Overcoming Data Sparsity in Group Recommendation

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Abstract—it has been an important task for recommender systems to suggest satisfying activities to a group of users in people’s daily social life. The major challenge in this task is how to aggregate personal preferences of group members to infer the decision of a group. Conventional group recommendation methods applied a predefined strategy for preference aggregation. However, these static strategies are too simple to model the real and complex process of group decision-making, especially for occasional groups which are formed ad-hoc. Moreover, group members should have non-uniform influences or weights in a group, and the weight of a user can be varied in different groups. Therefore, an ideal group recommender system should be able to accurately learn not only users’ personal preferences but also the preference aggregation strategy from data. In this paper, we propose a novel end-to-end group recommender system named CAGR (short for “Centrality-Aware Group Recommender”), which takes Bipartite Graph Embedding Model (BGEM), the self-attention mechanism and Graph Convolutional Networks (GCNs) as basic building blocks to learn group and user representations in a unified way. Specifically, we first extend BGEM to model group-item interactions, and then in order to overcome the limitation and sparsity of the interaction data generated by occasional groups, we propose a self-attentive mechanism to represent groups based on the group members. In addition, to overcome the sparsity issue of user-item interaction data, we leverage the user social networks to enhance user representation learning, obtaining centrality-aware user representations. To further alleviate the group data sparsity problem, we propose two model optimization approaches to seamlessly integrate the user representations learning process. We create three large-scale benchmark datasets and conduct extensive experiments on them. The experimental results show the superiority of our proposed CAGR by comparing it with state-of-the-art group recommender models.

Index Terms—Recommender system, network embedding, group recommendation, data sparsity

1 INTRODUCTION

As social animals, people consider group activities as essential needs for their social life. For example, families often watch TV programs together at night; friends often dine out, watch movies, attend parties and travel together. With the recent development and prevalence of smartphones and social networking services (e.g., Meetup and Facebook Events), it is becoming more convenient and easier for people to gather together to form a persistent or occasional group. It is highly urgent to develop group recommender systems to suggest relevant items/events (e.g., dining out, movie watching and parties) for a group of users, known as group recommendation. The first group recommender system MusicFX [1] was developed to recommend music to a group of gym users. Since then, group recommendation has been seen in various recommendation applications, such as tourism [2] and social events [3]. There are two types of groups: persistent and occasional groups [4, 5]. Persistent groups refer to relatively static groups with stable members and sufficient group-item interaction records [6, 7, 8, 9], such as interest-oriented groups in Meetup; while occasional groups are formed ad-hoc and users may just constitute the groups for the first time (i.e., cold-start groups) [3, 10, 11].

To make recommendations to persistent groups, each group can be treated as a virtual user and the personalized recommendation algorithms developed for individual users can be straightforwardly employed since there are sufficient persistent group-item interaction records. However, for occasional groups, their historical interaction data is extremely sparse and even unavailable. Thus, it is infeasible to directly learn the preference representation of an occasional group, and we can only learn the preferences of an occasional group by aggregating the personal preferences of its members. In this paper, we focus on a more general scenario of group recommendation, i.e., making recommendations to occasional groups, as the recommendation techniques developed for occasional groups can also be applied to persistent groups.

Group recommendation is much more challenging than making recommendations to individual users, as different group members may have different preferences. A good group recommendation system should be able to not only accurately learn users’ personal preferences, but also model how a decision or consensus among group members is reached. Prior studies [12, 13] on group recommendation systems have been focused on exploring various heuristic aggregation strategies (e.g., average, least misery and maximum pleasure) to find a consensus among group members on an item. However, all these heuristic and predefined aggregation strategies are too simple to model the real and complex process of group decision-making, leading to suboptimal group recommendation performance. Moreover, a user may exhibit different influences and have different weights in different groups. In this paper, we focus on the essential problem in group recommendation — preference aggregation, that is how to aggregate personal preferences of group members to decide a group’s choice on items.

In our previous work [14], we proposed a Social Influence-based Group Recommender (SIGR) framework. In the work,
rather than exploring new heuristic and predefined strategies, we introduced the notion of personal social influence to quantify and differentiate the contributions of group members to a group decision, and then proposed to automatically learn the social influence-based aggregation strategy from the group-item interaction data.

However, despite its success, the SIGR model suffers from the following three challenges regarding the model training, model expressiveness, and sparsity issue of user-item interaction data. In order to address these three challenges in this paper, we propose a novel solution called Centrality-Aware Group Recommender (CAGR) that significantly extends the SIGIR by improving both group and user representation learning.

**Challenge 1: End-to-end Learning.** In order to compute the social influence-based weight for each group member, SIGR first selects and extracts network features from the social network, and then takes these features as input of a deep neural network model to estimate each user’s social influence. This two-stage approach makes it infeasible to train SIGR in an end-to-end way and leads to suboptimal performance, as each stage has to be optimized separately under different criteria. In addition, it also requires extra supervision. **Challenge 2: Model Expressiveness.** SIGR utilizes a plain weighted sum operation to aggregate all raw member representations to obtain the group representation. This linear aggregation function is not expressive enough to capture the complex interactions and relations among group members and thus cannot accurately mirror the intra-group decision-making process. **Challenge 3: Data Sparsity of User-Item Interactions.** In order to overcome the data sparsity of group-item interactions, SIGR leverages the user-item interaction data. However, it ignores the sparsity issue of user-item interaction data itself which has been widely recognized in almost all recommendation datasets and also validated in our experiments. In our case, the number of events most users have attended is still far from sufficient to accurately learn user representation or embedding.

