Flickr Group Recommendation based on Tensor Decomposition

Nan Zheng[1], Qiudan Li[1], Shengcai Liao[2], Leiming Zhang[1]
Institute of Automation, Chinese Academy of Sciences, Beijing, China[1,2]
{nan.zheng, qiudan.li, leiming.zhang}@ia.ac.cn[1], scliao@nlpr.ia.ac.cn[2]

ABSTRACT
Over the last few years, Flickr has gained massive popularity and groups in Flickr are one of the main ways for photo diffusion. However, the huge volume of groups brings troubles for users to decide which group to choose. In this paper, we propose a tensor decomposition-based group recommendation model to suggest groups to users which can help tackle this problem. The proposed model measures the latent associations between users and groups by considering both semantic tags and social relations. Experimental results show the usefulness of the proposed model.

Categories and Subject Descriptors
H.2.8 [**Database Management**]: Database Applications – *Data mining,* H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *Information filtering*

General Terms: Algorithms, Experimentation.

Keywords
Flickr Group, Tensor Decomposition, Group Recommendation.

1. INTRODUCTION
Flickr offers a number of ways for users to browse and find photos, such as exploring or searching through members, tags, groups or interesting photos. Groups in Flickr are self-organized communities to share photos and conversations with common interests. As groups are self-organized, plenty of groups fall into a similar topic, i.e. 22,183 groups are returned by searching with the keyword *cat*. Indeed, people need an easy-to-use tool to guide their selection. In this paper, we provide a group recommendation model to help people more easily engage in group activities.

Typically, only group members can contribute to a group pool. A user attaches tags to a photo and shares it with one or several suitable groups. Semantic relations among tags could be detected by their overlaps in groups or users. The joint patterns of two users can be denoted by their semantic tag usage and similar groups involved. Similarly, the joint patterns of two groups can be expressed by semantic tags co-occurrence and the number of users who participated in both groups. However, the multiple facets introduce challenges of modeling, as a result, most prior work has focused on specific points, such as applying two-mode relations: group-tag, user-tag or group-user [1,2] or incorporating data into two dimensions [3] to construct topic models. Although these models are effective by considering semantic data like tags or social data like group membership respectively, it may bring better performance if integrating all these information together. As tensor model offers a natural representation for multiple facets, we propose a tensor decomposition-based group recommendation model in this paper to combine semantic tags with social relations. In the following of this article, we will illustrate the details of this model, along with the experimental results.

2. METHOD
2.1 Data Representation
The idea of group recommendation is to suggest groups which may have latent associations with the active user. We provide a small example shown in Figure 1 to illustrate the benefits of three modes compared with two modes. In the two-mode relations (on the left), we cannot find any associations between user U_1 and group G_3, while in the three-mode relations (on the right), tags perform as a bridge between users and groups. We can see that U_1 has latent association with G_3 through tag T_1.

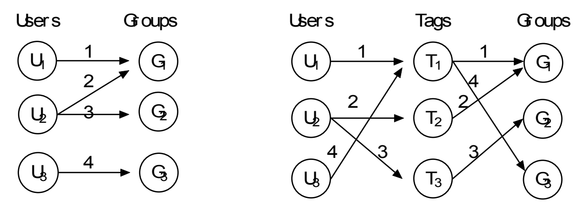

Figure 1. Usage data of an example.

From Figure 1, a three-mode tensor $\mathbb{Z} \in \mathbb{R}^{I \times J \times N}$ can be constructed from the usage data, where I, J, N are the numbers of users, tags and groups respectively. Each element z_{ijn} in the tensor denotes user i's corresponding photo count with tag j in group n. The advantage of a three-way tensor is that we can explicitly model the relations among users, tags and groups in a unified way.

2.2 Tensor Decomposition-based Group Recommendation Model
We employ CANDECOMP/PARAFAC (CP) tensor decomposition [4] to capture the underlying patterns in the user-tag-group tensor. The basic idea of the CP decomposition is to fit $\mathbb{Z}$ with a sum of component rank-one tensors, such that

$$\mathbb{Z} \approx \sum_{r=1}^{R} \lambda_r \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r \qquad (1)$$

where the symbol $\circ$ denotes the outer product, R is the decomposed rank of the tensor, λ_r is a weight that indicates how important the r-th component is, and vectors $\mathbf{a}_r \in \mathbb{R}^I$, $\mathbf{b}_r \in \mathbb{R}^J$ and $\mathbf{c}_r \in \mathbb{R}^N$. Combining the vectors from the rank-one components, we get three factor matrices: user matrix **A**, tag matrix **B** and group matrix **C** of

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size $I \times R$, $J \times R$, $N \times R$ respectively. The advantages of the CP model lie in: (i) the model transforms rich relations among users, tags and groups into R components, which present the principal axes of entities across the three modes and (ii) the results project users, tags and groups to the same R components, which reduces dimensions and brings conveniences for further applications based on such a model. Specially, we compute the non-negative CP decomposition by multiplicative updates like non-negative matrix factorization (NMF) adopted [5] by using the Tensor Toolbox. Such an approach could retain the non-negative characteristics of the original data which facilitates easier interpretation.

