Tag Tree Creation of Social Image for Personalized Recommendation

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Introduction

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. The users are allowed to upload social images and to tag them with tags. 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. A tag tree creation method of social image is proposed for personalized recommendation in this paper. Firstly, the tag ranking is realized to remove noisy tags. Then, the first layer tags are selected from re-ranked tags lists. Finally, the personalized recommendation of social image is achieved by using tag tree.

Proposed Method

1. Tag tree creation of social image

The tag tree creation of social image includes tag ranking of social image and tag tree creation of social image (see Fig.1).

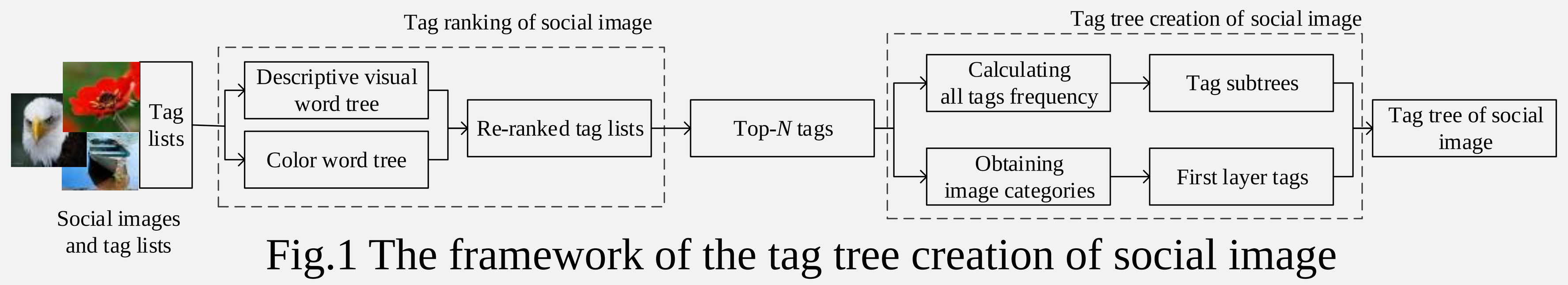

Fig.1 The framework of the tag tree creation of social image

1.1 Tag Ranking of Social Image

The tags are re-ranked by extracting the refined SIFT features, corner SIFT features and HSV color features to remove the noisy tags (see Fig.2) .

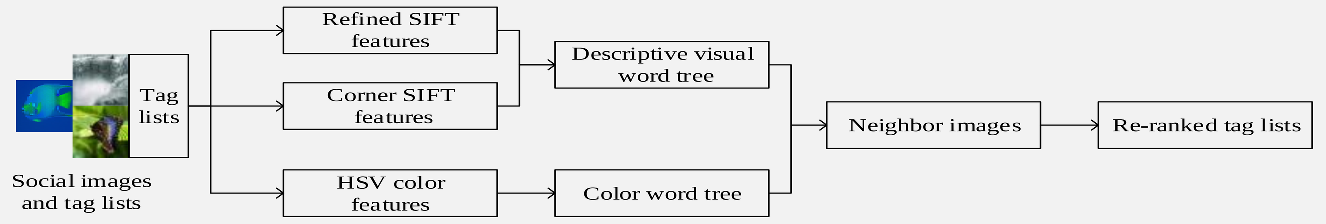

Fig.2 The process of tag ranking of social images

- ◆The SIFT features are clustered to create the descriptive visual word tree and the HSV color features are clustered to create the color word tree.
- ◆The neighbor images can be found to obtain the re-ranked tag lists.

1.2 Tag Tree Creation of Social Image

The tag tree creation of social image consists of two steps, selecting the first layer tags which have the higher popularity and creating the tag subtrees.

- ◆According to the tag frequencies of all tags, Top-*N* tags are selected as the first layer tags without the category tags .
- ◆The tag subtrees are created by the co-occurrence relationship between two tags (see Fig. 3).

