Hybrid Deep Framework for Group Event Recommendation

RUICHANG LI, HONGLEI ZHU, LIAO FAN, AND XUEKUN SONG

School of Information Technology, Henan University of Chinese Medicine, Zhengzhou 450046, China

Corresponding author: Ruichang Li (lrchang@126.com)

ABSTRACT Group recommender systems suggesting items for a group of users have received many attentions recently. Some aggregation-based and model-based group recommendation methods have been proposed. However, the cold-start problem in group recommendation has not been well studied, which limits the application of group recommendation in many important domains, such as recommending offline events for a group of users. In this paper, we propose a new hybrid deep framework to solve cold-start problem of group event recommendation. Our framework incorporates multiple Restricted Boltzmann Machines (RBM) and conditional RBM. The former extracts high latent group preference from user feedback and group feedback. The latter obtains latent event features based on contextual information, such as location and organizer of events. Thus, the hybrid deep framework can utilize user feedback and contextual information of events to overcome cold-start problem. We conduct exhaustive experiments on two real-world datasets and the results show that our proposed framework outperforms the baseline group recommendation methods and alleviates the cold-start problem of group event recommendation effectively.

INDEX TERMS Group recommendation, hybrid recommendation, cold-start problem, restricted Boltzmann machines, deep belief networks.

I. INTRODUCTION

In recent years, event-based social networks (EBSNs), such as Meetup[1] and Douban Event[2], have increased rapidly. EBSNs combine online social relations with offline social relations by allowing users to create and participate offline events. However, there are many events distributed on EBSNs every day, which makes it difficult to find the events attracting users. To overcome this problem, event recommendation aiming to find the events that are most likely to be of interest to users are proposed. Recently, event recommendation have become one of hottest topics in recommender systems domain [1]–[4]. Because the candidate events are always in the future and have not received any feedback from users, the main challenge of event recommendation is the new items cold-start problem. Therefore, traditional collaborative filtering (CF) techniques are ineffective for alleviating the cold-start problem of event recommendation. The previous study on event recommendation utilizes

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[1] https://www.meetup.com

[2] https://beijing.douban.com/

various contextual information, e.g., time, location, organizer of event, to alleviate the cold-start problem in event recommendation.

Most of existing works only focus on recommending events for individual users and ignore that users often attend events as a member of group, e.g., watching event with friends, going to picnic with families. Therefore, we need to recommend events for a group of users, called group event recommendation. Because individual-based recommendation techniques can not be used to generate recommendations for groups directly, group recommender systems in many other domains have been studied [5]–[9]. The basic idea of GRSs is aggregating group members' preferences into group preferences and the aggregation-based methods can be divided into two categories: 1) preference aggregation (PA) methods first aggregate members' ratings into group profile, then using CF approach to groups [9], [10]; 2) recommendation aggregation (RA) methods first generate recommendations for members, then aggregate these recommendations list for group [5], [11]. Aggregation-based methods overlook the interactions among group members and lack the capability to build a good representation of the group preferences. To overcome this problem of aggregation-based methods,

some model-based methods are proposed recently [7], [8], [12], [13]. The hottest techniques, such as deep learning and representation learning, are exploited to learn group preferences based on interactions among group members. However, the cold-start problem in group recommendation has not been well studied.

In this paper, we propose a hybrid deep framework based on RBMs to overcome this challenge in group event recommendation. The proposed deep framework consists two parts. The first part includes two connected RBMs, which are used to learn latent group preferences based on both group members' feedback and group feedback. To alleviate cold-start problem of group event recommendation, we construct a conditional RBMs (CRBMs) connected with the two RBMs in the second part. The CRBMs can learn events features from low-level interaction between users and additional contextual information of events, such as organizers, location and textual information. Because CRBMs and two RBMs are connected as a unit model, the latent high-level features of events and user feedback can be used to jointly model group preferences. In summary, our main contributions include:

- We propose a hybrid deep framework based on RBMs and CRBMs to exploit additional information to alleviate cold-start problem in group event recommendation.
- We propose new training and prediction methods for proposed hybrid deep framework.
- We conduct comprehensive experiments on two real-world EBSNs datasets. The results show that our proposed framework outperforms baseline methods for groups with different sizes.

The remainder of this paper is arranged as follows. In section II provides an overview of related work. Section III formulates the problem and introduce the background of RBM. Section IV details hybrid deep framework, training method and group event recommendation method based on the hybrid deep framework. We report experimental results and discussion in section V, then conclude the paper in section VI.

II. RELATED WORK

The most popular group recommendation methods are based on aggregation. Yu *et al*. [9] build group preference model for each feature of TV programs. Pera and Ng [10] aggregate movie tags given by group members to construct group model and exploit content-based method to generate recommendation. Some aggregation strategies are adopted in both PA and RA methods, such as average [8], [9], least misery [5], average without misery [6], most respected person [6] and most pleasure [14]. Some experiments results show that the influence of the aggregation method on the effective of group recommendation is largely dependent on the individual-based algorithm and aggregation strategy [6]. Moreover, aggregation-based methods still have some problem: 1) RA methods trade each group member individually and ignore interaction between them. 2) Group preference

model may be hard to construct effectively by aggregating preferences due to sparsity of user feedback.

In recent years, some model-based methods are proposed to model the interaction between group members [7], [8]. Ye *et al.* [15] propose a generative model to consider social influence in group recommendation. Yuan *et al.* [8] propose a probabilistic model to describe the generative process of group activities and make group recommendation. DLGR [7] exploits multiple RBMs [16] to learn group features, which are abstract representation of group preference, from low-level member features and take advantage of group features as the priors to model the probability of making each group choice. To overcome the data sensitivity of traditional aggregation strategy based on heuristic method, Cao *et al.* [17] incorporate attention network into neural collaborative filtering to learn the weight for each member-item pair from data automatically.