In order to address the above three challenges, we make the following new contributions in our CAGR. 1) Instead of using the social influence-based attention mechanism developed in [14], we propose to represent the group by simulating the complex interactions among its members and automatically identifying their different group-aware influences based on the self-attention mechanism [15]. This method not only significantly enhances the expressiveness of our CAGR, but also facilitates end-to-end model learning that uses a single optimization criterion for enhancing the system and requires less supervision during training. 2) In order to address the data sparsity issue of user-item interactions, we propose a novel centrality-aware graph convolution module to leverage the social network in terms of homophily and centrality [16] to enhance user representation learning. The homophily refers to the tendency that people are more likely to interact with individuals similar to themselves [17]. Due to homophily, in almost all social networks, it has been observed that neighboring users (e.g., friends) share many common or similar preferences in respect to a variety of qualities and characteristics. Meanwhile, the node centrality information is also critical because group decisions are largely influenced or even determined by the group members with high social impacts. The enhanced user representation/embedding can accurately capture both user preference and centrality information, which provides solid foundation for accurately learning group representation.

To seamlessly integrate the user-item interaction data and social network data with group-item interaction data, we propose two model optimization approaches to implement our CAGR: a two-stage optimization approach and a joint optimization approach. Specifically, the two-stage approach first learns embedding of users and items from the user-item interaction data using BGEM in the first stage, which is then utilized to initialize the user/item embedding in the second stage. We will update the user/item embedding and learn the group embedding from both group-item interaction data and social network data in the second stage. The joint approach simultaneously learns the user/item embedding and group embedding from user-item interaction data, group-item interaction data and social network data under the same optimization criteria. The key difference between these two approaches is that there are two objective functions to optimize in the two-stage approach, while there is only one unified objective function to optimize in the joint approach.

The main contributions of this paper are summarized below.

- To the best of our knowledge, we are the first work to simultaneously address the critical group-item and user-item data sparsity challenges in the group recommendation task. Specifically, we propose a novel self-attention mechanism to aggregate the member embeddings to represent a group. Furthermore, we leverage the social networks to enhance user representation learning through a centrality-aware graph convolution operation.
- We propose two model optimization approaches to leverage the user-item interaction data to overcome the limitations and alleviate the sparsity of the group-item interaction data, in which both novel positive sampling approach and negative sampling strategy are developed to advance the conventional stochastic gradient descent algorithm.
- We create three large-scale benchmark datasets for evaluating group recommendation systems, especially the recommenders that are able to make recommendations to occasional groups. Extensive experiments are conducted to evaluate the performance of our proposed CAGR, and the experimental results show its superiority by comparing with the state-of-the-art techniques.

### 2 Notations and Problem Formulation

Technically, our proposed CAGR model consists of two major components: 1) group representation learning that aggregates its member representations with self-attention mechanism on the group-item data; and 2) centrality-aware user representation learning module that overcomes the user-item data sparsity. We first present the notations and then formulate the group recommendation problem in this section.

Following the convention, we use bold capital letters (e.g., $\mathbf{X}$) to represent both matrices and graphs, squiggle capital letters (e.g., $\mathbf{\lambda}$) to denote sets, lowercase letters with superscript $^\top$ (e.g., $\mathbf{\tilde{f}}$) to denote vectors, normal lowercase letters (e.g., $x$) to denote scalars. All vectors are in column forms if not clarified.

We assume that there are a set of users $\mathcal{U}$, a set of groups $\mathcal{G}$ and a set of items $\mathcal{V}$ in the group recommender system. The $m$-th group $g_m \in \mathcal{G}$ consists of a set of users, and we use $\mathcal{G}_m$ to denote this set of users. There are three kinds of observed interaction data among $\mathcal{U}$, $\mathcal{G}$ and $\mathcal{V}$: user-item interactions, group-item interactions and user-user interactions. We use bipartite graphs $\mathbf{G}_{UV}$ and $\mathbf{G}_{GV}$ to represent user-item interactions and group-item interactions respectively, and use a general graph $\mathbf{G}_{UU}$ to denote user-user interactions, i.e., user social network. Fig.
Fig. 1: Illustration of the input data for the task of making recommendations to occasional groups, including user-item, group-item and user-user interaction data.

illustrates the input data of our group recommendation task. Then, given an occasional group \( g_m \), our task is to recommend a ranked list of items that group \( g_m \) may be interested in, which is formally defined as follows.

**Input:** A set of users \( U \), a set of groups \( G \), a set of items \( V \), group-item interactions \( G_{GV} \), user-item interactions \( G_{UV} \) and user-user interactions \( G_{UU} \).

**Output:** A personalized ranking function that maps an item to a ranking score for a target occasional group \( f_g : V \rightarrow \mathbb{R} \).

