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Flickr Group Recommendation using Content Interest and Social Information

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***Abstract*—Social networks have been an important part of human's life. Online photo sharing websites like Flickr allow users to experience others' lifestyles by browsing photos. To gather users who have the same interests, the websites allow users to build their own interest groups and invite other users to join in. A commonly adopted recommendation in social networks such as Sina Microblog uses the social information of users. However, it performs poorly for inactive users. In this paper, we propose a group recommendation scheme by using both the content interest and social information of users. We use tag information, which is not only from users' photos but also from their favorite photos, to study the content interests of users and use the user-based collaborative filtering for recommendation. The trust-aware collaborative filtering is adopted to study the social information of users for recommendation. Finally, we combine the user-based collaborative filtering and trust-aware collaborative filtering to obtain a promising result on a real-world Flickr dataset.**

I. Introduction

In recent years, surfing the Internet has become an essential part in people's daily life and social networks have been the major approaches by which people get fresh news. Such social networks usually contain various media data with which their users can express themselves lively. With rich metadata, users can communicate with others conveniently and share/find the contents they are interested in. To gather the users who share the same hobbies, social networks nowadays allow users to join the interest groups which contain rich contents for some topics. For a social website, an efficient group recommendation system should help users find their favorite groups effectively. This work will be helpful for users and advertisements. Efficient group recommendation can therefore have a positive effect on both social network members and other recommendation applications.

We take Flickr, one of the most popular photo sharing social network, to study the group recommendation. Flickr as one of the oldest social network has a large number of users and is reported to have millions of new images uploaded daily. Flickr offers many services to its members. Flickr allows users to share and self-annotate their photos. Users can follow others to browse photos and experience others' lifestyles. Groups in Flickr are self-organized. Each user can create own interest groups, join in others, and find their favorite photos easily. The availability of rich media data helps us explore the behavior of users from different views.

Group recommendation is an interesting topic. We need to study the tastes and the social relationship of users to find out the major factors which push the users to join a group. In previous work, group recommendation studied how to recommend an item to a group of users. For item recommendation, user-based collaborative filtering (CF)[1][2] is the most commonly used technique in social networks. Usually, we can obtain ratings from users on items and calculate the similarity among users. Whereas on group recommendation, we can only get a binary value which indicates whether a user join a group or not. The binary value is not precise enough to estimate the similarity among users, so we cannot adopt the same technique used in item recommendation. To solve this problem, Zhuang et al. took full advantage of the Flickr heterogeneous data, estimated the similarity among users from six views, and then used the user-based CF for group recommendation [3].

Trust-aware CF is a commonly used technique for group recommendation [4]. It solves the problem by using the trust networks among users instead of estimating the similarities. We can easily obtain the trust value from user A to user B. The value will be 1 if B is in the contact list of A or 0 if not. Finally we calculate the number of users both in user A's contact list and in group G's member list to present the social relation of A to G. This trust-aware CF is commonly adopted in social networks such as Sina Microblog. However, it has some drawbacks that will perform badly for cold-start users. If a user only has a small number of followees in his contact list, the algorithm can not recommend groups which fit the user's interests.

On the other hand, researchers tried to find the users' interests from the contents of photos. Luckily, the self-annotated photos in Flickr can help us bridge the semantic gap to obtain a series of tags which present the users' interests. In fact, users are willing to provide this semantic context through manual annotations to make them better accessible for the general public [5]. Many works focus on analyzing the topic modal of groups [6][7]. Also some researchers tried to connect users to groups through tags using tensor decomposition [8]. However, existing studies reveal that many tags provided by Flickr users are noise. There are only around 50% of those tags actually related to the photos [9]. Also even for the same object, different users will use different tags. As a result, it is hard to find out the true interests of users.

In this paper we propose a group recommendation model incorporating the content interest and social information. We take advantage of the tag information to find out the content interest of users and make recommendation using user-based CF. Meanwhile, we exploit users' contact lists and groups' member lists to estimate the social relationships and recommend groups using trust-aware CF [4].