With popularity of event-based social networks, event recommendation has become one of hottest topics in recommendation domain recently [1], [3], [18], [19]. Some works recommend events only based on traditional CF approach and not consider events cold-start problem derived by new events [3]. Quercia *et al.* [19] focus on user cold-start problem rather than new events problem. Minkov *et al.* [18] combine collaborative method with content-based method based on RankSVM to solve events cold-start problem. Macedo *et al.* exploit context information such as social relation, location, content and time, to overcome events cold-start problem in EBSNs. However, recommending events for a group of users who want to attend together has not been well studied. Liu *et al.* [12] propose a topic model to explore social influence for group recommendation and conduct experiments on a EBSNs dataset. Yuan *et al.* [8] indicate the assumption of Liu *et al.* [12] may be not true in some cases and propose another topic model for general group recommendation and evaluate the model on EBSNs dataset. These studies only focus on group modeling and ignore the cold-start problem in group event recommendation.

III. PRELIMINARIES

In this section, we first formulate the group event recommendation problem and introduce some key concepts in this paper. Then, we give a brief review on RBMs which are used to build our hybrid deep framework.

A. PROBLEM SETTING

Let $U = \{u_1, u_2, \cdots, u_{|U|}\}$ be a set of users, $G = \{g_1, g_2, \cdots, g_{|G|}\}$ be a set of groups, where $g_i \subset U$. $C = \{c_1, c_2, \cdots, c_{|C|}\}$ denotes a set of events. The history events is denoted as $C_{old} \subset C$ and $C_{new} \subset C$ represents the future events. For each event $c \in C$, there is an organizer $o_c \in O$ and a venue $v_c \in V$ associated with event c. Moreover, there is a set of words $W_c \subset W$ describing the event c. The goal of group event recommendation is to generate a list of future events for a given target group g. Because there are no user feedback to future events, the traditional collaborative

FIGURE 1. Cold-start problem in event recommendation.

FIGURE 2. A graphical depiction of an RBM.

filtering method faces cold-start problem, shown in Figure 1. It is intuitive to exploit user feedback, such as attendance records, and additional information of events to construct an effective predictive model.

B. RBM
RBM is an energy-based model which has binary visible layer units $v \in \{0, 1\}^M$ and binary hidden layer units $h \in \{0, 1\}^N$ in general. RBM can be represented by undirected graph where connections only exist between visible layer units and hidden layer units, shown in Figure 2. The joint distribution of units v and h is defined through an energy function as follows.

$$P(v, h) = \frac{e^{-E(v,h)}}{Z} \tag{1}$$

where Z is normalization constant and $E(v, h)$ is an energy function defined as:

$$E(v, h) = -a^T v - b^T h - v^T W h \tag{2}$$

where $W \in \mathbb{R}^{M \times N}$ is weight matrix of connections between v and h. $a \in \mathbb{R}^M$ and $b \in \mathbb{R}^N$ are biases of visible units v and hidden units h respectively. The conditional distributions, also known as active function, for visible units and hidden units can be easily derived from joint distribution of them as follows.

$$P(v_i = 1|h) = s(a_i + \sum_{j=1}^{N} W_{ij} h_j) \tag{3}$$

$$P(h_j = 1|v) = s(b_j + \sum_{i=1}^{M} v_i W_{ij}) \tag{4}$$

where $s(x) = 1/1 + e^{-x}$ is the logistical function. The model parameters $\theta = \{W, a, b\}$ can be estimated by maximizing log-likelihood given training data $v^{(i)}$.

$$-\langle \frac{\delta E(v^{(i)}, h)}{\delta \theta} \rangle_{P(h|v^{(i)})} + \langle \frac{\delta E(v, h)}{\delta \theta} \rangle_{P(v,h)} \tag{5}$$

where $\langle . \rangle_P$ denote the expectation with respect to the distribution P. Because computing the second term in Equation 5 is very hard, Hinton [20] proposed contrastive divergence (CD) to approximate the expectation with a short k-step Gibbs sampling, called CD_k. Furthermore, RBM can be generalized to Gaussian RBM (GRBM) that can model real-value data.
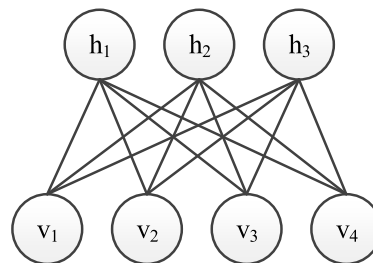
IV. HYBRID DEEP FRAMEWORK
Model-based group recommendation methods [7], [8], [15] model group preference more accurately than aggregation-based methods by considering interaction between group members. However, these existing methods have not been applied to group event recommendation, because of the cold-start problem where the events recommended to users have not received any responses from users. To overcome this issue, we propose a hybrid deep framework based on RBMs and conditional RBMs, shown in Figure 3. This framework can learn high-level features from additional information about events and high-level group features from group member feedback for recommending future events for groups.

A. MODELING EVENT FEATURES BASED ON CONTEXT AND GROUP PROFILE
To address the cold-start problem lead by new events, various contextual information about events can be used to extract event features, such as organizers, venues, start time and textual content of events. The existing study [21] shows that a user who has attended an event organized by an organizer will be more likely to attend the future events that organized by the same organizer. In addition, the user may not want to attend this new event, because the location where the event will be held in is far away from the user's home. Note that each organizer can create many events and more than one event can be held in the same venue at different times in EBSNs. In other words, there are many-to-many relationship between organizers and events, and one-to-many relationship between venues and events. Therefore, we take the organizers and venues of events into account to find a bridge from new events to history events. Then we can predict group preference to new events through the bridge.