### 3 Methodologies

#### 3.1 Bipartite Graph Embedding Model

First, we introduce how to extend BGEM model \[18\], which achieves great success in the bipartite graph embedding problem \[18\], to capture the group representations based on group-item interaction data. The interactions between groups and items can be represented by a bipartite graph \( G_{GV} = (G \cup V, E_{GV}) \) where \( G \) is a set of groups and \( E_{GV} \) is a collection of edges between groups and items. If group \( g_m \) interacts with item \( v_j \), there will be an edge \( e_{mj} \) between them. As the rating information of an occasional group is rarely available, we simply set the weight on the edge \( e_{mj} \) to be 1. Given a group \( g_m \), we define the probability of \( g_m \) interacting with an item \( v_j \) as follows:

\[
p(v_j | g_m) = \frac{\exp(\vec{g}_m \cdot \vec{v}_j)}{\sum_{v_j' \in V} \exp(\vec{g}_m \cdot \vec{v}_{j'})},
\]

where \( \vec{g}_m \) is the embedding of group \( g_m \) in the latent space, and \( \vec{v}_j \) is the embedding of item \( v_j \). Following the recent word and network embedding techniques \[19\], BGEM tries to minimize the KL-divergence between the estimated neighbor probability distribution of each group \( p(\cdot | g_m) \) and the empirical distribution \( \hat{p}(\cdot | g_m) \). The empirical distribution is defined as \( \hat{p}(v_j | g_m) = \frac{w_{mj}}{d_m} \), where \( w_{mj} \) is the weight on the edge \( e_{mj} \) and \( d_m \) is the out-degree of group node \( g_m \), i.e., \( d_m = \sum_{v_j \in V} w_{mj} \).

By omitting some constants, we obtain the following objective function:

\[
O_{GV} = - \sum_{e_{mj} \in E_{GV}} w_{mj} \log p(v_j | g_m).
\]

By minimizing the above objective function, we are able to learn each group’s embedding \( \vec{g}_m \) and each item’s embedding \( \vec{v}_j \) in a low-dimensional latent space.

To achieve high efficiency in model training, BGEM adopts the approach of negative sampling technique proposed in \[19\], which samples multiple negative items to form corrupted examples (or negative edges) according to some noise distribution for each positive example \((g_m, v_j)\). The group learning objective \( O_{GV} \) can be reformulated as:

\[
O_{GV} = - \sum_{e_{mj} \in E_{GV}} w_{mj} (\log \sigma(\vec{g}_m \cdot \vec{v}_j))
\]

where \( \sigma(x) = 1/(1 + \exp(-x)) \) is the sigmoid function and \( M \) is number of corrupted (negative) examples drawn from a given noise distribution \( P_n(v) \). Following \[19\], we set the noise distribution \( P_n(v) \propto d_v^{-0.75} \), where \( d_v \) is the out-degree of item node \( v \).

#### 3.2 Self-Attentive Group Representation Learning

However, it is infeasible to directly learn the embedding of an occasional group \( \vec{g}_m \) from the group-item interaction data due to the cold-start nature of occasional groups. In contrast to persistent groups, an occasional group is defined as a number of persons who do something occasionally together, like having a dinner, watching a movie, attending a party and visiting a POI \[20\]. Its members have a common aim only in a particular moment. There are many contexts where a group of persons is not established for some shared long-term interests, but might be occasionally interested in getting together for a common aim, e.g., people attending events together or traveling together. As occasional groups are typically short-lived by definition and many new occasional groups are being created, they often have little or no historical interaction data. The group-item interaction matrix is much sparser than user-item matrix (referring to relevant statistics of three real-life datasets in Table I). The problem of cold-start groups arises naturally, and the classic group recommendation techniques \[6\], \[9\] that assume groups have ample historical interaction records would significantly underperform in this scenario.

To address the cold-start problem, we propose to learn a group’s embedding by aggregating the embedding of its members. Specifically, given an occasional group \( g_m \), its embedding is represented as follows:

\[
\vec{g}_m = f_a(\vec{u}_i | \forall u_i \in G_m),
\]

where \( f_a(.) \) is the aggregating function, \( G_m \) represents the set of users who constitute group \( g_m \) and \( \vec{u}_i \) is the embedding of group member \( u_i \). As group members have different social statuses, expertise, reputation, personality and other social factors \[21\], \[22\], they are not equal and have different social influences in the group’s decisions and choices. A user can exhibit different social influences in different groups that consist of different members. An important aspect of group activities is the need to reach consensus. In non-virtual environments, consensus results from negotiation among group members, especially those group members with low social influences are often willing to modify their initial individual opinions and compromise to satisfy the preferences of the influential members. Sometimes, a group’s preferences reflect the preferences of a few influential members (e.g., group leaders or opinion leaders) rather than the common preferences of most group members.

Motivated by this, we proposed a social influence-based group representation framework SIGR in our previous work \[14\] that adopts the linear weighted sum over the embeddings of its members as the aggregating function \( f_a(.) \):

\[
\vec{g}_m = f_a(\vec{u}_i | \forall u_i \in G_m) = \sum_{u_i \in G_m} \lambda_i \vec{u}_i,
\]
where the attention weight $\lambda_{im}$ denotes $u_i$’s social influence/weight in group $g_m$, and it also reflects how much $u_i$ contributes to the group’s decision-making. The challenge is how we can learn the attention weight $\lambda_{im}$. As occasional groups have few historical interactions on items, it is infeasible to directly learn the group-aware personal social influence $\lambda_{im}$. In [14], we introduced a non-negative latent variable to represent the global social influence of user $u_i$, which is independent from specific groups and used to compute $\lambda_{im}$ based on the vanilla attention mechanism [23]. In order to learn this global latent variable, we proposed a two-stage approach in [14]. We first precomputed both global centrality features (e.g., PageRank centrality, closeness centrality, betweenness centrality and eigenvector centrality) and local structure features of each node, and then took these network features as the input of a neural network model to estimate the global latent variable value for each user node. Note that we adopted network embedding models such as DeepWalk [24] and node2vec [25] to extract local structure features in the form of node embedding.

