Modeling Group Dynamics for Personalized Group-Event Recommendation

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Abstract. Event-Based Social Networks (EBSNs) such as Meetup, Plancast, etc., have become popular platforms for users to plan and organize social events with friends and acquaintances. These EBSNs provide rich *online* and *offline* user interactions, and rich event content information which can be leveraged for personalized group-event recommendations. In this paper, we propose collaborative-filtering based Bayesian models which captures group dynamics such as user interactions, user-group membership etc., for personalized group-event recommendations. We show that modeling group dynamics learns the group preferences better than aggregating individual user preferences, and that our approach out-performs popular state-of-the-art group recommender systems. Moreover, our model provides interpretable results which can be used to study the group participations and event popularity.

Keywords: Personalized group recommendation · Group dynamics · Event-based Social Networks · Bayesian models · Collaborative filtering

1 Introduction

Growth and popularity of online social networks has changed how users connect and interact with friends and family in today's internet age. Event-based Social Networks (EBSNs) such as Meetup, Plancast, Eventbrite etc., have become popular convenient platforms for users to co-ordinate, organize and participate in social meet-ups/events and share these activities with their friends and family. Event recommendation in EBSNs has been recently studied in the past couple of years [3], [8], [11], for recommending events or to recommend event-sponsoring groups to the EBSN users. Most of the previous works were designed for single user recommendations by making use of user event participation information. However, many users use EBSNs to organize personal group activities (such as dining with friends, etc.) since EBSN services provide easy to use online interfaces, and they provide rich user interaction and networking options. We believe that EBSN provides a natural platform for studying personalized recommendation of events to group of users i.e. group-event recommendations. Recommendation to groups (for example, recommending a movie for friends to watch together), in general, is a very challenging problem, since the users of the group

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may or may not share similar tastes, and user preferences may change due to other users in the group. Therefore, it is important for recommender systems to capture group dynamics such as user interactions, user group membership, user influence etc. for personalizing group recommendations. Personalized event recommendation for groups is possible for EBSNs since they provide rich social network information in terms of *online* user interactions and *offline* user participations, and rich event information (location tags, time-stamps, group sponsoring the event, etc.) which help in accurate modeling of group dynamics. Thus, modeling and mining of EBSNs help us to study research issues of group dynamics and group recommendation by leveraging the social and event characteristics of users and locations.

In this paper, we present a novel collaborative filtering based Hierarchical Bayesian model for personalized group-event recommendation in EBSNs, and study how modeling group dynamics affects group-event recommendation. Our contributions include: (1) proposing novel probabilistic modeling framework for capturing group dynamics for group-event recommendation, (2) Studying the group and event characteristics of a large EBSN, and (3) Handling data sparsity and cold-start recommendation challenges associated with group recommenders.

2 Related Work

There is abundant body of research on Group recommendation, however, there is limited previous work on personalized group-event recommendations in EBSNs. Recently, [10] proposed a probabilistic approach to model group activities of online social users using generative processes; though the final group recommendation is done by aggregation of user preferences without directly learning group preferences. In our previous works [6], [7], we proposed a probabilistic approach, where we model groups and activities as generative processes to capture user-group interactions and location semantics respectively, to perform group-activity recommendations in Location-Based Social Networks (LBSNs). However, in our previous works, we investigated group recommendation in LBSNs, and we did not study group-event recommendation in EBSNs which we feel requires dedicated study since EBSNs and LBSNs are quite different and have different characteristics [4].

In this paper, we present a hierarchical Bayesian model to incorporate group dynamics such as user's offline social interactions and user-group membership into our probabilistic framework, and study their effect on personalized group-event recommendation in EBSN. In the following sections, we present our model, and report our experimental results on a real-world large EBSN (Meetup) dataset.

3 Our Approach

We first define the group-event recommendation problem in section 3.1 and then we present our proposed Personalized Group-Event Recommender model in section 3.2.

3.1 Problem Statement

Let U, E, G_{on}, G_{off} represent the set of Users, Events, Online Social Groups and Offline Social Groups of the EBSNs. As the name indicates 'Online Social Groups' correspond to groups whose users interact online, i.e. these groups arise due to the online social interactions. On the other hand, 'Offline Social Groups' corresponds to groups of users who physically meet and participate in events organized by members of online social groups. Offline social group users interact at a location during a particular interval of time while participating in a social event. Mathematically, Online and Offline social groups correspond to the connected components of the Online and Offline Social Network Graphs [4].