First, to overcome the disadvantage of the tags to some extent, we study the tag information and extract two kinds of content features. We order the different tags on a user's photos by frequency. The tags with high frequency will be precise enough to describe the interests of the user. To solve the various tags description problem, we crawl the tags from the photos which are in the user's favorite photo list and also order them by frequency. The tags with high frequency from different annotators will be more general and reliable than the tags only from the owner. Thus we have two methods to describe the users' interests. Then we have four ways to get the similarity among users. After employing the kernel alignment algorithm [10] to combine the four similarity kernels, we use user-based CF for group recommendation.

Second, for social information, we use the trust-aware CF algorithm. Instead of directly using the number of users who are both in user A's contact list and in group G's member list, we normalize the number by the quantity of users in A's contact list. This step should not change the recommendation lists. Finally, we combine the content interest and social information to perform the group recommendation. We find that users with a large number of followees tend to join groups by social relationship, whereas users with few followees tend to join groups by interests.

In summary, this paper has the following contributions:

- We study the content interests of users for group recommendation. We expand the tag information from user's favorite photos, and find that usually there is a gap between user's uploaded photos and favorite photos. Combining the tag information from different views will improve the performance of our group recommendation.
- We study the relation between users and groups from two aspects. Content interests try to describe the relation at the semantic level which abstracted from the tag information of photos. Social information starts from the trust networks of users. We combine the content interest and social information to make group recommendation.

The rest of the paper is organized as follows. Section 2 introduces our group recommendation model which combines the content interest and the social information of users. Section 3 presents the experiment results, followed by the conclusion in Section 4.

II. Group Recommendation Modeling

In this section, we present our group recommendation model which combines the content interest and social information on Flickr. To find out the content interests of users, we choose the tags abstracted from the uploaded photos to represent users' tastes and use user-based CF for recommendation. Moreover,

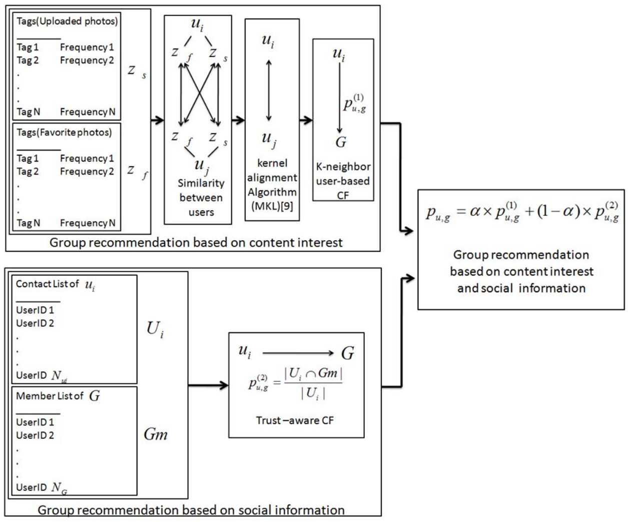


Fig. 1. The structure of our group recommendation model.

we expand the tag information from the users' favorite photos to extract the interests of users more precisely. Then we use the trust-ware CF for social information and construct a simple model to combine the two different recommendation results. The group recommendation model architecture is presented in Fig. 1.

A. User's similarity by tag features

To recommend groups to users, we should know what kinds of topics that will attract users. However, it is hard to find the semantic information only from photos. Luckily, the self-annotated tags of photos in Flickr can help us bridge the semantic gap to some extent. We can get the top 100 tags with highest frequency for each user by Flickrapi. Then we use the traditional tf-idf method to get the weight of tags and can use a tag vector z_s to present the tag information of a user u .

Since Flickr allows users to self-annotate photos, users can describe the same photo using different tags. This makes the tags imprecise. To solve this problem, we expand the tag information. By intuition, it is more complicated for a user to upload a photo than to mark a photo as favorite. We crawl the tags from users' favorite photo lists and choose the top 100 tags with highest frequency for each user. Also we use traditional tf-idf method to get the weight of tags and use a tag vector z_f to present the tag information of u. Since the favorite photos are uploaded and annotated by different users, the tags chosen by frequency should be more precise and applicable than the tags chosen directly from the photos uploaded by users themselves.