However, the social influence-based attention mechanism faces two major challenges. First, it is not an end-to-end solution and requires extra supervision during training, which has the risk of damaging the overall system performance. Second, it is not expressive enough to accurately model the complex intra-group interactions to infer final group decisions because it uses a plain attention mechanism to the queries, keys and values, where the weight assigned to each value is determined by the dot-product of the query with all the keys:

$$\alpha_i = \frac{\exp(\langle \tilde{u}_i, \tilde{v}_j \rangle)}{\sum_j \exp(\langle \tilde{u}_i, \tilde{v}_j \rangle)}.$$ (7)

Then the self-attention mechanism is used to compute the relevance between queries and keys, and output the mixed representations:

$$M_i = \text{Attention}(M_i^Q, M_i^K, M_i^V).$$ (8)

After that, we concatenate all those heads, and fed it through a feed-forward layer.

$$O = \text{Concat}(M_1, \ldots, M_k)W^O,$$ (9)

where $W^O \in \mathbb{R}^{d \times d}$ is a trainable matrix.

Finally, inspired by [27], we again apply the vanilla attention mechanism to the output matrix $O$ to select the influential users and form the group representation $\tilde{g}_m$:

$$\tilde{a}_i = \text{tanh}(W_s\tilde{O}_i + \tilde{b}_s),$$

$$\lambda_i = \frac{\exp(\langle \tilde{a}_i, \tilde{d}_s \rangle)}{\sum_j \exp(\langle \tilde{a}_j, \tilde{d}_s \rangle)},$$

$$\tilde{g}_m = f_s(\tilde{u}_i | \forall u_i \in G_m) = \sum_i \lambda_i \tilde{a}_i,$$ (10)

where $W_s$ and $\tilde{b}_s$ are the parameters for the feed-forward network, $\text{tanh}(\cdot)$ is the hyperbolic tangent activation function, and $\tilde{d}_s$ is the group level context vector and can be randomly initialized and jointly learned during the training process.

By introducing the aggregation function to our group representation learning, we update the basic objective function $O_{GV}$ to $O_{SGV}$ as follows:

$$O_{SGV} = - \sum_{e_{mj} \in E_{GV}} w_{mj}(\log \sigma(f_s'(\tilde{u}_i | \forall u_i \in G_m)) \cdot \tilde{v}_j) + \sum_{k=1}^{M} E_{v_k \sim P_v} [\log \sigma(-f_s'(\tilde{u}_i | \forall u_i \in G_m)) \cdot \tilde{v}_k)].$$ (11)

### 3.3 Centrality-Aware User Representation Learning

Directly optimizing the above objective function $O_{SGV}$ in Equation (11) would lead to inaccurate user and group embeddings due to the sparsity of group-item interaction data. Therefore, we propose to enhance the representation learning of users from other auxiliary data sources, which further improves the quality of group representation learning.

To alleviate the group data sparsity issue, the SIGR model [14] simply applies the BGM model [13] to the user-item interaction data to enhance user representation learning. However, this approach ignores the data sparsity issue of user-item interactions that has been widely recognized by the community of recommender systems and also evidenced by the relevant statistics in Table 1. Even though an individual user usually interacts with more items compared to a group. To address this challenge, we exploit and...
integrate the social network to further enhance user representation learning motivated by the phenomenon of assortativity in social networks [29]. On the other hand, the social networks provide strong signals about users’ global social influences [3, 21], which are critical factors for modeling the decision-making process within groups as discussed in [14]. However, current network embedding techniques including BGEM focus on capturing only the low or high-order proximity between vertices, and ignore the crucial centrality information that indicates how important/influential a user is in the social network. Therefore, it is necessary to encode both global node centrality and local neighborhood information in the social networks into the user representations via an end-to-end and computationally efficient manner. In what follows, we give a detailed description on how to enhance the user representations by exploiting and integrating the centrality information in the social network based on the GraphCSC [29] model.

Given a user-user social network $G_{UU} = (\mathcal{U}, \mathcal{E})$ where $\mathcal{U}$ and $\mathcal{E}$ are the sets of users and their social ties. Following GraphCSC, we define a graph convolution operation, whose core idea is to aggregate information from the neighborhood of a given node $i$. This procedure is listed in Algorithm 1 CONVOLVE. Specifically, in Line 1, we transform the representations of user $i$’s neighbors $\{\tilde{u}_n | \forall n \in \mathcal{N}_i\}$ through a dense neural network parameterized by the weights matrix $\mathbf{P}$ and bias vector $\mathbf{b}$, and activated by the rectified linear unit ReLU [30]. The ReLU activation function is employed due to its two advantages over the sigmoid/tanh functions. First, it enables faster convergence in the SGD optimization process [31]. Second, it does not involve expensive operation because it can be implemented by simply thresholding a matrix of activations at zero. Then we apply an aggregator/pooling function such as an element-wise mean or weighted sum on the resulting set of vectors to obtain a vector representation $\tilde{h}_i$ for the local neighborhood. In Line 2, we concatenate the aggregated neighborhood vector $\tilde{h}_i$ with user $i$’s current representation $\tilde{u}_i$ and transform the concatenated vector through another dense neural network layer parameterized by the weights matrix $\mathbf{W}$ and bias vector $\mathbf{w}$, and also activated by ReLU, where the concatenation operation instead of the average operation is employed due to its significant improvement shown in [32]. Finally, Line 3 normalizes the representations.