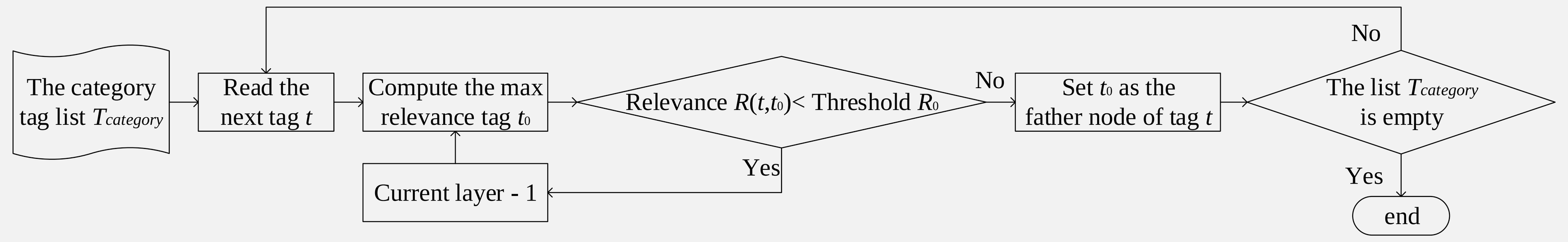

Fig.3 The flowchart of creating the tag subtree

Step 1: In an image category C, calculate all tags’ tagged frequencies $f_{category}(t)$ and rank them in descending order to generate a list $T_{category}$.

Step 2: Read the next tag t to create the tag subtree in the list $T_{category}$.

Step 3: Define the tree’ bottom layer as the current layer. Compute the relevance of tag t with tag t_i in the current layer by using the Eq. (1) and then obtain the max relevance tag t_0.

$$R(t,t_i) = \frac{relevance(t,t_i)}{relevance(t)} \quad (1)$$

$$t_0 = \arg\max_{t_i} R(t,t_i) \quad (2)$$

Step 4: Set the threshold value R_0 with Eq.(3). 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.

$$R_0 = R(t, t_{category}) \quad (3)$$

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

The tag subtrees will be combined with a first layer tag based on the co-occurrence relationship between category tag and the first layer tag.

2. Personalized Recommendation of Social Image With Tag Tree

The tag tree is utilized to personalized recommendation of social image to prove the effectiveness of our method. For each tag, the user’s preference is computed by using the TF-IDF.

The user’s preferences are added to the tag tree shown in Fig.4. A tags path with the maximum preferences is firstly chosen, such as “flower-rose-red”. Then, the images tagged these tags are recommended. If the number of recommended images is not enough, the bottom tag is removed in the tags path, such as “flower-rose” tags.

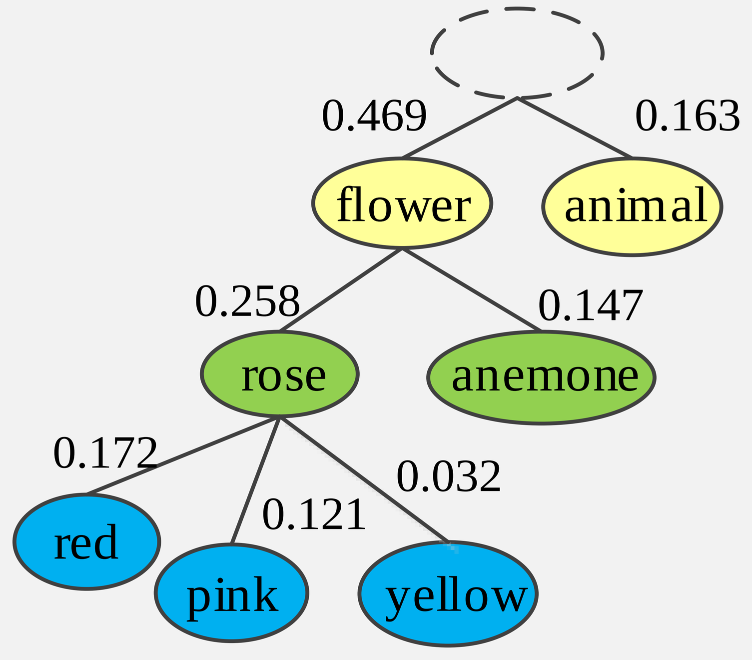

Fig. 4. The user’s preference in a part of tag tree

Experimental Results and Analysis

●The normalized discounted cumulative gain (NDCG) (Table 1) is used to evaluate the accuracy of tag tree[1].