Different from models proposed in [7], [22], where they construct user-based RBM by using visible units to represent user feedback and the hidden units to represent the abstract user preference, we construct an item-based RBM [23], where the hidden units denote the event features and visible units denote group profiles, i.e., groups that attend the event. Because this model only considers the interactions between groups and events, we call this item-based RBM as collaborative group model. However, this model can not alleviate the cold-start problem and ignore the group decision process, i.e., the contribution of each group member to the

group decision should be considered. Therefore, we design other two item-based RBMs with Gaussian visible units and binary hidden units, known as Gaussian-Bernoulli RBMs (GBRBMs), to exploit venue and organizer information, respectively. These GBRBMs is called contextual models, because the models are used to extract contextual features. The hidden units of contextual models denote the venue features and organizer features. The visible units denote the venue and the organizer associated with the event, shown as event-venue matrix and event-organizer matrix in Figure 3.
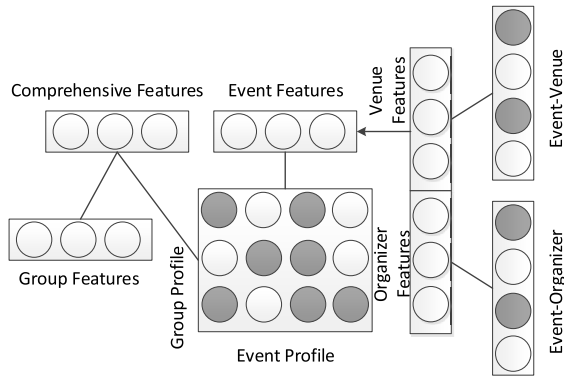

FIGURE 3. Hybrid deep framework for group event recommendation.

Different with the standard RBMs described in previous section, the energy function of GBRBMs is defined as follow.

$$E(v, h) = \sum_{i=1}^{M} \frac{(v_i - a_i)^2}{2\sigma_i^2} - \sum_{j=1}^{N} b_j h_j - \sum_{i=1}^{M} \sum_{j=1}^{N} v_i W_{ij} h_j \quad (6)$$

where $v \in \mathbb{R}^M$ denotes the visible units. In our problem, v can be a row of user-venue matrix or user-organizer matrix. a and b are biases of visible units v and hidden units h respectively, σ^2 is variance of Gaussian distribution of visible units. $W \in \mathbb{R}^{M \times N}$ encodes the interaction between visible units and hidden units. We can also easily derive the conditional distributions w.r.t each visible unit and each hidden unit.

$$P(v_i|h) = \mathcal{N}(\sigma_i \sum_{j=1}^{N} W_{ij} h_j, \sigma_i^2) \quad (7)$$

$$P(h_j|v) = s(b_j + \sum_{i=1}^{M} W_{ij} v_i / \sigma) \quad (8)$$

where $\mathcal{N}(x, \sigma^2)$ denotes Gaussian distribution with mean x and variance σ^2. In practice, we use mean x to estimate the value of visible units for given the states of hidden units instead of random sampling from Gaussian distribution to avoid sampling noise [24]. According to energy function and conditional distributions, the update rule of GBRBM parameters $\theta = \{W, a, b\}$ for one training sample using CD_k can be derived as follow.

$$\Delta W_{ij} = v_i^{(0)} P(h_j = 1|v)^{(0)} / \sigma_i - v_i^{(k)} P(h_j = 1|v)^{(k)} / \sigma_i \quad (9)$$

$$\Delta a_i = v_i^{(0)} / \sigma_i^2 - v_i^{(k)} / \sigma_i^2 \quad (10)$$

$$\Delta b_j = P(h_j = 1|v)^{(0)} - P(h_j = 1|v)^{(k)} \quad (11)$$

Note that we trade σ as a constant instead of learning it as other parameters in θ. In our experiments, the model achieves best performance when we set $\sigma = 1$.

When the organizer features and venue features are learned by contextual model, the two features are combined with collaborative group model to construct a conditional RBM [22], which has been proved that it is very useful to overcome cold-start problem in recommender systems [25]. Specifically, we use binary vector q to denote the organizer feature of each event and use d to denote the venue feature of each event. The energy function of joint distribution over (v, h) condition on binary vector $f = (q, d)$, called contextual features, is defined as follows.

$$E(r, e, f) = \frac{||r - a||^2}{2\sigma^2} - r^T Y e - m^T e - f^T Z e \quad (12)$$

where $r \in \{0, 1\}^{|G|}$ event profile of each event where $r_g = 1$ if group g attended the event, $r_g = 0$ otherwise. σ is the bias of event profile r and m is the bias of hidden event features e. $Y \in \mathbb{R}^{M \times E}$ encodes the interaction between event profile r and event features e. $Z \in \mathbb{R}^{F \times E}$ encodes the interaction between contextual features f and event features e.

