Data Augmented Maximum Margin Matrix Factorization for Flickr Group Recommendation

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Abstract. User groups on photo sharing websites, such as Flickr, are self-organized communities to share photos and conversations with similar interest and have gained massive popularity. However, the huge volume of groups brings troubles for users to decide which group to choose. Further, directly applying collaborative filtering techniques to group recommendation will suffer from *cold start* problem since many users do not affiliate to any group. In this paper, we propose a hybrid recommendation approach named Data Augmented Maximum Margin Matrix Factorization (DAM^{3}F), by integrating collaborative user-group information and user similarity graph. Specifically, Maximum Margin Matrix Factorization (MMMF) is employed for the collaborative recommendation, while the user similarity graph obtained from the user uploaded images and annotated tags is used as an complementary part to handle the *cold start* problem and to improve the performance of MMMF. The experiments conducted on our crawled dataset with 2196 users, 985 groups and 334467 images from *Flickr* demonstrate the effectiveness of the proposed approach.

1 Introduction

With the dramatic development of Web 2.0 and social network technologies, social media become more and more important as a way for users to obtain valuable information, express individual opinions, share experiences as well as keep in touch with friends. Online photo sharing sites, such as *Flickr*[1] and *Picasa Web Album*[2], become popular with numerous images uploaded every day (over 6 billion images in *Flickr*) [18]. User groups on such sites are self-organized communities to share photos and conversations with similar interest and have gained massive popularity. Joining groups facilitates flexibility in indexing and managing self photos, making them more accessible to the public and searching photos and users with similar interests. As the support of above view, Negoescu *et al.* provide an in-depth analysis of the structure of *Flickr* groups and the motivation of group activities [10][11].

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[1] http://www.flickr.com
[2] http://picasaweb.google.com

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Although the information contributed by user groups could greatly improve the user's browsing experience and enrich the social connections, the real situation is that many users rarely join in any group. By studying 3 million images and the respective users and groups crawled from *Flickr*, we discover an interesting fact that only 6.7% users have ever joined one image group and only 1.9% users have joined more than 5 groups. Thus, it is necessary to design a recommendation approach that could automatically recommend appropriate groups for users.

Group recommendation for photo sharing sites is a relatively novel scenario that have not been systematically studied. Current works commonly employs traditional recommendation techniques such as *collaborative filtering* [9] and *matrix factorization* [7,15] to recommend groups in a collaborative way. However, the recommendation performances of current work are not satisfied enough, due to two following points which are not yet considered carefully:

– **Sparse User-Group Matrix.** As discussed above, many users rarely join in any group. According to the statistic of our crawled dataset, the density of the user-group relationship matrix is only 0.46%. Simply implementing state-of-the-art recommendation techniques on such sparse dataset can't achieve satisfied result.
– **Cold Start Problem.** It should be noted that the *cold-start* problem in this paper means recommending groups to the users haven't joined in any group. The sparse user-group matrix makes it more difficultly to handle the *cold-start* problem.

As an early explorer in group recommendation for online photo sharing sites, we propose a hybrid recommendation approach named Data Augmented Maximum Margin Matrix Factorization (DAM^{3}F) to handle the above two problems, by integrating collaborative user-group relationship and user similarity graph. On one hand, Maximum Margin Matrix Factorization (MMMF) [17] is adopted for collaborative recommendation, by jointly learning the latent factors of users and groups from the original user-group relationship. As an improvement of tradition matrix factorization approaches, Maximum Margin Matrix Factorization uses hinge loss instead of sum-square loss and has been proven to be an effective approach for collaborative recommendation on sparse dataset. On the other hand, the user similarity graph obtained from the user uploaded images and annotated tags is used as an complementary part to handle the *cold start* problem and to improve the performance of MMMF. Specifically, graph regularization is introduced to preserve the user similarity, which provides a more interpretable way to characterize the users and groups. Further, a novel objective function is proposed which jointly consider the above issues, and an efficient optimization algorithm is provided to solve the objective function.

In particular, the main contributions of this paper can be summarized as follows:

1. This paper proposes a hybrid approach named DAM^{3}F to handle the *sparse user-group matrix* and *cold-start* problems in *Flickr* group recommendation.