We adopt the normalized linear kernel to measure the similarity between u_i and u_j.

$$S_{i,j} = \frac{z_i^T z_j}{\sqrt{z_i^T z_i}\sqrt{z_j^T z_j}} \tag{1}$$

Since we have two kinds of descriptors to represent the tag information (z_s, z_f), we can get four similarity matrixes using Eqn.(1). We denote $S^{(1)}$ to be the matrix in which both u_i and u_j use the z_s tag descriptor, $S^{(2)}$ to be the matrix in which both u_i and u_j use the z_f tag descriptor, $S^{(sf)}$ to be the matrix in which u_i uses z_s tag descriptor and u_j uses z_f tag descriptor, and finally $S^{(fs)}$ to be the matrix in which u_i uses z_f tag descriptor and u_j uses z_s tag descriptor. In fact $S^{(fs)}$ is the transposed matrix of $S^{(sf)}$. To make it easy for the latter kernel alignment algorithm, we define $S^{(3)}$ to be the average of $S^{(sf)}$ and $S^{(fs)}$, i.e. $S^{(3)} = (S^{(sf)} + S^{(fs)})/2$.

B. Kernel alignment

In Section II-A, we define three tag similarity matrixes that describe the relation between users. To get a combination matrix that is helpful for group recommendation, we use the kernel alignment algorithm [10]. Before combination, we should give a target matrix Y. Firstly, We define the G to be the common interest groups matrix which measures the number of interest groups that both users join.

$$G_{i,j} = \#group\ u_i\ and\ u_j\ joined$$

When $i = j$, the value is the group number that u_i joined.

To make the format of G matrix the same as that of S matrix, we define the target matrix Y as one transformed from G by Eqn.(2)

$$Y_{i,j} = \frac{G_{i,j}}{\sqrt{G_{i,i}}\sqrt{G_{j,j}}} \tag{2}$$

Definition 1 (Centering kernels). Let K be a kernel function defined over $m \times m$, then the centering kernels equation is defined as:

$$[K_c]_{i,j} = K_{i,j} - \frac{1}{m}\sum_{i=1}^{m} K_{i,j} - \frac{1}{m}\sum_{j=1}^{m} K_{i,j} + \frac{1}{m^2}\sum_{i,j=1}^{m} K_{i,j} \tag{3}$$

Definition 2 (Kernel Alignment). Let K and Y be two kernel functions defined over $m \times m$ such that $0 < E[K_c^2] < +\infty$ and $0 < E[Y] < +\infty$, and then the alignment between K and Y is defined as:

$$\rho(K, Y) = \frac{E[trKY]}{\sqrt{E[trKK]}\sqrt{E[trYY]}} \tag{4}$$

The algorithm is based on the notion of centering in the feature space. So the similarity matrixes should be centered by Eqn.(3). We aim to find a linear combination to make the users fit their neighbors' tastes, i.e $K = \Sigma_{i=1}^{N_k} \theta_i K_i$ .The following theorem guarantees that the optimal solution can be computed efficiently.

Theorem 1. The optimal solution θ^* can be obtained to solve the following quadratic program:

$$\theta^* = \arg\min_{\theta \geq 0} \theta^T M \theta - 2\theta^T a, \tag{5}$$

where a is the vector $[trK_1Y, ..., trK_{N_k}Y]^T$ and M is matrix $[M]_{kl} = trK_kK_l$.

C. User-based CF

Collaborative filtering is the most commonly used technique in recommendation domain. Researchers have modeled a number of collaborative filtering approaches. Collaborative filtering aims to recommend items to a user based on the tastes of the user's neighbors. For user-based CF, we need to estimate the similarity between users and then we can use the similarity matrix which we get above to replace it.

