve the hierarchical structure [7-8]. The method has a higher computation complexity and greatly increases the time consumption for a large number of social image tags.

To solve above problems, a method of tag tree creation of social image is proposed in this paper. Meanwhile, the personalized recommendation of social image is realized to prove the effectiveness of our tag tree. However, there are many ambiguous and noisy tags in the social images, such as "bw", "nikon" and "beautiful". It is obviously these tags do not have actual meaning for creating tag tree. Firstly, the tags are re-ranked according to the image content. Then, the category of each image can be obtained based on the re-ranked tags lists. The tag tree can be created by selecting the first layer tags and creating the tag subtrees. Finally, the tag tree can be used to recommend social images by computing users' personalized preferences.

The rest of the paper is organized as follows: Section 2 introduces the detailed process of tag tree creation of social image; the personalized recommendation of social image is presented by using tag tree in Section 3; Section 4 analyzes the experimental results; conclusions are drawn in Section 5.

2. TAG TREE CREATION OF SOCIAL IMAGE

The hierarchical tag structure can effectively represent the relationships among tags. The most existing methods cannot be directly utilized to create tag tree of social image because of the images in different categories can be tagged with the same tag. In other words, some tags need to be inserted in many times to make sure the tag tree accurately expresses the image content. In this Section, we will introduce the creating process of the tag tree of social image, in which the framework can be seen in Fig. 1.

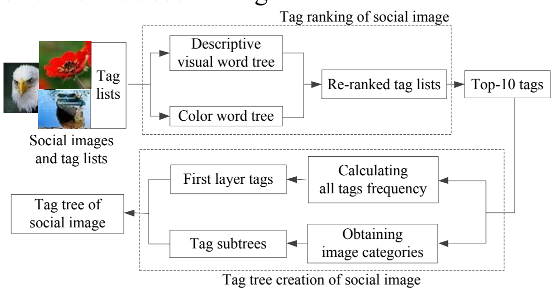

Fig. 1. The framework of the tag tree creation of social image.

2.1. Tag ranking of social image

The tags are re-ranked by extracting the image features to remove the noisy tags. The detailed process of tag ranking by creating descriptive visual word tree can be seen in our previous work [9]. Firstly, we extracted the refined Scale Invariant Feature Transform (SIFT) features and corner SIFT features from the saliency region, which can be obtained by using visual attention model. And then, the hierarchical K-means clustering is utilized to create the descriptive visual word tree.

Since SIFT features merely exploit gray information, we extract the HSV color features to improve the accuracy of tag ranking [10]. The HSV color features are extracted from the saliency region of images after transferring to HSV color space. We divide the H, S and V into 16, 4 and 4 bins through the non-interval quantization to obtain the suitable feature dimensions. Thus, the color feature has 16×4×4=256 bins. The three quantization vectors are represented as the **H**, **S** and **V** to compound a one-dimensional feature vector **L**.

$$\mathbf{L} = \mathbf{H}Q_S Q_V + \mathbf{S}Q_V + \mathbf{V} \tag{1}$$

where the Q_S and Q_V are the quantization levels of S and V respectively, Q_S=4, Q_V=4. The range of **L** is from 0 to 255. The HSV color feature $\mathbf{C}(I)$ can be represent by

$$\mathbf{C}(I) = (c_0, c_1, \ldots, c_n), n = 255 \tag{2}$$

$$c_i = l_i / N, i \in [0,255] \tag{3}$$

where l_i denotes the number of pixels which the value of **L** is i in image I, N is the total number of pixels in image I.

rose	cat	waterfalls	anemone
flower	white	river	pink
roses	animal	boat	flower
red	standing	landscape	ladybird
yellow	window	travel	ladybug
love	cute	nature	spring
colorful	wall	beauty	springtime
friendship	heaven	view	garden
photo	contrast	interestingness	macro
dramatic	beautiful	exploretop500	bravo

Fig. 2. The social images and corresponding Top-10 re-ranked tags lists.