2. A novel objective function is proposed by jointly considering the collaborative user-group information and the user similarity graph.
3. To evaluate the performance of the proposed approach, a real-world dataset consists of 2196 users, 985 groups and 334467 images is crawled from *Flickr*. The experimental results demonstrate that the proposed approach outperforms the state-of-the-art techniques in terms of six well-known evaluation metrics.

The rest of this paper is organized as follows: Section 2 gives a survey of related work in group recommendation. Section 3 shows the details of the proposed approach for *Flickr* group recommendation, while Section 4 reports the performance of DAM^{3}F based on real-world dataset. Finally Section 5 concludes this paper.

2 Related Work

User groups on social Websites, are self-organized communities to share photos and conversations with similar interest and have gained massive popularity. Group recommendation is an important paradigm that discovering the interesting groups for users, and attracts a lot of attention in recent years. In this section, we briefly introduce the related work in this area, by classifying them into three categories according to the employed approaches.

– ***Content-based recommendation*:** This category of methods recommends a group to a user based on the content of user or group, e.g., description of the group, the profile of the users interests, etc. Sihem *et al.* utilize the user profiles and propose a formal semantics that accounts for both item relevance to a group and disagreements among group members [1]. Liu *et al.* propose a tag-based group recommendation method on Flicker dataset by building a tag ranking system [8]. Kim *et al.* represent items with keyword features by a content-based filtering algorithm, and propose a community recommendation procedure for online readers [6].
– ***Collaborative filtering based recommendation*:** This category of methods was successfully applied in traditional recommender systems, and is based on the assumption that similar users are likely to attend similar groups. Chen *et al.* propose an improved collaborative filtering method named combinational collaborative filtering(CCF), which considers multiple types of co-occurrences in social data and recommends personal communities [4]. Zheng *et al.* implement several collaborative filtering methods, and provide a systematic experimental evaluation on Flicker group recommendation [20]. Yu *et al.* propose a collaborative filtering recommendation algorithm for Web communities, in which the latent links between communities and members are utilized to handle the sparsity problem [12].
– ***Hybrid recommendation*:** This category of methods combines several algorithms to recommend groups. Chen *et al.* compare association rule mining

(ARM) and latent dirichlet allocation (LDA) for the community recommendation, and find that LDA performs consistently better than ARM when recommending a list of more than 4 communities [3]. Chen *et al.* design a group recommendation system based on collaborative filtering, and employ genetic algorithm to predict the possible interactions among group members [5]. This strategy makes the estimated rating that a group of members might give to a group more correct. Zheng *et al.* propose a tensor decomposition model for Flickr group recommendation, which measures the latent relations between users and groups by considering both tags and users social relations [19]. Zheng *et al.* also propose an approach which combines the topic model and collaborative filtering, and this method is demonstrated to have better performance than traditional CF and negative matrix factorization [18].

The proposed approach DAM^{3}F in the paper is a hybrid one, in which we take the advantage of the above related works (e.g., user-annotated tags are utilized), and introduce some novel data (i.e., visual features extracted from the uploaded images) to further improve the performance of recommendation. In the technology aspect, we extend the traditional MMMF, and propose a novel objective function in which both user-group relationship and user similarity graph are considered. Further, an efficient optimization approach is proposed to solve the objective function.

3 DAM^{3}F Based Flickr Group Recommendation

In this section, we show the details of Data Augmented Maximum Margin Matrix Factorization (DAM^{3}F), which is the extension of the classical Maximum Margin Matrix Factorization approach by taking the uploaded images and user-annotated tags into consideration. To begin with, we give the main framework of DAM^{3}F in Figure 1.

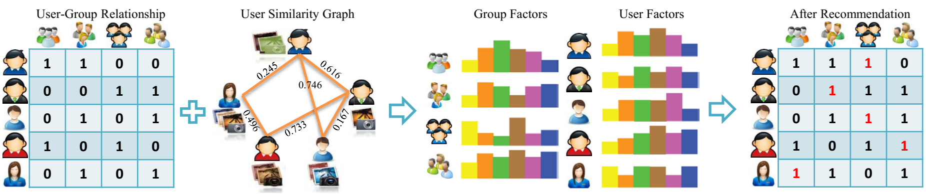


Fig. 1. The main framework of the proposed DAM^{3}F. The user-group relationship and user similarity graph are integrated in Data Augmented Maximum Margin Matrix Factorization framework to obtain the user and group latent factor matrices. Specifically, the similarity graph is computed based on the features extracted from images and annotated tags. Then the recommendation results can be calculated from the latent factors of users and groups.