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

Method	Average NDCG
Heymannn [2]	0.498
SR [3]	0.532
Our method	0.736

Our method outperforms Heymann and SR 23% and 20%, respectively. The reason is that tag tree based on different image categories can better express the relationships among tags.

●Figure 5 shows a part of tag tree of social image in our method.

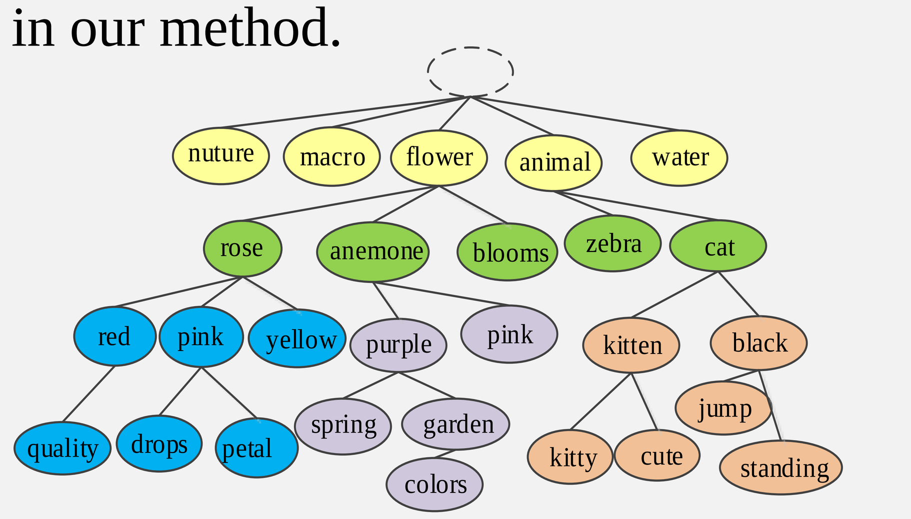

Fig. 5 A part of tag tree of social image.

The yellow tags are the first layer tags, the green tags are the category tags and the other tags are the tag subtrees.

●Figure 6 illustrates the precision-recall curves of UIT, Heymann, SR and our method.

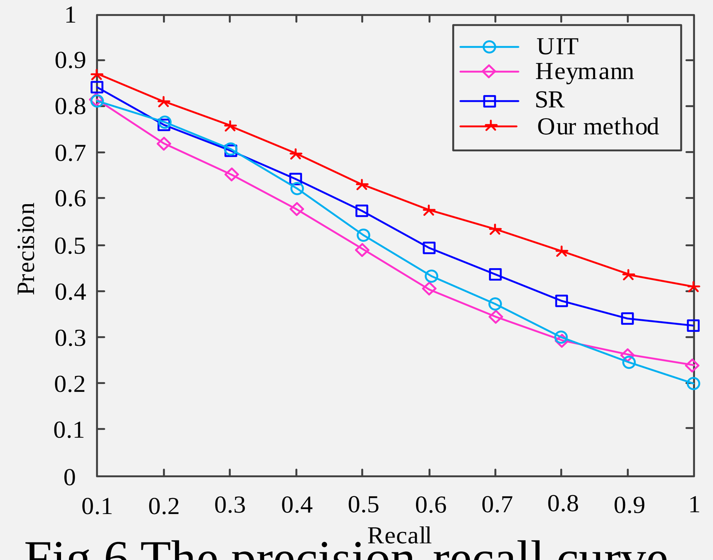

Fig.6 The precision-recall curve

The results indicate that our precision-recall curves is higher than other methods at least 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.

Main References

1. M. Strohmaier, D. Helic, D. Benz, C. Rner, R. Kem, “Evaluation of folksonomy induction algorithms,” *ACM Transactions on Intelligent Systems and Technology*, vol. 3, no. 4, pp. 565-582, September 2012.
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