After extracting HSV color features, we create the color word tree using the method of creating descriptive visual word tree. The tag ranking can be realized by neighbor images found by descriptive visual word tree and color word tree [11]. To improve the accuracy of tag tree, we select the Top-10 tags in each re-ranked tags list as tags sets to create tag tree. Here, the social images and corresponding Top-10 re-ranked tags are listed in Fig. 2.

2.2. Tag tree creation

Some image tags usually describe the similar significance for different image categories. Hence, a method of tag tree creation of social image is proposed in this paper. To create reasonable tag tree of social image, we assume each tag has one and only one father tag. The tag tree creation of social image consists of the following two steps: 1) selecting the first layer tags which have the higher popularity; 2) creating the tag subtrees and combining them with the first layer tags.

2.2.1. Selecting the first layer tags

Many tags are tagged in higher popularity, such as “animal”, “flower” and “nature”. These tags should be put in a higher layer of tag tree because they can include many image categories as well as have the more semantic information. Thus, we select the higher popularity tags as the first layer tags of tag tree.

We first divide the social images into different categories based on the re-ranked tags lists, in which the first tag in re-ranked tags lists is defined as category tag. We divide the social images into different categories “rose”, “cat”, “waterfalls” and “anemone”, which can be seen in Fig. 2. Then, we calculate the tagged frequencies $f_{all}(t)$ of all tags to obtain the list T_{all} which describes all tags and their frequencies in descending order.

$$f_{all}(t) = num(t) \tag{4}$$

where $num(t)$ denotes the image number of tagged tag t. It is noted that some category tags also have a higher frequency. To accurately get the tags which include the more semantic information, the Top-n tags can be selected as the first layer tags in list T_{all} without the category tags. As can be seen from Fig. 3, the total number of selected first layer tags is twelve in this paper. The top node of tag tree is a virtual tag.

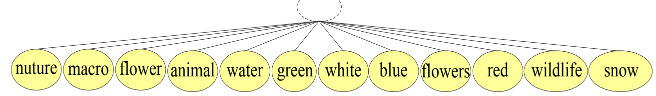

Fig. 3. The first layer tags.

2.2.2. Creating the tag subtrees

After selecting the first layer tags, we create the tag subtree of each image category and combine them with a first layer tag. The tag subtrees are created by the co-occurrence relationship between two tags in Fig. 4, which includes the following steps:

Step 1: The images are divided into different categories by the first re-ranked tag. In an image category C, we calculate all tags' tagged frequencies $f_{category}(t)$ and rank them in descending order to generate a list $T_{category}$.

$$f_{category}(t) = num_C(t) \tag{5}$$

where $num_C(t)$ denotes the image number of tagged tag t in image category C. The category tag $t_{category}$ is regarded as the root node of tag subtree, in which it is the first tag in list $T_{category}$.

Step 2: The tags are put into tag subtree in turn based on their tagged frequencies in descending order. According to the list $T_{category}$, the next tag t can be read to create the tag subtree.

Step 3: We define the tree' bottom layer which may include the tag t's father tag as the current layer. The relevance of tag t with each tag in the current layer is computed by the Eq. (6).

$$R(t,t') = \frac{relevance(t,t')}{relevance(t)} \tag{6}$$

where t' denotes the tag of current layer, $relevance(t, t')$ represents the co-occurrence frequency of tag t and t' in an image. In order to normalize the calculation results, the $relevance(t, t')$ can be defined as follow:

$$relevance(t,t') = \frac{num(t,t')}{num(t_{category})} \tag{7}$$

where $num(t, t')$ is the co-occurrence number of tag t and t' in an image, the $num(t_{category})$ is the image number of tagged tag $t_{category}$. The $relevance(t)$ is the sum of relevance of tag t with each tag in current layer.

$$relevance(t) = \begin{cases} \dfrac{\sum_i num(t,t_i)}{num(t_{category}) \cdot i} & i \neq 1 \\ 1 & i = 1 \end{cases} \tag{8}$$

where i is the tags number of current layer. After computing the relevance with each tag in current layer, we get the maximum max to obtain the most relevant tag t_0.