3.1 Maximum Margin Matrix Factorization

Given the sets of M users, N images and P groups respectively, $R \in \mathbb{R}^{M \times P}$ is the affiliation matrix between users and groups, where $R_{ij} = 1$ means that the ith user is the member of the jth group and 0 otherwise. Furthermore, we use matrix $S \in \mathbb{R}^{M \times N}$ to denote the ownership between users and images where $S_{ik} = 1$ indicates that the kth image is uploaded by the ith user. By extracting the D dimension visual feature of the N images, we obtain the image feature matrix $X = [x_1, x_2, \ldots, x_N]^T \in \mathbb{R}^{N \times D}$. Given the information above, the aims of group recommendation is to recover a new affiliation matrix R_{rec} denote the relationship between users and groups, and more importantly to recommend new groups to users based on R_{rec}.

The traditional matrix factorization approaches for recommendation tries to factorize the affiliation matrix R into two $M \times K$ and $N \times K$ dimensional low-rank matrices U and G by:

$$\operatorname*{argmin}_{U,G} \| R - UG^T \|_F + \lambda(\| U \|_F + \| G \|_F), \tag{1}$$

where $\| \cdot \|_F$ denotes the Frobenius norm and K is dimensionality of the latent factors of both users and groups. Besides, the regularization penalties $\lambda(\| U \|_F + \| G \|_F)$ is utilized to avoid over-fitting. Afterwards, the recommendation results can be obtained by calculating similarity between the latent factors of users and groups as $R_{rec} = UG^T$.

As for our group recommendation problem, $R_{rec_{ij}}$ only has two entries, i.e. 0 and 1, which indicates whether the ith user affiliates to the jth group. Therefore, comparing with traditional recommendation techniques which obtain the rating matrix, group recommendation is more appropriate to be formulated as a binary classification problem. Besides, since there are much more 0's than 1's in matrix R, the resulting recommendation results will be heavily biased towards 0 by using traditional matrix factorization approaches.

In order to overcome such limitations, Maximum Margin Matrix Factorization (MMMF) is proposed by replacing the sum-squared loss with hinge loss which has been widely used in classification application, such as Support Vector Machines. According to [13][17], the objective function of MMMF can be written as:

$$\operatorname*{argmin}_{U,G} h(R - UG^T) + \lambda(\| U \|_F + \| G \|_F), \tag{2}$$

where $h(z) = (1 - z)_+ = max(0, 1 - z)$ corresponds to the hinge loss.

Above formulation can be also interpreted as simultaneous learning of feature vectors and linear classifiers. By viewing matrix U as the feature vectors of the users, matrix G can be regarded as linear classifiers that map the user feature vectors into binary labels that indicate whether the user is interested in that group. In addition, hinge loss is adopted for learning maximum margin classifiers with respect to each group.

3.2 Data Augmented Maximum Margin Matrix Factorization

Similar to other collaborative filtering algorithms, MMMF based recommendation still suffers *cold-start* problem, i.e., recommendation results for new users who have not joined groups tend to be very inaccurate. This problem could be solved, to some extent, by exploiting content information of the users, i.e., the features extracted from their uploaded images and the corresponding annotated tags. The basic assumption is: *if two users have joined in the same group, then their uploaded images to this group will probably be visually similar or semantically (tag-based) similar.* Based on this assumption, we can incorporate such user similarity graph into the MMMF based recommendation framework. Firstly, the feature vector f_i w.r.t. the i_{th} user can be calculated by averaging the feature vectors of all his images or tags as:

$$f_i = \frac{\sum_{j=1}^{N} S_{ij} X_j}{\sum_{j=1}^{n} S_{ij}}, \tag{3}$$

where S_{ij} denotes the j_{th} image uploaded by u_i, X_j means the visual or semantic (tag-based) feature of S_{ij}. It should be noted that the process of feature extraction is introduced in Section 4.1. Then we can construct the adjacency matrix W of the user similarity graph as follows:

$$W_{ij} = \begin{cases} exp(\frac{\|f_i - f_j\|}{t})^2, & if\ x_j \in \mathcal{N}(x_i)\ or\ \ x_i \in \mathcal{N}(x_j) \\ 0, & otherwise, \end{cases} \tag{4}$$