B. JOINT MODELING EVENT FEATURES AND GROUP FEATURES

The model described above aims to alleviate cold-start problem of group event recommendation. However, this model only exploit event profile and ignore the interaction between group members and events. To solve this problem, we construct a non-IID hybrid RBM to combine CRBM described in the last section and dual-wing RBM [7], which jointly models group profile and group features using a two-layer collective DBN. As illustrated in Figure 3, one wing of dual-wing RBM is connected to group profile and another wing is connected to group features which are learned from the lower member features. Note that group profile and event profile are column and row of group-event interaction matrix, respectively. Specifically, given a group-event interaction matrix $\Phi \in \{0, 1\}^{|G| \times |C|}$, group profile $t_g \in \{0, 1\}^{|C|}$ of group g is the g-th row of Φ and event profile $r_c \in \{0, 1\}^{|C|}$ of event c is the c-th column of Φ. More details about group features are described in [7]. Let h be the comprehensive features and c be the group features. The energy function of our proposed hybrid deep framework is defined as follow.

$$\begin{aligned} E(c, t, r, h, e, f) \\ = \frac{||r - a||^2}{2\sigma^2} - t^T W h + \frac{||t - \delta||}{2\beta^2} - b^T c \\ - c^T X h - d^T h - r^T Y e - m^T e - f^T Z e \quad (13) \end{aligned}$$

where W encodes the interaction between group profile t and comprehensive features h, and X encodes the interaction between group features c and comprehensive features h. b, d and δ are biases of group features c, comprehensive features h and group profile t, respectively. β is standard deviation of Gaussian visible units r. According to this energy function,

we can easily obtain the conditional distribution w.r.t each group profile t_j, each event profile r_i, each comprehensive feature h_k and each event feature e_l, respectively.

$$P(h_k = 1|c,t) = s(d_k + \sum_{j=1}^{D} c_j X_{jk} + \sum_{i=1}^{M} t_i W_{ik}/\sigma_i) \quad (14)$$

$$P(r_i = 1|e) = \mathcal{N}(a_i + \sigma_i \sum_{l=1}^{E} e_l Y_{i,l}, \sigma_i^2) \quad (15)$$

$$P(t_j = 1|h) = \mathcal{N}(\delta_j + \beta_j \sum_{k=1}^{E} h_k W_{j,k}, \beta_j^2) \quad (16)$$

$$P(e_l = 1|r,f) = s(m_l + \sum_{i=1}^{M} r_i Y_{il}/\sigma_i + \sum_{q=1}^{F} f_q Z_{ql}) \quad (17)$$

Given a group profile, member profile and contextual information of events, i.e., organizer and venue, the goal of model training is to estimate the set of model parameters $\Theta = \{W, X, Y, Z, a, \delta, d, m, f\}$. We exploit greedy layer-wise training based on CD as demonstrated in the previous subsection.

C. RECOMMENDATION FOR GROUP

When model parameters are learned, we can reconstruct the group profile and event profile as follow.

$$\hat{h}_j = s(b^h + \sum_{i=1}^{D} c_i X_{ij} + \sum_{k=1}^{M} r_k W_{kj}/\sigma_k) \quad (18)$$

$$\hat{e}_p = s(b_p^e + \sum_{i=1}^{M} r_i Y_{ip} + \sum_{j=1}^{F} f_j Z_{jp}) \quad (19)$$

$$P(r_i = 1|e) = \mathcal{N}(a_i + \sigma_i \sum_{l=1}^{E} \hat{e}_l Y_{i,l}, \sigma_i^2) \quad (20)$$

$$P(t_j = 1|h) = \mathcal{N}(\delta_j + \beta_j \sum_{k=1}^{E} \hat{h}_k W_{j,k}, \beta_j^2) \quad (21)$$

The ranking score of group g and event c is defined as $S_{g,e} = 1/2(t_{g,e} + r_{e,g})$. Then we rank the recommendation events C_g for a given group g by sorting their ranking score $S_{g,e}$ to generate top-k recommendation list.

V. EXPERIMENTS

In this section, we first introduce the experimental settings. Then, we report and discuss the experimental results.

A. EXPERIMENTAL SETTINGS

1) DATASETS

Our experiments are conducted on two real world EBSNs datasets collected from Meetup and Douban Event, respectively. EBSNs provide an online platform for users to organize, find and participate offline events. For an event distributed on EBSNs, users can provide feedback to it with RSVP, where "Yes" denotes users want to attend the

TABLE 1. The statistics of EBSNs datasets.

Dataset	Douban Event		Meetup	
City	Beijing	Shanghai	Chicago	Phoenix
#Users	1146	3204	1976	1048
#Events	1050	2286	23882	13702
#Organizers	390	758	722	369
#Venues	539	1055	1813	922
#RSVPs	10697	28123	54798	30089
#Groups	10000	10000	10000	10000
Avg. #Events per group	5.5	10.02	2.96	5.15
Sparsity	99.11%	99.62%	99.88%	99.79%

event or "No" represents users do not attend the event. The Meetup dataset [1] is collected from January, 2010 to April, 2014 based on the Meetup REST API. For Meetup dataset, we only select the events held in Chicago and Phoenix for our experiments. We exploit Douban API to collect the information of events held in Beijing and Shanghai from September, 2016 to June, 2017. For each event in two datasets, we obtain its contextual information including organizer, participants, venue and start time. To reduce the sparsity of datasets, data preprocessing is conducted before experiments. For Douban Event dataset, we extract the events that are held between September, 2016 and December, 2016. For Meetup dataset, the events held between January, 2013 to December, 2014 are considered for experiments. Moreover, the users who attended less than 10 events are removed to reduce noisy data. Table 1 shows basic statistics of Meetup dataset and Douban Event dataset.

2) EVALUATION METHOD

As we discussed in the previous sections, the main challenge of event recommendation is to alleviate cold-start problem, where the events to be recommended are always in the future and have received few feedback from users. Therefore, our experiments are designed to evaluate the effectiveness of our approach and baseline methods in the cold-start scenario of group event recommendation. To simulate the realistic group event recommendation scenario, a time dependent cross-validation method is exploited following [21]. Specifically, the events are sorted chronologically based on their start time. Then, events are divided into four parts evenly based on event start time and 3-fold time-dependent cross validation can be conducted as follows. In the first validation, the first part of data is used for training and the rest of data is used for test. In the second validation, the first two parts of data are used for training and the last two parts are used for test. In the third validation, the first three parts of data are used for training and the last part is used for test. Because the training data of latter validation is more sparse than that of previous validation, we can evaluate the effectiveness of recommendation methods on datasets with different data sparsity.