$$t_0 = \arg\max_{t_i} R(t,t_i) \tag{9}$$

Step 4: In order to avoid the limitation that all tags only have a child tag, we set a threshold value R_0 to improve the tag subtree. The R_0 is the relevance of tag $t_{category}$ with tag t.

$$R_0 = R(t,t_{category}) \tag{10}$$

If $R(t, t_0)<R_0$, the current layer tags is reduced by 1, then return to **Step 3**; otherwise, tag t_0 is the t's father tag.

Step 5: If the all tags in list $T_{category}$ are put into the tag subtree, the algorithm ends; else, return to **Step 2**.

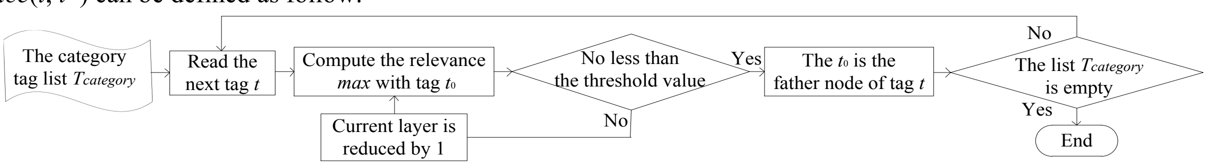

Fig. 4. The flowchart of creating the tag subtree.

The tag subtrees will be combined with a first layer tag. For tag subtree's root node $t_{category}$, the relevance with each first layer tag can be calculated by Eq. (11). The first layer tag which has the maximal relevance with $t_{category}$ is the father node of the tag subtree. If the relevance with all first layer tags is 0, the father node of tag subtree is the root node of tag tree.

$$r(t_{category}, t_{first}) = num(t_{category}, t_{first}) \tag{11}$$

3. PERSONALIZED RECOMMENDATION OF SOCIAL IMAGE WITH TAG TREE

In this Section, the tag tree is utilized to personalized recommendation of social image to prove the effectiveness of our method. For each tag, we compute the user's preference using the Term Frequency-Inverse Document Frequency (TF-IDF) [12].

$$w_t = tf_t \times idf_t = \frac{U_t}{U} \times \lg \frac{N}{N_t} \tag{12}$$

where U_t denotes the image number of tagged tag t. U is the image number of collected images. N_t is the total image number of tagged tag t in dataset. N is total number of images in dataset. After this, the user's preference values are added to the tag tree which is shown in Fig. 5. The yellow tags are the first layer tag, the green tags are the category tag and the blue tags are a part of tag subtree. We first choose a tags path with the maximum preferences, such as "flower-rose-red" in Fig. 5. Then, the images tagged the three tags are recommended. If the number of recommended images is not enough, we will recommend the images tagged the "flower-rose" tags. In other word, the bottom tag is removed in the tags path with maximum preferences. Finally, the users' preferences are updated by the latest collected images to improve the recommendation results.

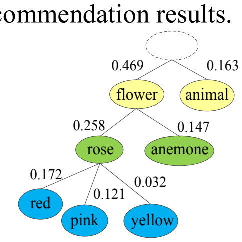

Fig. 5. The user's preference in a part of tag tree.

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1. Experimental dataset and setting

In order to evaluate the performance of tag tree of social image, 10000 images are selected from the NUS-WIDE object image dataset including 36 image categories and 5077 no repeating tags in Flickr. The NUS-WIDE is a large-scaled real-world dataset from National University of Singapore and widely used as public dataset in many related social image works [9, 12, 13]. The experimental platform is a PC with 3.60GHz CPU, 4.00G memory, windows 7 operating system, visual studio 2010 programming and SQL Server 2008 R2 database. The tag tree is stored in SQL database based on the level number.