where $\mathcal{N}(x_i)$ denotes the k-nearest neighbor of x_i and the Heat Kernel is exploited to measure the similarity of two feature vectors. To guarantee that users who upload visually or semantically similar images will also obtain similar latent factors, we introduce the following graph regularization term:

$$\begin{aligned} &\frac{1}{2}\sum_{i,j} \| u_i - u_j \|_2 W_{ij} \\ =&\sum_{ij} u_i W_{ij} u_i^T - \sum_{ij} u_j W_{ij} u_j^T \\ =&\sum_{i} u_i D_{ii} u_i^T - \sum_{ij} u_j W_{ij} u_j^T \\ =&tr(U^T(D-W)U) \\ =&tr(U^T L U), \end{aligned} \tag{5}$$

where $tr(\cdot)$ denotes the matrix trace, $D_{ii} = \sum_i W_{ij}$ is a diagonal matrix and $L = D - W$ is the Laplacian matrix of the user similarity graph.

By leveraging the collaborating information and user similarity graph, we propose the Data Augmented Maximum Margin Matrix Factorization (DAM^{3}F) framework, which unifies maximum margin matrix factorization and graph regularization as:

$$\underset{U,G}{\operatorname{argmin}}\ h(R - UG^T) + \mu tr(U^T(\gamma L_1 + (1-\gamma)L_2)U) + \lambda(\| U \|_F + \| G \|_F) \tag{6}$$

where μ is the trade-off parameter between collaborating information and content information, L_1 is the Laplacian matrix of the image based user similarity graph (visually), L_2 is the Laplacian matrix of the tag based user similarity graph (semantically), and γ is the trade-off parameter between visual information and tag information.

Although the proposed objective function is not a convex function of U and G, but it is convex to one variable when the other one is fixed. Therefore, we could obtain the local optimal solution by alternatively updating the two variables using gradient descent methods.

Denoting the objective function as $J(U, G)$, we can calculate the gradient of $J(U, G)$. The partial derivative with respect to U is:

$$\frac{\partial J}{\partial U} = -h'(R - UG^T)G + 2\mu(\gamma L_1 + (1-\gamma)L_2)U + 2\lambda U \tag{7}$$

The partial derivative with respect to G is:

$$\frac{\partial J}{\partial G} = -h'(R - UG^T)^T U + 2\lambda G \tag{8}$$

Since the hinge loss function $h(z)$ is non-smooth at $z = 1$, following [13], we adopt smooth hinge instead of hinge loss for the ease of optimization. The further details of optimization process is omitted due to the space limitation.

4 Experiments

In this section, we evaluate the performance of the proposed approach on the real-world dataset crawled from *Flickr* by using kinds of metrics, and compare it with state-of-the-art approaches. Sepcifically, all experiments are conducted on a windows workstation with Intel 2.67GHz Xeon CPU and 32GB RAM by using Matlab 8.0.

4.1 Experiment Setup

To evaluate the performance of the proposed approach, we collect an image dataset from *Flickr* by using its API[3]. The details of this dataset could be found in Table 1. To obtain this dataset, we first select popular groups in *Flickr* by keyword searching. Then, active users of these groups and their uploaded images as well as the annotated tags are crawled, respectively. As for the process of feature extraction, we extract 81-dimensional color histogram/moments feature and 37-dimensional edge histogram feature to generate the visual feature to represent these images by using FELib[4], and employ Latent Dirichlet Allocation (LDA) to generate 50-dimensional semantic feature to represent the annotated

[3] `http://www.flickr.com/services/api/`
[4] `http://www.vision.ee.ethz.ch/~zhuji/felib.html`

Table 1. Overview of Dataset Crawled from Flickr

#Image	#Group	#User	#Tag	#Tag Token
334467	985	2196	3603353	239557

Table 2. Group Recommendation Performance Comparison ($\alpha = 60\%$)

Method	F_1 score	RMSE	P@5	P@10	MAP	MAE
CB	0.1702	0.0796	0.1315	0.4691	0.2149	0.3936
CF	0.1962	0.0811	0.1533	0.5909	0.2208	0.3923
SVD	0.2847	0.0863	0.2303	0.5719	0.3778	0.3963
NMF	0.3024	0.0799	0.2472	0.6589	0.4322	0.3912
MMMF	0.2992	0.0779	0.2478	0.7193	0.4316	0.3859
DAM^{3}F$_{tag}$	0.3184	0.0757	0.2612	0.7337	0.4504	0.3743
DAM^{3}F$_{visual}$	**0.3219**	**0.0755**	**0.2635**	**0.7353**	**0.4527**	**0.3722**

tags of the uploaded images. Due to the space limitation, we don't give the details of the tag-based feature extraction.