Because there are very few group information included in the most of datasets, we create some synthetic groups for our evaluation experiments. This is a common setting in many group recommendation studies [8], [10], [11], [26].
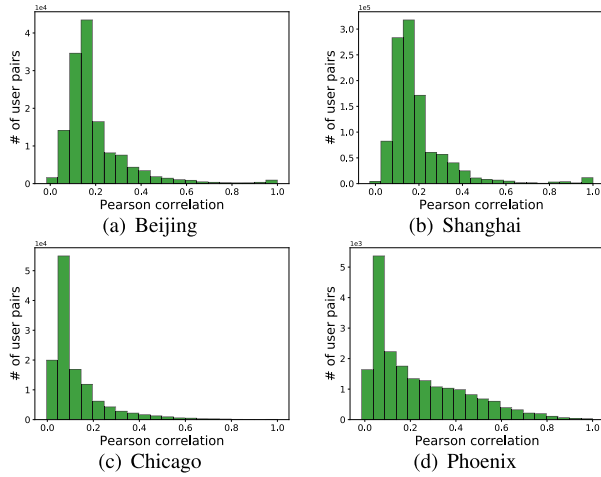
FIGURE 4. User-to-user similarity.

The synthetic groups can be divided into three categories: random groups, high similarity groups and low similarity groups. Because generating groups by selecting users randomly may be difficult to find enough groups due to the exceeding sparsity of EBSNs datasets, we generate synthetic groups based on the similarity between users following [11], where Pearson correlation coefficient (PCC) is used to measure the user-to-user similarity. The distributions of user-to-user similarity in Beijing, Shanghai, Chicago and Phoenix are shown in Figs. 4a, 4b, 4c and 4d, respectively. To generate enough groups, we set a certain threshold of user-to-user similarity and create high similarity groups where the similarities between members are higher than the threshold. Our threshold is set to the average of user-to-user similarity following [27]. Then, the thresholds of Beijing, Shanghai, Chicago and Phoenix are set to 0.197, 0.192, 0.128 and 0.233, respectively. Finally, we set the number of group members (i.e., group size) as 2, 3, 4, 5, 6, respectively, and generate 2000 groups for each group size and each dataset. Because it is not common scenario in the real world that very large group attend events and it is difficult to find enough groups containing more than 6 members, the the size of largest synthetic group is limited to 6.

We employ Recall and Normalized Discounted Cumulative Gain (NDCG) to evaluate the effectiveness of group event recommendation methods in our experiments. Recall and NDCG are popular metrics for evaluating recommender systems and have been widely used to measure the effectiveness of group recommendation [10], [11], [26]. We do not adopt Precision to evaluate our model, because Precision is defined as the proportion of relevant events in recommendation lists and misses unknown positives [28], [29]. Specifically, Recall@k and NDCG@k, which measure the Recall and NDCG of a group event recommendation method that produces a list of k events for each group respectively, are computed as follows.

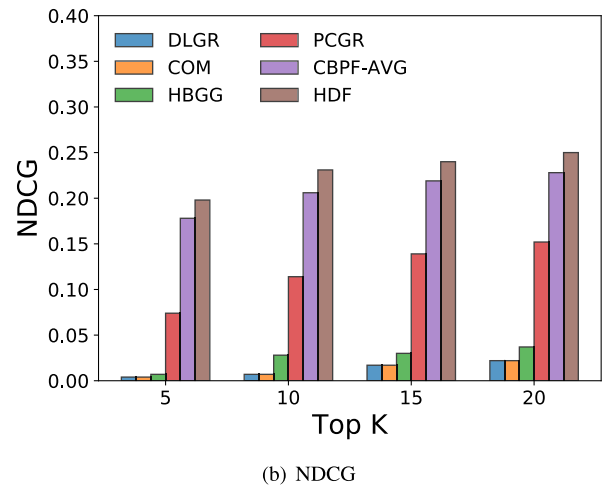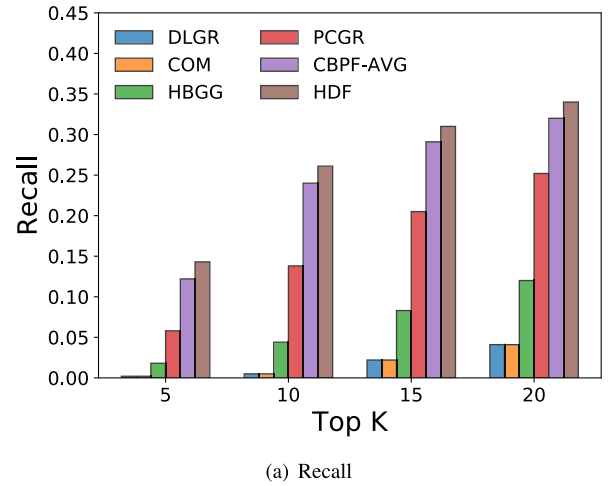$$Recall@k = \frac{|R_k \cap T|}{|T|}, \quad (22)$$

(a) Recall

(b) NDCG

FIGURE 5. Top-k performance on Beijing dataset.

where R_k denotes the set of events in the recommendation list, T is the set of events in the test set.

$$DCG@k = rel_1 + \sum_{i=2}^{k} \frac{rel_i}{log(i+1)}, \quad (23)$$

$$NDCG@k = \frac{DCG@k}{IDCG@k}, \quad (24)$$

where rel_i is the graded relevance of the event at position i in the recommendation list. If the event at position i in the recommendation list appears in the test set of the group, we have $rel_i = 1$, otherwise, we have $rel_i = 0$. IDCG@k is the maximum DCG@k value of all possible recommendation lists containing k events. The higher Recall@k and NDCG@k indicate the better performance of group event recommendation. The final evaluation metrics are defined as the average of Recall@k and NDCG@k for all groups, respectively.