The problem of group-event recommendation is defined as recommending a list of events that the users of offline social groups may participate in. It is related to the group-event rating prediction task where the group's event participation is predicted as (implicit) group-event rating. Throughout this paper, we consider the 'Offline social groups' as 'groups' for our group-event recommendation task since they provide rich event content and user interactions to model and study group dynamics for personalization of group recommenders.

3.2 Personalized Group-Event Recommender (PGER)

In this section, we briefly discuss our proposed model- Personalized Group-Event Recommender (PGER), shown in Figure 1. Our model is a generalized hierarchical Bayesian model which jointly learns the group and event latent spaces. We use topic models based on Latent Dirichlet Allocation (LDA) [1] to model the descriptions of events and the groups, and we use matrix factorization to match the latent features of group to the latent features of events. Our model fuses topic models with matrix factorization to obtain a consistent and compact feature representation. We introduced this model in our previous work [7]. In this paper, we adopt the same model for studying Group-event recommendation in EBSN. We urge the readers to refer to our previous work [7] for detailed description of our algorithm, the parameter learning and the definitions for prediction tasks (in-matrix and out-matrix prediction).

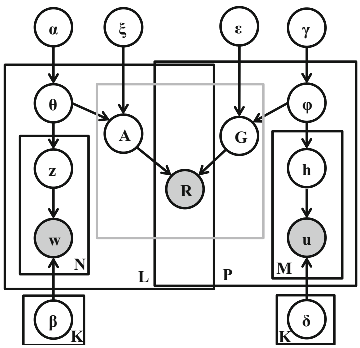

Fig. 1. Our proposed model -Personalized Group Event Recommender (PGER)

4 Experiments

We conduct several experiments to evaluate our model on a EBSN dataset for group-event recommendation. Our experiments help us to answer the following key questions: (a) What are the group and event characteristics of EBSNs? (b) How does our model perform when compared to the state-of-the-art group recommenders? (c) How to interpret the group preferences learned by our model?

4.1 Dataset Description

Our experiments were conducted on Meetup dataset [4] which is a real-world EBSN. We study the event & offline group characteristics and group-event locality properties of EBSNs on the Full Meetup dataset, while we do performance comparsions using a small Meetup dataset (Small dataset was chosen due to limited computing power, however, our model works for larger dataset). Table 1 shows the description of these datasets. Due to space constraints, we don't discuss the group and event characteristics of Meetup dataset[1]. To make our analysis and experiments on group-event recommendation more sound, we considered only the offline social groups who have participated in atleast 10 events.

Table 1. Meetup Dataset Description

Dataset	**Meetup (Full)**	**Meetup (Small)**
#Users	4,111,476	3,650
#Events	2,593,263	27,244
#Online Groups	70,604	454
#Offline Groups of size 2	345,998	2,000
#Offline Groups of size 2 at atleast 10 events	126,141	511
#Events attended by Offline groups of size 2	790,547	9510

4.2 Experimental Settings

We split Meetup dataset into three parts - training (∼80%), held-out (∼5%) and test datasets (∼15%). The model is trained on training data, the optimal parameters obtained on the held-out data and ratings are predicted for the test data. We ran 5 simulations for all our comparison experiments. For performance evaluation, we consider three metrics, namely: (1) Average Group-Event Rating Prediction Accuracy (Avg. Accuracy), (2) Average Root Mean Squared Error (Avg. RMSE) and (3) Average Recall. We define the avg. accuracy for test data as the ratio of correctly predicted ratings compared to the total ratings in test data. RMSE is given by: $RMSE = \sqrt{\frac{1}{|\mathcal{T}|}\sum_{(i,j)\in\mathcal{T}}(\hat{R}_{ij} - R_{ij})^2}$ Where $\hat{R}_{ij}$ is predicted ratings of group-event pairs (i, j) for a test set $\mathcal{T}$, and R_{ij} are

[1] The group and event characteristics is discussed in the longer version of this paper which is available at $http://www-scf.usc.edu/\sim spurusho/$

true ratings. 'Recall' only considers the events participated within the top M suggestions. For each group, we define the *recall@M* as the ratio of number of events the group participates in Top M suggestions to the total events the group participates in.