The output of the algorithm is a representation of node $i$ that incorporates both information about itself and its local graph neighborhood. How to select the neighbors to enhance the user representation learning is the key to the performance of this algorithm. In order to incorporate the centrality information, we sample the neighbors of a node based on their scores of a given centrality measurement $c$. Specifically, we first rank all the neighboring nodes w.r.t. $c$, then we only consider a fixed number of the top ranked nodes to perform the convolution operation. In this way, the centrality information measured by $c$ is encoded into the eventual node representations. A simplified illustration of this process is shown in Fig. 2.

Moreover, we know that different centrality measurements $c = \{c_1, c_2, \ldots\}$, we define centrality oriented views for the graph $G_{UU}$ by ordering the network vertices based on each of these centrality measurements, which enables corresponding view-specific graph convolutions. Each of these convolutions follows the aforementioned method to generate the node embeddings but with different centrality rankings to form the receptive field. We denote the user representation for user $u_i$ under the centrality-specific view associated with the measurement $c_k$ as $\tilde{u}_{i,k}$. The final robust user representation is calculated as the weighted combinations of the centrality-specific representations with coefficients as the voting weights of centrality-specific views:

$$\tilde{u}_i = \sum_{k=1}^{\left|\mathcal{C}\right|} \alpha_i^{c_k} \tilde{u}_{i,k},$$

where $\alpha_i^{c_k}$ is the weight for $\tilde{u}_{i,k}$ in view $c_k$, and is calculated via a Softmax function:

$$\alpha_i^{c_k} = \frac{\exp \left( \tilde{z}_{i} \cdot \tilde{u}_{i,k}^{c_k} \right)}{\sum_{k=1}^{\left|\mathcal{C}\right|} \exp \left( \tilde{z}_{i} \cdot \tilde{u}_{i,k}^{c_k} \right)},$$

where $\tilde{u}_{i,k}^{c_k}$ is the concatenation of all centrality-specific representations of node $i$, and $\tilde{z}$ is a trainable feature vector of centrality-specific view $c_k$, describing what centrality information has a strong impact on certain nodes. If the dot product between feature vector $\tilde{z}$ and concatenated representations $\tilde{u}_{i,k}^{c_k}$ is large, it means that centrality $c_k$ is informative for $u_i$, correspondingly, the weight of this view is relative large.

After the convolution operation is applied to all user nodes, we can obtain their centrality-aware representations. These user representations are learned on the user-item interaction data following the BGEM framework to get the final user embeddings. We denote this learning objective function as $O_{UV}$:

$$O_{UV} = - \sum_{e_{ij} \in \mathcal{E}_{UV}} w_{ij} \log \sigma \left( \sum_{k=1}^{\left|\mathcal{C}\right|} \tilde{c}_i^{c_k} \tilde{u}_{i,k}^{c_k} \cdot \tilde{v}_j \right) + \sum_{k=1}^{M} \sum_{u \sim P_u(c_k)} \log \sigma \left( - \sum_{k=1}^{\left|\mathcal{C}\right|} \alpha_i^{c_k} \tilde{u}_{i,k}^{c_k} \cdot \tilde{v}_k \right).$$

Fig. 2: The simplified process to generate a centrality-aware network embedding based on the algorithm CONVOLVE.
Two-stage Training and Joint Training.

To optimize the above joint objective function, we cannot straightforwardly use SGD, because $O_{SGV}$ and $O_{UV}$ in Equation 15 have different training instances: group-item pairs vs. user-item pairs. To address this issue, one possible solution is to first merge all edges in edge sets $E_{UV}$ and $E_{GV}$ into a big edge set, and then randomly sample a positive edge from the merged edge set in each gradient step, just as done in [18], [34]. However, the group-item interaction graph is much sparser than the user-item interaction graph, i.e., the number of edges in $E_{GV}$ is much smaller than the number of edges in $E_{UV}$. If we uniformly draw a positive edge from the merged edge set to perform stochastic gradient descent, most of sampled positive edges would be user-item edges, and there would not be enough group-item interaction edges for accurately estimating the trainable parameters of the aggregating function. To overcome the challenge of data skewness, we propose a novel joint training procedure in Algorithm 2. Instead of merging all edges into a big edge set, we will first draw or choose a bipartite graph with the sampling probabilities $\frac{1}{d_{uk}}$ and $\frac{1}{d_{vk}}$ for the group-item graph and user-item graph respectively, and then randomly draw a positive edge and $M$ negative edges from the sampled bipartite graph to update the gradients. By doing so, the joint objective function is actually changed to the following equation:

$$O_{GVU} = O_{SGV} + \eta O_{UV},$$

(16)

where $\eta$ is a non-negative hyper-parameter that is used to control the weight or contribution of the objective $O_{UV}$.