B. COMPARISON METHODS
We compare our hybrid deep framework with some group event recommendation methods and other competitive
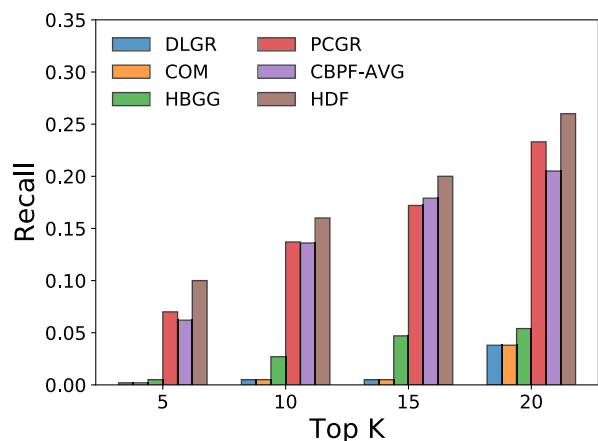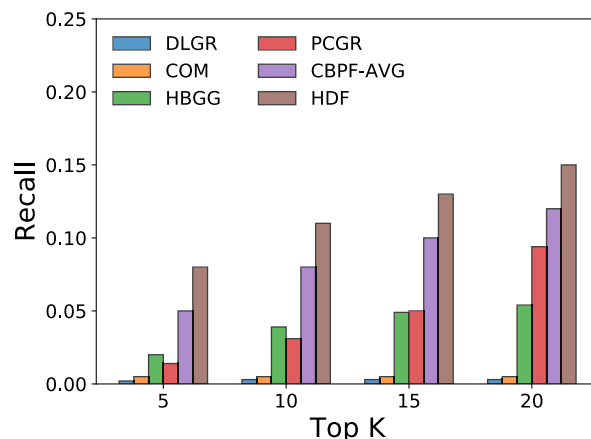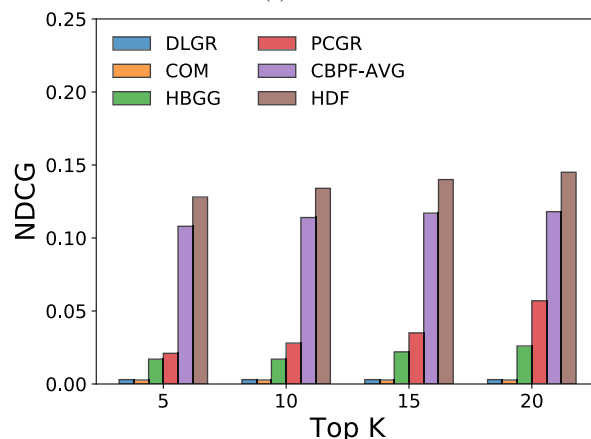
(a) Recall
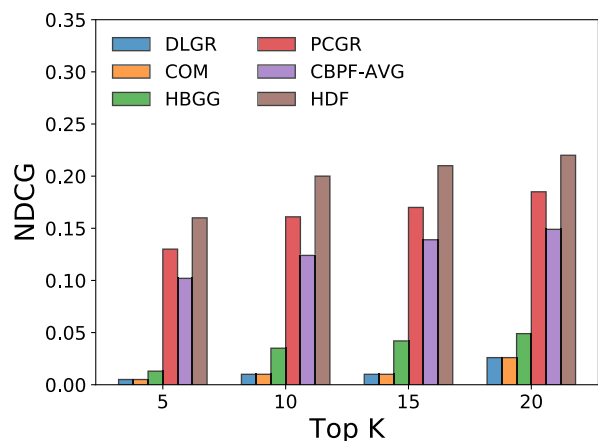
(b) NDCG

FIGURE 6. Top-k performance on Shanghai dataset.

(a) Recall

(b) NDCG

FIGURE 7. Top-k performance on Chicago dataset.

recommendation approaches that are not developed to suggest events for a group of users, because group event recommendation task has not been well studied in the existing literature. Moreover, personalized event recommendation methods [2] can be compared with our approach by adopting some aggregation strategies [6] to incorporate recommendations for individual users into recommendations for the whole group. We evaluate and compare following approaches in our experiments.

- DLGR [7] is a group recommendation model based on collective deep belief networks, where the high-level features can be extracted from lower-level features and used to represent more complex group preference than other aggregation-based group recommendation methods.
- COM [8] is a probabilistic generative model for group recommendation. It assumes that the group decision making process is based on group topics and individual choice. Moreover, the content information can be incorporated into COM via prior distribution. In our experiments, geographical information is incorporated into COM for our group event recommendation task.