In the user-based CF, we predict the votes of the active user (indicated with a subscript a) based on some partial information from the active user and a set of weights calculated from the user database. We assume that the predicted vote of the active user for item j, $p_{a,j}$ is a weighted sum of the votes of the other users [2].

$$p_{a,j} = \overline{r_a} + \frac{\Sigma_{u=1}^{n}(r_{u,i} - \overline{r_u} \times w_{a,u})}{\Sigma_{u=1}^{n} w_{a,u}} \tag{6}$$

n is the number of neighbors and $w_{a,u}$ is the similarity weight between the active user a and the neighbor u.

For group recommendation, we only have the binary values indicated if a user joins a group. We follow the user-based CF idea and simplify the Eqn.(6) to Eqn.(7) to make it fit the group recommendation.

$$p_{a,j}^{(1)} = \sum_{u=1}^{n} \delta_{u,j} \times w_{a,u} \tag{7}$$

where $\delta_{u,j} \in \{0, 1\}$ indicates whether u joins group j.

D. Trust-aware CF

Trust-aware CF [4] is similar to user-based CF. The only difference is that trust-aware CF uses the trust networks between users instead of estimating the similarities. In the social networks, one's behavior can well predict the trust value among users. We define $f_{a,u}$ as whether the active user s follows another user u (1 if follow; 0 if not) and normalize it by the number of the users' followees to estimate the trust value among users.

$$T_{a,j} = \frac{f_{a,u}}{|U_a|} \tag{8}$$

U_a is the set of users whom user a follows.

Using the $T_{a,u}$ to replace the $w_{a,u}$ in Eqn.(7) and defining n as the number of users whom user a follows, we can transform the trust-aware CF into another form.

$$p_{a,j}^{(2)} = \frac{|U_a \cap Gm_j|}{|U_a|} \tag{9}$$

Gm_j is the set of users who join group j.

E. Combination of content interest and social information

User-based CF and trust aware CF use the relation among users from different views. The user-based CF presented above focuses on the content interests. The active user has much more topics to share with his/her neighbors. As a result, the predicted vote of the active user for a group will be highly possible to be accepted. Trust-aware CF recommends groups more socially than user-based CF. It focuses on the social relationship of users to find their trust neighbors instead of similar neighbors. We try to combine the two different recommendations with a simple linear method.

$$p_{a,j} = \alpha \times p_{a,j}^{(1)} + (1 - \alpha) \times p_{a,j}^{(2)} \tag{10}$$

III. Experiment

We evaluate the proposed model on the same dataset as [3] comprised of multimodal information of 16,346 users from Flickr. To find a big component, we start from a random user as seed and expand the crawling according to users' contact lists in a breadth-first search manner. We stop at 5,000 users.

We conduct a basic data analysis on those 5,000 users. We calculate the number of users whose number of followees falls into a certain region. Fig. 2 shows the statistical histogram. We set the width of the bins to be 25. As Fig. 2 shows, the tendency of the histogram fits the asymptotic power-Law distribution and also has the heavy-tail property. So we can use it to study the real-world social network.

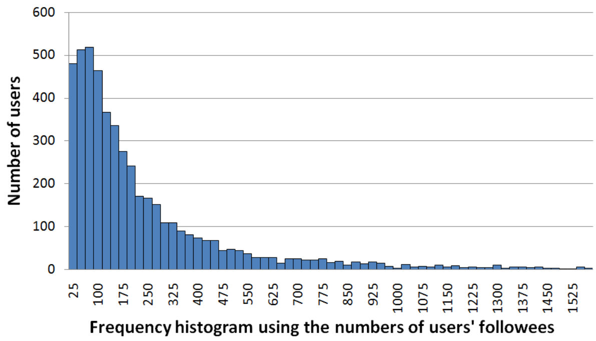


Fig. 2. The statistical histogram using the number of the 5,000 users' followees. The width of each bin is set to be 25.

A. Similarities of users

To construct the two tag vectors z_s and z_f presented in Section 2, we crawl the users' profiles. In fact, Flickrapi provides the top 100 tags with highest frequency for each user. Unfortunately, we could not obtain those 100 tags from users' favorite photos directly. We solve this problem by crawling Flickr online. We expand the tag information by downloading the metadata of photos from the users' favorite photo lists and abstracting the tags of each photo. After doing some statistics, we also obtain the top 100 tags with highest frequency. We use the traditional tf-idf method to get the weight of tags to build the z_s tag vector. Same to the method of deriving z_s, we obtain the z_f vector.