To evaluate the performance of group recommendation, we randomly sample $\alpha \times 100\%$ of the user-group assignments from the user-group affiliation matrix to generate the matrix R for training and use the full user-group affiliation matrix as the ground-truth for evaluation.

Evaluation Metrics. To comprehensively evaluate the performance of the proposed approach, we consider the following evaluation metrics: Precision@k (P@k), Mean Average Precision (MAP), Mean Absolute Error (MAE) [2], Root Mean Squared Error (RMSE), and F_1 score. In particular, k is chosen to 5 and 10 for P@k metric.

4.2 Recommendation Performance Comparison

In order to demonstrate the effectiveness of the proposed approach, we implement the following approaches and compare the performances:

1. **CB:** Content based recommendation by using the user similarity graph.
2. **CF:** Collaborative Filtering recommendation by using user-group relationship [14].
3. **SVD:** Singular Value Decomposition based recommendation by using user-group relationship[9].
4. **NMF:** Nonnegative Matrix Factorization based recommendation by using user-group relationship[15].
5. **MMMF:** Maximum Margin Matrix Factorization based recommendation by using user-group relationship[17].
6. **DAM^{3}F$_{tag}$:** One version of the proposed DAM^{3}F in this paper, while only sematic (tag-based) user similarity graph is combined to MMMF.

7. **DAM^{3}F$_{visual}$:** One version of the proposed DAM^{3}F in this paper, while only visual user similarity graph is combined to MMMF.

In this experiment, parameter μ is set empirically to 1 and λ is set to 0.1. The dimensionality of latent factors K is set to 200. It should be noted that the parameters of all the competitive methods have been fairly tuned using cross-validate, and the average evaluation results after 10-fold cross-validation are selected.

Table 2 shows the performance comparison of above group recommendation approaches when $\alpha = 60\%$ in terms of multiple evaluation metrics. From Table 2, it can be observed that the two versions of DAM^{3}F largely outperform the other state-of-the-art approaches in terms of multiple metrics. The superior performance of the proposed approach comes from two aspects, one is the selection of hinge loss for matrix factorization, while the other one is the integration of user similarity graph. Further, it can be discovered that the DAM^{3}F$_{visual}$ outperforms DAM^{3}F$_{tag}$. The reason is two-fold: 1) extracted visual feature is more explicit than the semantic (tag-based) feature; 2) User-annotated tags are inherent uncontrolled, ambiguous, and overly personalized. Thus, a pre-processing should be implemented before adopting user-annotated tags. In the following experiments, we implement a tag recommendation process to smooth the distribution of tagging data, and the performance comparison could be found in Section 4.4.

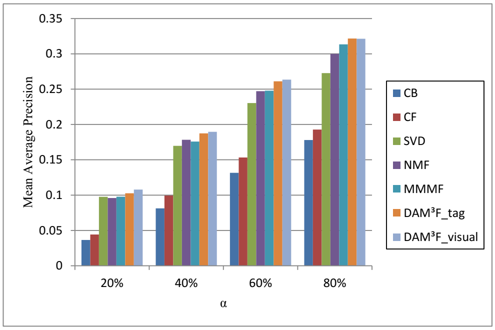
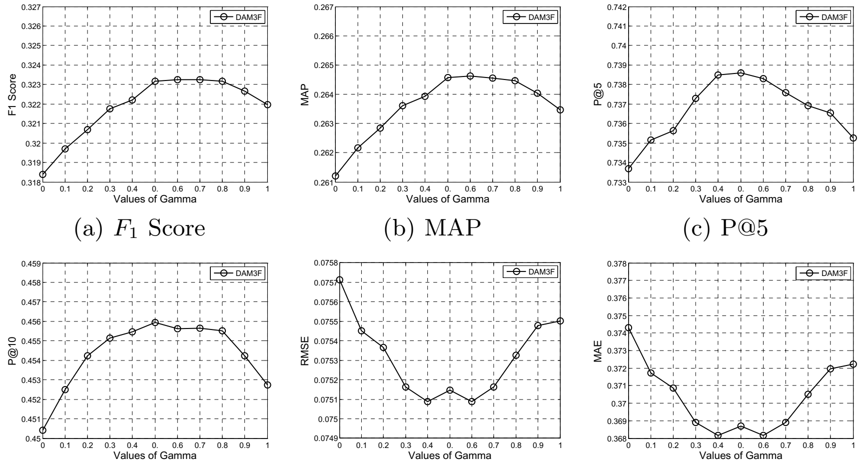