- PCGR [30] aims to recommend events and locations for a group of users. It considers content information of events and locations based on collaborative topic regression [31], which joint models latent Dirichlet allocation and matrix factorization.
- HBGG [32] is developed to recommend locations for a group of users. HBGG is a topic model which considers group geographical topic, group mobility regions and social information. In our experiments, we use HBGG to recommend events for a group of users through replacing geographical coordinates of locations by geographical coordinates of events.
- *CBPF* [2] adopts Bayesian Poisson factorization as basic unit to model contextual information, such as social relation, venue, organizer and textual content of event, respectively. Then units are connected through collective matrix factorization. Because CBPF is developed for individual users, we combine individual recommendations produced by CBPF to generate group recommendations via average aggregation strategies and this method is called CBPF-AVG.
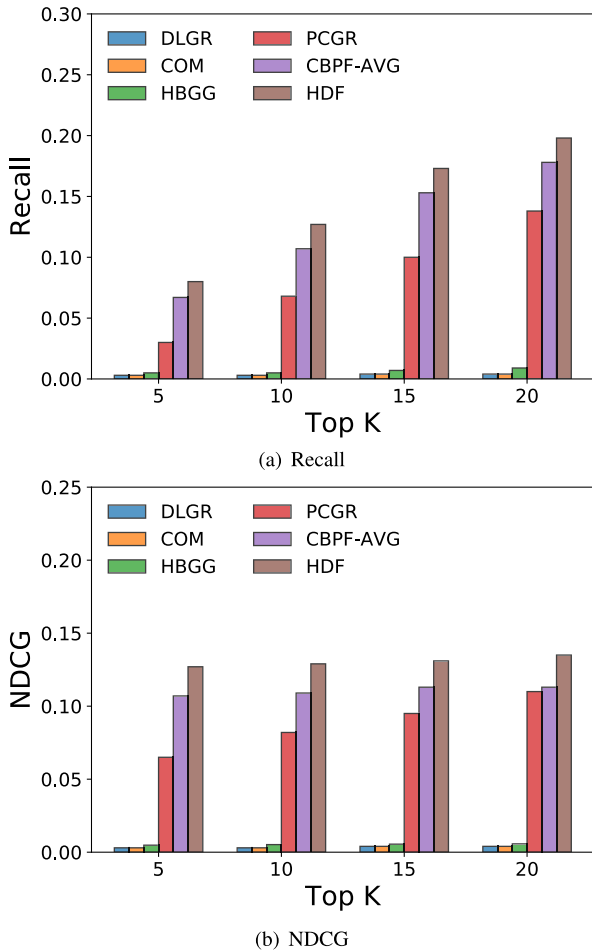- HDF is our proposed hybrid deep framework.

(a) Recall

(b) NDCG

FIGURE 8. Top-k performance on Phoenix dataset.

(a) Recall@10

(b) NDCG@10

FIGURE 9. Impact of different size of groups on Beijing dataset.

C. RECOMMENDATION EFFECTIVENESS

In this subsection, we report and discuss the effectiveness of our hybrid deep framework and other group event recommendation methods with well-turn parameters on two datasets. The Recall and NDCG scores of approaches on Beijing, Shanghai, Chicago and Phoenix datasets are shown in Figs. 5, 6, 7 and 8, respectively. We only show the Recall@k and NDCG@k scores when k is set to 5,10,15,20, because users only focus on several top events and longer recommendation lists are usually ignored for top-k recommendation [8], [21], [33].

Figs. 5a and 5b show Recall and NDCG values on Beijing dataset, respectively. We can observe that Recall@10 and NDCG@10 of HDF are about 0.261 and 0.231 and our proposed HDF outperforms other comparison methods. The improvements, in terms of Recall@10, are 51.2, 51.2, 4.93, 0.89, 0.088 compared with DLGR, COM, HBGG, PCGR and CBPF-AVG, respectively. There are some discussions about observations: 1) HDF achieves higher recommendation performance than HBGG and PCGR, showing the benefit of incorporating additional contextual information, i.e., organizer and venue, by hybrid deep framework. 2) The performance gap between HDF and CBPF-AVG indicates that the
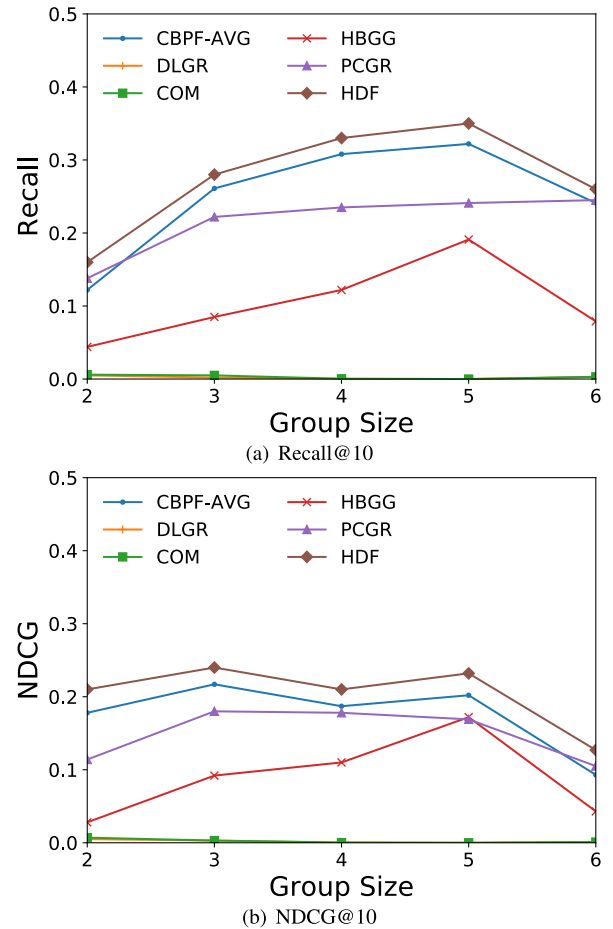
superiority of hybrid structure of HDF over traditional aggregation strategy, which is adopted in CBPF-AVG. 3) Among comparison methods, CBPF-AVG outperforms other baseline approaches. The reason is that CBPF-AVG jointly models multiple contextual factors including social relations, organizer and venue, while COM and HBGG only incorporate geographical influence of venue, and PCGR only considers the textual content of events. We can observe similar results, where HDF performs better than other baseline methods, from Figs. 6a and 6b showing the Recall and NDCG values on Shanghai dataset, respectively.