### Time Complexity Analysis

For each stochastic gradient step in Algorithm 2, the time complexity for the convolution operation is small and can be ignorable [29], so the time complexity is $O(d \cdot M \cdot |C|) = O(d)$, where $M$ and $|C|$ are often small (less than 10) in large-scale datasets [18] and thus can also be ignorable; $d$ is the embedding dimension and also typically small. We assume that our model needs $N$ samples (i.e., $N$ stochastic gradient steps) to reach convergence, thus its overall time complexity is $O(d \cdot N)$. In practice, the required number of stochastic gradient steps $N$ is typically proportional to the number of edges [18].

### 4.1 Negative Sampling of Items

How to sample $M$ negative items to form $M$ negative edges (i.e., corrupted examples) for each positive edge (i.e., each observed edge)? For a positive user-item edge $(u_i, v_j)$ on $G_{UV}$, we employ the widely adopted degree-based noise distribution $P_{n}(v_k) \propto d_{vk}^{0.75}$ [19], where $d_{vk}$ is the out-degree of item node $v_k$ on the user-item graph. However, this classic negative sampling method does not apply to the occasional group-item interaction graph $G_{GV}$, because the group-item graph is extremely sparse and the variance of its node degrees is not so obvious. In this case, the degree-based negative sampling strategy may degrade to the uniform negative sampling. Most negative examples generated in this way are “too easy” and will contribute little to learning an effective discriminator, because they are obviously false. To generate more difficult and informative negative examples for each positive edge $(g_m, v_j)$ on $G_{GV}$, we propose a novel group-aware negative sampling technique by leveraging the user-item interaction graph. Specifically, given a group $g_m$, the noise distribution is changed to be group-aware, i.e., $P_{n}^{g_m}(v_k) \propto (d_{vk}^{g_m} + \gamma)^{0.75}$, where $d_{vk}^{g_m}$ represents the popularity of item $v_k$ among its members, which can be easily derived from the user-item interaction graph $G_{UV}$ as follows $d_{vk}^{g_m} = \sum_{u_j \in g_m} w_{jk}$; $\gamma$ is a smoothing constant parameter which assigns a small probability to items that have no interactions with its group members. Thus, the generated negative items in this way will be more popular among the group’s members, and they are more informative and helpful to learn the discriminative weights in the self-attention mechanism.
4.2 Group Recommendation using CAGR

Once we have learned the model parameters in CAGR, given an occasional group \( g_m \), we first use the aggregation function defined in Equation 10 to aggregate its members (i.e., \( u_i \in G_m \), obtaining the group representation \( \tilde{g}_m \). Then, a ranking score for each item \( v_j \) can be computed according to the dot product of \( \tilde{g}_m \) and \( \tilde{v}_j \), i.e., \( s_g(g_m, v_j) = \tilde{g}_m \cdot \tilde{v}_j \). Finally the top-\( n \) items with highest ranking scores will be recommended to the group \( g_m \).

5 EXPERIMENT SETUP

In this section, we introduce the experimental settings, including research questions to answer, datasets, evaluation protocols and comparison methods.

5.1 Research Questions

We conduct extensive experiments on three large-scale benchmark datasets to answer the following research questions and validate our technical contributions.

RQ1: How does our proposed model recommender model CAGR perform compared with state-of-the-art group recommenders and various predefined aggregation strategies?

RQ2: Can we improve the group recommendation by using GCNs-based techniques which leverage the social network structure information to enhance user embedding learning? If the answer is yes, can the centrality-aware GCNs method GraphCSC achieve better performance than the vanilla GCNs method in capturing user influence from the social network?

RQ3: Can we improve the group recommendation by integrating the user activity data, i.e., the user-item interaction and user social network data? If yes, how do our proposed two model optimization approaches perform on heterogeneous interaction data? Furthermore, for the joint optimization approach, which negative sampling strategy is more suitable for the group-item interaction data?

RQ4: How do some of the most important hyper-parameters (e.g., \( d \) and \( M \)) affect the performance of CAGR?

Besides those four research questions, we are also interested in the capability of BGEM in modeling and predicting interactions on the task of top-\( n \) recommendation for individual users (i.e., user-item interaction prediction). We have already conducted this experiment and showed the results in our previous work [14]. In the study, we compared BGEM with some strong baseline models such as BPR [35], eALS [36] and NCF [37] on the user-item interaction data for making recommendations to individual users, and the experimental results showed that BGEM outperforms those baseline methods. This justifies the choice of BGEM as a fundamental building block of our proposed SIGR and CAGR models. We refer the readers interested in this study to [14] for more details.

5.2 Datasets

As existing publicly available group recommendation datasets such as CAMRa2011 [1] and Movielens-Group [11] consist of either a smaller number of persistent groups or randomly generated groups and they do not contain the user social network information, they are not suitable to evaluate our solution CAGR. This is why we need to create three large-scale benchmark group recommendation datasets based on the Yelp Challenge dataset [2]. Douban-Event dataset [18] and Meetup [4]. Douban Event is the largest online event-based social network in China that helps people publish and participate in social events. For each user, we acquired her event attendance list and social friend list. For each event, its time and venue were also collected. Yelp allows users to share their check-ins about local businesses (e.g., restaurants) and create social connections with other users. Each check-in or review contains a user, a timestamp and a business, indicating the user visited the business at that time. In our Yelp dataset, we only focus on the restaurants located in the Los Angeles area, where there are 34,504 users and 22,611 restaurants. Meetup is an online social event service where users can publish and participate in social events. On Meetup, a social event is created by a user who specifies the time, location and event description. Other users may express their interests of attending this event.