We evaluate the similarity among users following the method presented in Section 2 and get the matrixes: S^1, S^2 and S^3. To prove that the z_s and z_f vectors are quite different even for the same user, we calculate the average similarity values which use the different combinations of z_s and z_f vectors in the 5,000 users dataset. The results of different combination are presented in Fig. 3.

As Fig. 3 shows, there are only three combinations because the combination of z_s and z_f is the same to the combination of z_f and z_s. The former two bins' values are not equal to 1 because some users have not uploaded any photos or marked any favorite photos. The average similarity using z_s and z_f descriptors is 0.14. This indicates that the compositions of z_s and z_f are different but still have some in common. One reason for this phenomenon is that the tags are self-annotated by users. There may be different tags annotated by different users even for the same photo. Another reason is that users may have interests in something that they do not have the ability to take the photo of it. For instance, a user loves the sea but he lives far away from it.

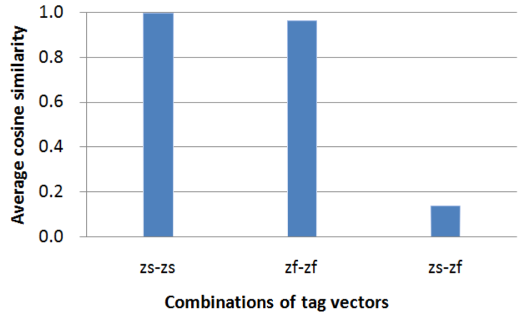


Fig. 3. The average similarity with different combinations of tag information among the 5,000 users dataset.

B. Content interest for group recommendation

In this part, we will perform the group recommendation by content interest using the user-based CF. We abstract the top 5,000 popular groups among the 5,000 users for recommendation.

We use the kernel alignment algorithm [10] to get a combination matrix with the three similarity matrix built above, i.e $S = \Sigma_{i=1}^{3}\theta_i S^{(i)}$. Since the kernel alignment algorithm requires the kernels to satisfy the positive semi-definite (p.s.d.) property and user-based CF just finds the neighbors rather than the users themselves, we assign the diagonal values of the similarity matrixes and the target matrix Y to be 1 and make them p.s.d. The learned weights of the kernels $S^{(1)}$,$S^{(2)}$ and $S^{(3)}$ are 0.27, 0.16 and 0.57. The $S^{(3)}$ kernel obtains the highest weight among the three kernels. This indicates that the combination of the two tag descriptors can describe the similarity among users better than each single tag kernels.

After combination, we evaluate the performance of the group recommendation using the user-based CF. The neighbor number n is set to be 25 for all users. The kernels include:

- Tag kernels: The tag similarity kernels defined in Section 2: $S^{(1)}$, $S^{(2)}$, $S^{(sf)}$ and $S^{(fs)}$.
- MKL kernel: The combination kernel using the similarity kernels $S^{(1)}$, $S^{(2)}$ and $S^{(3)}$ by the kernel alignment algorithm [10].

We use Normalized Discount Cumulative Gain(NDCG) [11] as the evaluation measure for our group recommendation. NDCG is used to consider the ranked position among top-k recommended list which is provided by a recommendation algorithm. It suggests that more relevant items will get higher scores than irrelevant items and the items ranked lower will score lower since it has less value for the user. Then, $NDCG@k$ is defined as follows:

$$DCG_R@k = \sum_{i=1}^{k} \frac{2^{r_{Ri}} - 1}{log(i+1)} \tag{11}$$

$$NDCG_R@k = \frac{DCG_R@k}{DCG_{ground-truth}@k} \tag{12}$$

r_{Ri} denotes the binary judgment (i.e., 1 for true and 0 for false). k is the length of the ranking list.