Figs. 7 and 8 show experiments results on Chicago and Phoenix datasets, respectively. We can observe that the comparison results are similar to the results on Beijing and Shanghai datasets. The main difference is that all methods achieve lower performance on Meetup dataset than Douban Event dataset. For example, HDF achieves 0.12 and 0.135 Recall@10 values on Chicago and Phoenix datasets, respectively, while HDF achieves 0.261 and 0.16 Recall@10 values on Beijing and Shanghai datasets, respectively. The possible reason is that user attendance records in Meetup dataset are more sparse than that in Douban Event dataset. Table 1 shows that the sparsity of Chicago
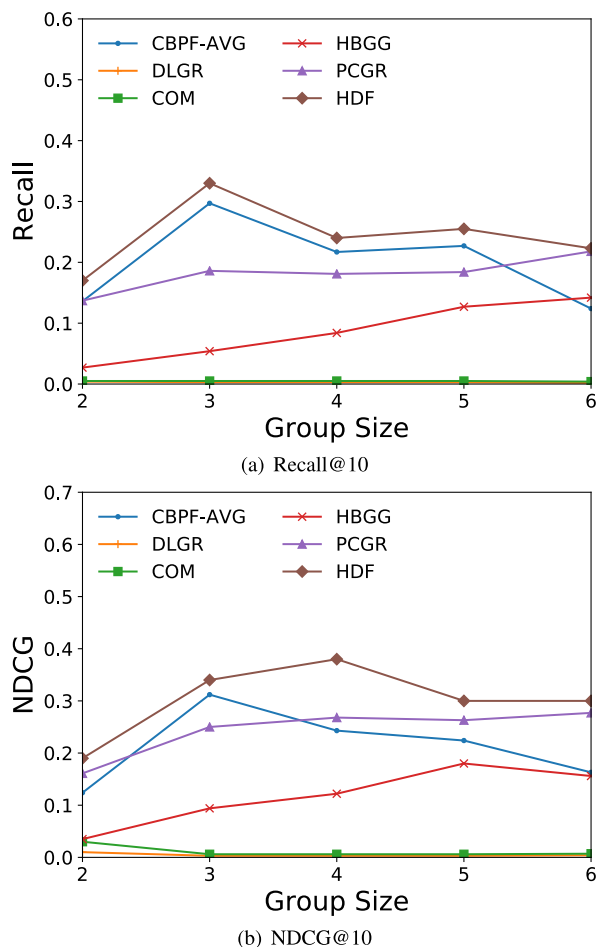
(a) Recall@10

(b) NDCG@10

FIGURE 10. Impact of different size of groups on Shanghai dataset.

dataset is 99.88 percent which is higher than 99.11 percent sparsity of Beijing dataset). We also observe that COM, HBGG and PCGR perform worse on more sparse dataset due to they consider fewer contextual information.

D. PERFORMANCE FOR DIFFERENT SIZE OF GROUPS

In this subsection, we evaluate the influence of different size of groups on group event recommendation. The Recall@10 and NDCG@10 values for group event recommendation methods on Beijing and Shanghai datasets are reported in Figs. 9 and 10, respectively. We first observe that HDF outperforms other baselines regardless of the size of groups on the two datasets in terms of Recall@10 and NDCG@10. The performance improvement of HDF over other methods decreases when group size is 6. The possible reason is that the group decision making process is very complex for large groups and it is difficult to model group preference by existing methods. Among baselines, CBPF-AVG achieves highest Recall@10 and NDCG@10 in most cases. Moreover, PCGR outperforms other two model-based methods, i.e., COM and HBGG, demonstrating that considering content information is more effective than modeling group mobility region and geographical influence for group event

recommendation task. We also observe that the recommendation performance does not decrease significantly for large groups. This is because the synthetic groups in our experiments are generated based on user-to-user similarity and the members in each group have similar interests.

VI. CONCLUSION

Recommending events for a group of users plays an important role in EBSNs. However, the inherent cold-start problem of group event recommendation has not been well studied. In this paper, we presented a hybrid deep framework based on RBM and conditional RBM, which exploits additional contextual information of events to addressing cold-start problem for group event recommendation. In particular, the special structure can combine event features learned by conditional RBM with group features which can be learn by *DLGR* model. The experimental results on two real-world EBSNs datasets show that our proposed HDF outperforms the state-of-the-art group event recommendation methods. In the future, we plan to exploit more contextual information and explore deeper network structure to improve recommendation performance.

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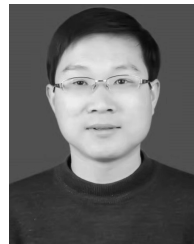
RUICHANG LI was born in 1982. He received the bachelor's and master's degrees in computer science from the Zhengzhou University of Light Industry, in 2006 and 2010, respectively. He currently works with the School of Information Technology, Henan University of Chinese Medicine. His current research interests include data mining, data stream computing, and recommendation systems.

HONGLEI ZHU was born in 1983. He received the master's degree in computer science and technology from Henan Polytechnic University, Henan, China, in 2010. He is currently pursuing the Ph.D. degree in computer science and technology with the State key Laboratory of Networking and Switching Technology, Beijing University of Posts and Telecommunications. He was with the School of Information Technology, Henan University of Chinese Medicine. His research interests include software testing and service computing.

LIAO FAN was born in Huangshi, in 1985. He is currently an Associate Professor with the Henan University of Traditional Chinese Medicine, mainly involved in the research of data mining and flow data management.

XUEKUN SONG was born in Yongcheng, Henan, in 1982. He received the Ph.D. degree in biomedical engineering. He was with the School of Information Technology, Henan University of Chinese Medicine. He is currently an Associate Professor of computer science. His main research area is data mining.

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