4.2. Accuracy of tag tree

Figure 6 shows a part of tag tree of social image in our method. We use the normalized discounted cumulative gain (NDCG) to evaluate the accuracy of tag tree [6, 14]. Given a tag tree, the NDCG is computed as

$$N_n = \lambda_n \sum_{i=1}^{n} (2^{s(i)} - 1) / \log(1+i) \tag{13}$$

where $s(i)$ is the score of i-th tag in tag tree, n is the number of tags and λ_n is a normalization constant to make the optimal NDCG score is 1 [9]. The scores of tags are set by three users and the score is from 5 to 1 which represents the accuracy of tag tree.

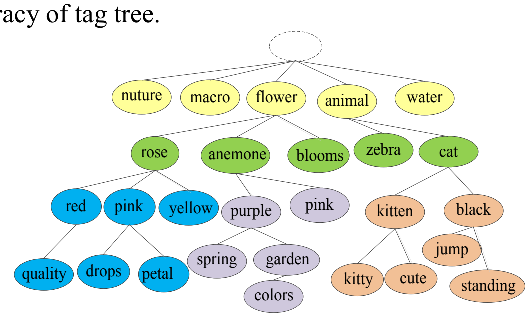

Fig. 6. A part of tag tree of social image.

In order to prove the accuracy of our tag tree, we compare our method with the following two tag tree methods in terms of average NDCG: 1) the classical method based on similarity relationships by Heymann [5], in which it is proved that the method is superior to other methods in Ref. [15]; 2) the method based on the subsumption relationships (SR) in Ref. [7]. The average NDCGs values of three methods are shown in Table 1. We can see that our method outperforms Heymann and SR as well as can meet the natural semantics. The reason is that tag tree based on different image categories can better express the relationships among tags than global hierarchical tag structure.

Table 1. The average NDCGs of different tag tree methods.

Method	Average NDCG
Heymann	0.498
SR	0.532
Our method	0.736

4.3. Precision-recall of personalized recommendation

The precision-recall is utilized to evaluate the accuracy of personalized recommendation of social image. Figure 7 illustrates the precision-recall curves of UIT, Heymann, SR and our method. The recommendation method of Section 3 is applied in Heymann method, SR and our tag tree. The results indicate that our tag tree can obtain better precision-recall curve than the others.

From the experimental results of UIT and our tag tree, we can see that the tree structure can contribute to personalized recommendation of social image. The reason is that tag tree can effectively represent the relationships among tags by calculating the co-occurrence information. Hence, different images can be easily distinguished by the tags with tree structure. In our tag tree, the tags are re-ranked to remove the noisy tags to create tag tree, which improve the accuracy of tag tree. Meanwhile, the tags' semantic information can be fully analyzed based on different image categories. Therefore, our tag tree can effectively express the relationships among tags by selecting the higher popularity tags and creating tag subtrees. Our method avoids the single tag semantics and reduces the complexity for a large number of tags sets.

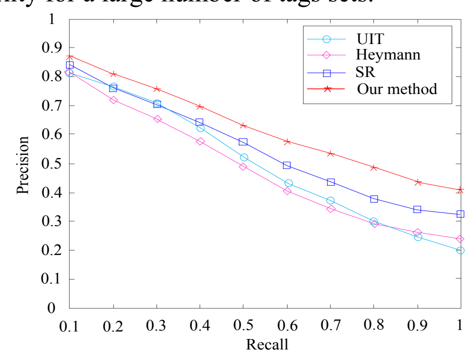

Fig. 7. The precision-recall curve.

5. CONCLUSIONS

A tag tree creation method of social image for personalized recommendation is proposed in this paper. Firstly, the tag ranking is achieved by extracting image features, including descriptive visual word tree and color word tree. Then, the tag tree is created by selecting first layer tags and creating tag subtrees with re-ranked tags lists. Finally, social images can be recommended to prove the effectiveness of our tag tree. The experimental results show that our method can significantly express the tags' semantic information in a tree structure. In the future, we will combine the image's content information with the tag tree to better implement the personalized recommendation of social image.

6. ACKNOWLEDGMENTS

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