Three factor matrices discover the latent topics that govern the associations among users, tags and groups. The i-th row of user matrix $\mathbf{A}$ provides an additive linear combination of components which indicate the topics of user i. The higher weight user i is assigned to a component, the more interested user i is in the relevant topic. The n-th row of group matrix $\mathbf{C}$ provides an additive linear combination of components that indicate the topics of group n. The higher weight a group is assigned to a component, the more related the group is with the relevant topic. Thus, groups can be recommended according to the captured associations. We define a score matrix $\mathbf{S}$ of size $I \times N$ as follows:

$$\mathbf{S} = \sum_{r=1}^{R} \lambda_r \mathbf{a}_r \mathbf{c}_r^{\mathrm{T}} . \qquad (2)$$

$\mathbf{S}$ measures the latent associations between users and groups in which S_{in} represents the likeliness user i will participate in group n.

3. EXPERIMENTS

3.1 Dataset and Parameter Settings

We use Flickr API to gather data about users, tags and groups. After stop-word removal and stemming, we end up with a size of 197×5328×4064 tensor and over 0.9 million nonzero entries. The ideal value of R should be large enough to capture all the important characterizations yet small enough to gain time efficiency. We range R from 10 to 100 by an interval of 10 and find that 50 is a suitable tradeoff. Thus, R is empirically set to be 50 in our experiments.

3.2 Results and Discussions

Before performing group recommendation, we first discuss if the proposed model could reasonably identify the latent associations among users, tags and groups. We examine the decomposition results to present the leading entities in the 5$^{\text{th}}$ component on each mode shown in Table 1. As shown, all the tags and groups express the topic of component 5 to be *self portrait*, and the first column of Table 1 lists 5 users who are most relevant to *self portrait*. In this way, our model can successfully discover the latent associations among users, tags and groups.

Table 1. Top 5 entities in the fifth component on each mode.

Users	Tags	Groups
Nic Temby	portrait	Self-Portraits!!!
Lee Bader	self	Artistic Self-Portraits
antonkawasaki	woman	365 Days
Steven Dempsey	girl	Self Portraits
Nikki P.	selfportrait	Autoportrait

We use the top-k recommendations metric [6] to evaluate group recommendation results. That is, we suggest the top k groups for each user. We randomly select one joined group and k-1 unjoined groups for each user to form the test set and the remaining joined groups form the training set. We repeat this procedure 50 times for different random samplings. The objective is to find the place of the joined group in the recommendation list. There are k possible ranks for the joined group and the best result is that no unjoined groups appear before it. Figure 2 shows the cumulative distributions of ranks for the joined groups in the test set (k=201). 0% means that the joined group is at the first place in the ordered list, while 100% means that it turns up in the last position. To demonstrate the usefulness and effectiveness of our model, we offer comparison tests on user-based model [7] and NMF-based model [8] on user-group matrix.

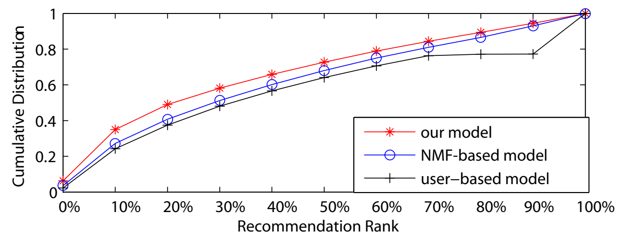

Figure 2. Top-201 recommendation performances.

Comparing the results, our model provides better group recommendations than user-based model and NMF-based model on our dataset. All these differences are statistically significant ($p<0.01$). It may be because the proposed model could capture more latent and complex associations among user-tag-group than two-mode relations and provide more reasonable results.

4. CONCLUSIONS AND FUTURE WORK

In this paper, we provide a tensor decomposition-based Flickr group recommendation model by combining semantic data with social data. Preliminary experiments support the validity and effectiveness of the approach. We plan to offer a deep analysis on the latent associations mined by such a model. This research is supported by projects 863 (No.2006AA010106), 973 (No.2007CB311007) and NSFC (No.60703085).

5. REFERENCES

[1] Negoescu, R. and Gatica-Perez, D. Analyzing flickr groups. *CIVR'08* pp. 417-426.

[2] Negoescu, R., Adams, B., Phung, D., Venkatesh, S. and Gatica-Perez, D. Flickr hypergroups. *MM'09* pp. 813-816.

[3] Negoescu, R. and Gatica-Perez, D. Topickr: flickr groups and users reloaded. *MM'08* pp. 857-860.

[4] Carroll, J. and Chang, J. (1970) Analysis of individual differences in multidimensional scaling via an N-way generalization of "Eckart-Young" decomposition. *Psychometrika*. 35(3) 283-319.

[5] Lee, D. and Seung, H. Learning the parts of objects by non-negative matrix factorization. *Nature'99*. 401(6755) 788-791.

[6] Koren, Y. Factorization meets the neighborhood: a multi-faceted collaborative filtering model. *KDD'08* pp. 426-434.

[7] Sarwar, B., Karypis, G., Konstan, J. and Riedl, J. Analysis of recommendation algorithms for e-commerce. EC'00.

[8] Zhang, S., Wang, W., Ford, J. and Makedon, F. Learning from incomplete ratings using non-negative matrix factorization. SDM'06 pp. 548–552.