4.3 Evaluated Recommendation Approaches

We compare our PGER with the following popular and state-of-the-art recommendation systems: (1) Matrix Factorization (MF) [5](2) Collaborative Topic Regression (CTR) [9] (3) Aggregation methods [2]: We considered the following popular aggregation methods: (a) Least Misery method (b) Most Pleasurable method (c) Averaging method, (d) Plurality Voting.

4.4 Results

In this section, we present our experimental results and answer the questions raised in section 4.

Table 2. Performance Comparison on Test Data

	Best Aggregation method (Averaging)	**MF** [5]	**CTR** [9]	**PGER** (Ours)
In-matrix Avg. Accuracy	0.870(0.10)	0.881(0.09)	0.915(0.05)	**0.955(0.03)**
In-matrix Avg. RMSE	0.359(0.12)	0.329(0.11)	0.282(0.08)	**0.205(0.06)**
Out-matrix Avg. Accuracy	-	-	0.794(0.16)	**0.908(0.08)**
Out-matrix Avg. RMSE	-	-	0.441(0.14)	**0.298(0.1)**
Avg. Recall@10 (K=50)	0.49	0.532	0.583	**0.792**

Performance Comparisons

Table 2 shows that our approach (PGER) outperforms all the state-of-the-art models in both in-matrix and out-matrix prediction tasks. Our model performs better than the state-of-the-art models by an impressive 20% in terms of recall@10 metrics. Variance of avg. accuracy and RMSE is shown in brackets. All our experiments were run on intel quad-core 2.2 GHz CPUs with 8 GB RAM.

4.5 Learned Group Preferences vs. Aggregating User Preferences

We compare our learned group preferences w.r.t aggregating user preferences using two scenarios. In first scenario, Group I has users who have similar user preferences and in second scenario, Group II has users who have different user preferences. From table 4.5 we observe that aggregating user preferences may recommend events that may not be relevant for their groups, while directly learning group preferences (by capturing group dynamics) will recommend events that are similar to the events that the group has participated in. Note: Event tags (provided in the dataset) are used to interpret the event-topics and the learned group preferences.

4.6 Examining Latent Spaces of Groups and Events

We can interpret our model's group recommendations by studying the latent spaces of the groups and events. Table 4 shows top 3 group preference topics for an example offline social group (say Group I). Group I has users who are interested in fantasy literature, fitness and adventure related events, and most of the recommended events belong to these topics. One advantage of our model is that it can predict if an event will become popular for groups (i.e. if an event will have more group participants) by studying the offsets of the event-topic proportions. An event whose topics have large offsets indicates that many groups (of different group sizes) will take part in that event. An example for such an event is a hiking trip organized by a school's travel club, or an author book reading session hosted by a book club.

Table 3. Learned Group Preferences vs. Aggregating User Preferences

	Group I	**Group II**
Learned group preferences	Book-club, Spirituality, Adventure	Sports, Fitness, Business Networking
Aggregating user preferences	Board games, Religion, Spirituality	Politics, Movies, Book club
Events participated by Groups	Harrypotter reading session, Meditation, Hiking	Baseball, Yoga, Conference

Table 4. Latent Topics for an Offline Social Group. We list the top 5 events recommended by PGER. Last column shows whether the group participates in the event.

	Group I	Event participation
Top 3 topics (top 5 words)	1. bookclub, sci-fi, harrypotter, kidlit, fantasy-literature 2. wellness, spirituality, self-empowerment, Yoga 3. nightlife, travel, adventures, dance, singles	
top 5 event recommendations	7466, 8994, 10298, 13200, 16194 (harrypotter, sci-fi, Yoga, book-club, hiking)	Yes,Yes,Yes,Yes,Yes

5 Summary and Future Work

In this paper, we presented Collaborative filtering based Hierarchical Bayesian Model that exploits event tag information, user interactions and user group memberships to learn group preferences and to recommend personalized group events. Our experiments on Meetup datasets showed that our model consistently outperforms the state-of-the-art group recommmender systems. Our framework models the group dynamics and allows us to address cold-start recommendation for new events. For our future work, we will study how to leverage online social network structure for improving group-event recommendations. We will study the impact of model parameters and investigate how to make our algorithms scalable to the ever-growing EBSNs.

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