We evaluate the Top-10 group recommendation performance. The top-10 group recommendation results are shown in Fig. 4. By analyzing the curves presented in Fig. 4, we suggest that:

- The recommendation based on kernel $S^{(2)}$ works better than kernel $S^{(1)}$. This means that generally the tags from users' favorite photos can present their interests more precisely than the tags that users self-annotate.
- The recommendation based on kernel $S^{(3)}$ works better than $S^{(1)}$ and $S^{(2)}$. The combination of the two tag descriptors will convey more information.
- The CF-MKL works best among all the evaluated kernels. Such a combination method can estimate the relation between users better than the other single kernels and make it more precise to find neighbors for group recommendation.

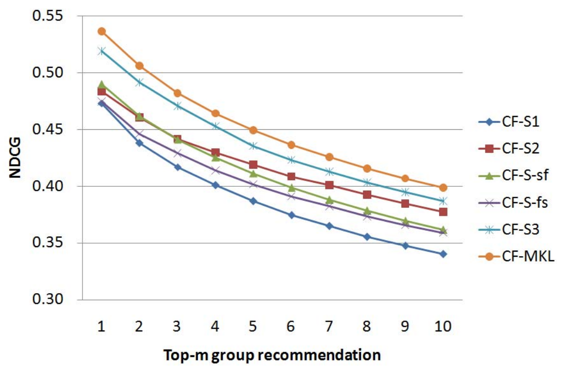


Fig. 4. The top-10 group recommendation results by tag kernels. The curves are the results of user-based CF using different kernels, e,g. CF-S1 is the result of the user-based CF using the $S^{(1)}$ kernel.

C. Combination of content interest and social information

In this section, we evaluate group recommendation combining the content interest and social information. After estimating the content interest of users above, we crawl the profiles of users and groups, and then abstract the contact lists and member lists. We use Eqn.(9) to get the social relation $p^{(2)}_{a,j}$.

We randomly choose 1,000 users for training purpose and find that we get the best performance when α is set to be 0.81. We estimate our model's performance on users with different active degree. In fact, researchers find that there is a tendency that more friends will bring in more logins [12]. So we use the number of users' followees to present their active degree. We divide the 4,000 test users into ten parts according to their followees' numbers by ascending ordering and make group recommendation. The group recommendation results of the ten parts of users at Top-1 NDCG are presented in Fig. 5.

We can see in Fig. 5 that the trust-ware CF works worse than our model among the users with a small number of friends, but they work the same when users have amount of followees. The CF-MKL performs better than trust-ware CF only for users with a small number of followees. Then we choose the users who have different followees to make the group recommendation respectively. The top-10 group recommendation results for users are presented in Fig. 5 respectively. The information about users in the experiment is presented in Table 1.

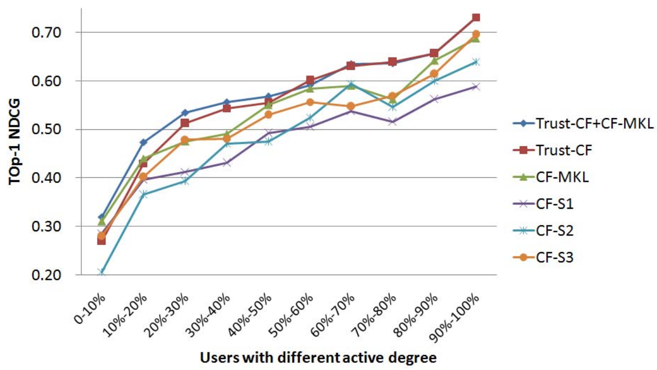


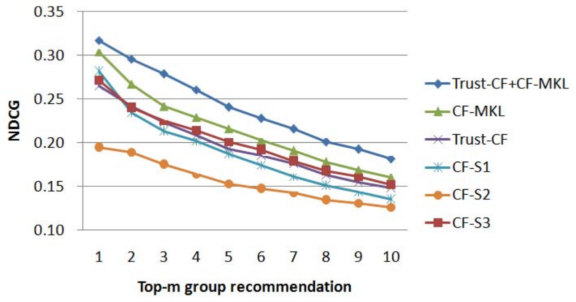
Fig. 5. The top-1 NDCG of users with different active degree by ascending ordering. We use the number of users' followees to present their active degree.