As Yelp and Douban-Event do not contain explicit group information, we extract implicit group activities as follows: we assume if a set of users who are connected on the social network visit the same restaurant at the same time or attend the same event, they are the members of a group and the corresponding activities are group activities. Meetup contains explicit group information, but it does not have explicit social network data. So we follow the approach proposed in [38] to form the social network. The statistical information of the three datasets is shown in Table 1. From the table, we can see that group-item interaction data is much sparser than the user-item interaction data. For example, in the Douban-Event dataset, a group has only 1.48 interaction records on average, but a user has 48.38 interaction records.

All datasets used in our work are publicly available.

5.3 Evaluation Methodology

To evaluate the performance of group recommendation systems, we first rank all group-item interaction records according to their timestamps in each dataset, and then use the 80-th percentile as the cut-off point so that the group-item interactions before this point will be used for training, and the rest are for testing. In the training dataset, we choose the last 10% records as the validation data to tune the model hyper-parameters such as \( \eta \) and \( M \). According to the above dividing strategies, we split the group-item interaction records in each dataset \( D \) into the training set \( D_{training} \) and the test set \( D_{test} \).

We employ the widely adopted metric \( \text{Hits ratio} \) [18], [39], [40], [51] to measure the recommendation accuracy. Specifically, for each group-item interaction \( (g, v) \) in the test set \( D_{test} \):

1. (1) We compute a ranking score for item \( v \) as well as other items that group \( g \) has never interacted with.
2. (2) We form a top-\( n \) recommendation list by picking \( n \) items with the highest ranking scores. If the ground-truth item \( v \) appears in the top-\( n \) list, \( \text{Hits ratio} \) is increased by 1.

| Dataset          | # Users  | # Groups | # Items | Avg. group size | Avg. #interactions for a group | Avg. #interactions for a user | Avg. #friends for a user |
|------------------|----------|----------|---------|-----------------|-------------------------------|-------------------------------|---------------------------|
| Yelp             | 34,504   | 70,743   | 24,631  | 4.45            | 4.82                          | 8.79                          | 1.12                      |
| Douban-Event     | 70,743   | 24,631   | 22,611  | 1.12            | 1.48                          | 1.40                          | 1.40                      |
| Meetup           | 24,631   | 19,031   | 90,245  | 5.15            | 5.15                          | 5.15                          | 5.15                      |

| Dataset          | Avg. group size | Avg. #interactions for a group | Avg. #interactions for a user | Avg. #friends for a user |
|------------------|-----------------|-------------------------------|-------------------------------|---------------------------|
| Yelp             | 4.45            | 4.82                          | 8.79                          | 1.12                      |
| Douban-Event     | 1.12            | 1.48                          | 1.40                          | 1.40                      |
| Meetup           | 5.15            | 5.15                          | 5.15                          | 5.15                      |

TABLE 1: Basic Statistics of the Three Datasets.
the top-$n$ recommendation list, we have a hit. Otherwise, we have a miss.

The metric Hits ratio is defined as follows:

$$\text{Hits@}n = \frac{\# \text{hit@}n}{|D_{\text{test}}|},$$

where $\# \text{hit@}n$ denotes the number of hits in the test set, and $|D_{\text{test}}|$ is the total number of test cases in the test set. A good group recommender model should achieve higher Hits@$n$.

Besides Hits ratio, we also adopt the commonly used metric Mean Reciprocal Rank (MRR) to measure the recommendation accuracy, and it is defined as follows:

$$\text{MRR} = \frac{1}{|D_{\text{test}}|} \sum_{(g,v) \in D_{\text{test}}} \frac{1}{\text{rank}(v)}.$$

MRR is an average of the reciprocal rank of the ground-truth item $v$ among all items except those which group $g$ has also interacted with, and a good recommender model should have a bigger MRR value.

Similarly, we also apply the above evaluation procedure to the personalized recommendation for individual users.

### 5.4 Comparison Methods

To answer the four research questions, we design the following four experiments with different comparison methods.

**Experiment 1** To answer RQ1, we compare our CAGR with a wide range of state-of-the-art group recommender models.

- **SIGR** [14]: Social Influence-based Group Recommender is our previously proposed group recommendation model that leverages BGEM and the attention mechanism as building blocks to learn both user embeddings and user social influences in a unified way. SIGR uses the pure BGEM to model user embeddings from the user-item interaction data, and SIGR represents a group using a simple weighted sum aggregation function over raw member embeddings in a two-stage manner.

  In [14], SIGR has already been compared with the AGREE model [9], the PIT model [3] and various simple aggregation strategies such as the simplest average strategy [10], the least misery strategy [12] and the maximum pleasure strategy [10]. SIGR has shown its superior performance over them. Therefore, we do not compare CAGR with these models in this work, and we refer the interested readers to [14] for the results.

- **GroupSA** [42]: The Group Self-Attention model treats the group decision making process as multiple voting processes, and develops a stacked social self-attention network to simulate how a group consensus is reached. Based on the user-item and user-user interactions, GroupSA proposes two types of aggregation methods (i.e., item aggregation and social aggregation) to enhance the representation of users.

- **SACML** [43]: The Self-Attention and Collaborative Metric Learning model employs the self-attention mechanism to automatically learn the weight of each group member, which are then aggregated to form a group. After that, the collaborative metric learning technique is leveraged to obtain the group and item representations in the embedding space.