Fig. 2. Performance comparison with different α in terms of Mean Average Precision (MAP)

Figure 2 shows the group recommendation performance comparison of different approaches while the proportion of training data α varies from 20% to 80% in terms of MAP. The superior performance at different α further verified the effectiveness of the proposed approach. In addition, it can be observed that the two versions of DAM^{3}F are of greater advantage than other approaches when α gets smaller. The reason is that the user similarity regularization plays a more important role when the initial affiliation matrix is sparse, which is consistent with our motivation.



(a) F_1 Score (b) MAP (c) P@5

(d) P@10 (e) RMSE (f) MAE

Fig. 3. Impact of γ to The Performance of DAM^{3}F

4.3 Performance Evaluation of DAM^{3}F

In the proposed DAM^{3}F, we utilize both visual feature extracted from uploaded images and semantic feature extracted from annotated tags. In the above experiment, we implement two versions of DAM^{3}F, in each only one feature is utilized. In this section, we evaluate the performance of DAM^{3}F by utilizing these two features, and evaluate the impact of trade-off parameter γ to performance of DAM^{3}F in terms of multiple metrics.

Figure 3 shows the performance of DAM^{3}F and the impact of γ to it. The approach is DAM^{3}F$_{tag}$ when γ=0, while the approach is DAM^{3}F$_{visual}$ when γ=1. From Fig. 3, it could be observed that DAM^{3}F outperforms both DAM^{3}F$_{tag}$ and DAM^{3}F$_{visual}$ in terms of all metrics. It can be easily explained that the increase of relevant feature improves the performance of recommendation. Further, it could be found that the optimal value of γ is different for different metric. Thus, the selection strategy of the optimal value of γ should be adjusted according to the application scenario.

4.4 Impact of Tag Recommendation to DAM^{3}F

As discussed above, user-annotated tags are inherent uncontrolled, ambiguous, and overly personalized. Thus, a pre-processing should be implemented before adopting user-annotated tags. In this section, we implement two commonly accepted tag recommendation approach, i.e., *Sum* and *Vote* [16], to recommend relevant tags to the images with few tags and to delete irrelevant tags for the purpose of smoothing the tagging data distribution.

Table 3 show the performance comparison of DAM^{3}F with different tag recommendation approaches in terms of multiple metrics. From Table 3, it can

Table 3. Performance Comparison of DAM^{3}F with Different Tag Recommendation Approaches

Method	F_1 score	RMSE	P@5	P@10	MAP	MAE
DAM^{3}F+ Original Tag	0.3184	0.0757	0.2612	0.7337	0.4504	0.3743
DAM^{3}F+ Vote	0.3197	0.0754	0.2625	0.7358	0.4532	0.3709
DAM^{3}F+ Sum	**0.3202**	**0.0752**	**0.2628**	**0.7367**	**0.4534**	**0.3706**

be observed that the introduction of tag recommendation process improves the performance of DAM^{3}F in terms of all metrics. It can be easily understood as the irrelevant tags don't contribute to the representation of the uploaded images or even have negative effect, while the addition of relevant tags improves the representation quality of the tag-based feature.

5 Conclusion and Future Work

In this paper, we propose a hybrid approach for *Flickr* group recommendation by leveraging traditional collaborative recommendation with user similarity regularization. More specifically, the proposed Data Augmented Maximum Margin Matrix Factorization (DAM^{3}F) approach integrates the maximum margin matrix factorization with the user similarity graph calculated from their uploaded images and the annotated tags. Experiments implemented on the real-world dataset crawled from *Flickr* demonstrates the effectiveness of the proposed approach, by comparing it with state-of-the-art approaches in terms of multiple metrics. As a general framework, DAM^{3}F can be also applied to other recommendation tasks.

In our future work, we will try to employ more personal and contextual information of *Flickr* users in the framework of DAM^{3}F for the purpose of improving group recommendation performance.

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