TABLE I. THE NUMBER OF TESTING USERS WITH DIFFERENT FOLLOWEES

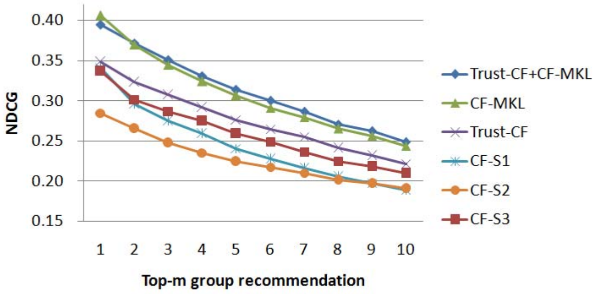
Range	[0 25]	[0 50]	[0 100]	(100 ∞)
Number	377	781	1586	2414

We analyze the results of the group recommendation shown in Fig. 6.

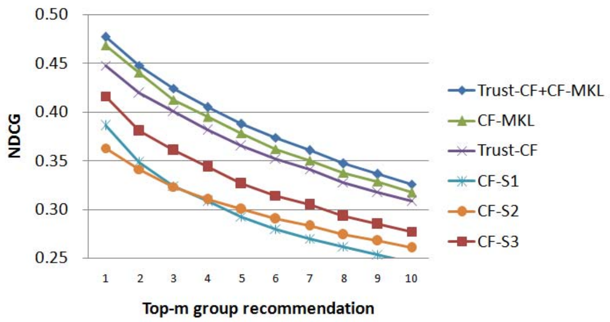
- Our combination model yields the best and our CF-MKL yields the second best when users are inactive. For active users, our combination model performs the same as Trust-CF. Such a promising result infers that using the content interest for group recommendation is possible.
- Trust-CF works better than CF-MKL when users have a large number of followees while CF-MKL works better when users have a small number of followees. It is easy to find that the gap between trust-based CF and user-based CF gets smaller when the number of users' followees becomes smaller. Users with a smaller number of followees tend to find interest groups by interests more often than social relation. When the users become more social and have more followees, they tend to join groups which their followees have joined.
- CF-S1 works better than CF-S2 when users have a small number of followees while CF-S2 works better when users have a large number of followees. This phenomenon indicates that if a user is not a active user, he/she is not familiar to the social network and will only use some basic services(such as uploading photos). When a user becomes active, he/she will integrate himself/herself into the social network.



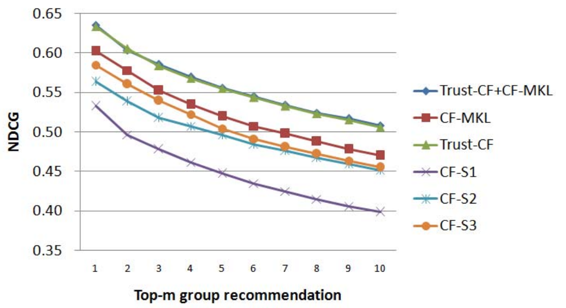
(a) Top-10 group recommendation for users who have less than 25 followees.



(b)Top-10 group recommendation for users who have less than 50 followees.



(c)Top-10 group recommendation for users who have less than 100 followees.



(d)Top-10 group recommendation for users who have more than 100 followees.

Fig. 6. Top-10 group recommendation for users who have different followees.

IV. CONLUSION

In this paper, we propose a group recommendation model and test it on a real-world dataset from Flickr. We find that users with a smaller number of followees tend to find interest groups by interests more often than social relation. When the users becomes more social and have more followees, they tend to join groups which their followees have joined. Our group recommendation model combined content interest and social information performs well especially on inactive users. In our future work, we will attempt to adopt some multi-view learning methods [13][14][15] to combine various features for group recommendation.

V. ACKNOWLEDGEMENT

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