- **SA-NCF** [44]: This method also employs the self-attention mechanism to learn the weight of each group member, and then learn the group and item embeddings via the Neural Collaborative Filter (NCF) [17] based on the group-item interaction data.

**Experiment 2** To answer RQ2, we design three versions of our CAGR with different user embedding learning approaches:

- **CAGR-N**
- **CAGR-G**
- **CAGR-C**

CAGR-N does not use the GCNs-based method to learn user embeddings, i.e., CAGR only adopts the pure BGEM on the user-item interaction data. CAGR-G uses the vanilla GCNs method GraphSAGE and CAGR-C uses the centrality-aware GraphCSC to learn user embeddings from both the user-item interaction and the user social network data.

**Experiment 3** To answer RQ3, we compare three model optimization approaches: Simple Training (ST), Two-stage Training (TST) and Joint Training (JT). ST optimizes our CAGR model only on the group-item interaction data, while TST and JT integrate the user activity data. For the joint training approach, we further compare two different negative sampling strategies: the classic degree-based sampling strategy and our proposed group-aware sampling strategy. Thus, we implement two versions of JT: JT-C and JT-G.

**Experiment 4** To answer RQ4, we investigate how the performance of our CAGR varies w.r.t. different key hyper-parameter setups, including the model dimension $d$ that we set for all model embeddings such as the user and group embeddings, the number of parallel heads $h$ in the multi-headed self-attention mechanism, the number of iterations $N$, the number of negative samples $M$ and the number of neighbors to sample for any user $i$ $|N_i|$ in Algorithm 1. For other hyper-parameters in the GraphCSC component, we follow their optimal setup in [29, 32]. For other hyper-parameters in the model, we perform cross-validation and use the grid search algorithm to obtain the optimal hyper-parameter setup on the validation dataset.

### 6 Experimental Results

In this section, we report and analyze the results of our four experiments.
6.1 Overall Group Recommendation Performance (RQ1)

Fig. 3 shows the results of Experiment 1 on Yelp, Douban-Event and Meetup datasets. We have the following observations. (1) Our proposed CAGR achieves the best performance on the three datasets for group recommendation, significantly outperforming other state-of-the-art group recommender models (all the p-values between our CAGR and each comparison method are much smaller than 0.01, which indicates that the improvements are statistically significant). This validates the effectiveness of our CAGR solution. In particular, CAGR outperforms SIGR, proving the superiority of our centrality-aware user representation learning in capturing and integrating the centrality information from the social network to overcome the user data sparsity, and the end-to-end self-attention group representation method in modeling the complex intra-group interactions. CAGR also outperforms GroupSA, which validates the importance of taking the centrality information in social network for group representation learning. (2) GroupSA achieves the second best performance, which validates that it is crucial to leverage the users’ social information in group recommendation, and also demonstrates the effectiveness of the self-attention mechanism to learn user representations. (3) SIGR outperforms SACML and SA-NCF in this experiment, and SIGR also outperforms many other baseline methods such as AGREE and PIT shown in [13], which proves that it is important to exploit and integrate the user-item interaction data and the social network data to overcome the sparsity issue of the group-item interaction data in learning user embedding and personal social influence respectively. This is in contrast with AGREE that cannot leverage the social network structure information and PIT that is incapable of integrating user-item interaction data. (4) CAGR, GroupSA, SIGR, SACML and SA-NCF consistently outperform the simple group aggregation strategies BGEM+avg, BGEM+mp and BGEM+ml (see the results in [14]), showing the advantage of automatically learning the aggregation strategy from data over the predefined aggregation strategies.

6.2 Importance of User Embedding Techniques (RQ2)

Fig. 4 shows the results of Experiment 2 on Yelp and Douban-Event datasets. The following observations are made from the results. (1) Both CAGR-G and CAGR-C significantly and consistently outperform CAGR-N on both Yelp and Douban-Event datasets, showing that it is important to leverage the social network information to enhance the user embedding learning for group recommendation. As the user-item interaction data is sparse, directly applying BGEM to estimate user embeddings from it would generate sub-optimal group recommendations. On the other hand, the improvement by CAGR-G and CAGR-C demonstrates that integrating the social network data using GCNs can effectively alleviate the user-item interaction data sparsity. (2) CAGR-C achieves higher recommendation accuracy than CAGR-G, which validates that incorporating the centrality information into the user embeddings is helpful to model user social impacts and leads to more accurate group representations.

6.3 Importance of User Activity Data (RQ3)

Fig. 5 shows the results of Experiment 3. We make three observations from the results. (1) All TST, JT-C and JT-G significantly outperform ST on both Yelp and Douban-Event datasets, showing the importance and necessity of leveraging the user activity data for training our CAGR model. (2) JT-C and JT-G perform better than TST, which shows the advantage of our proposed joint model optimization approach over the two-stage optimization approach. This is because the embedding spaces separately learned from the user activity data and group-item interaction data may not be compatible. Besides, the experimental results also indicate that our proposed joint model optimization approach can effectively perform model optimization on heterogeneous interaction data (e.g., the mixture of the user-item interaction data, user social network data and group-item interaction data) and address the issue of data skewness. (3) JT-G achieves better performance than JT-C, showing that our proposed group-aware negative sampling strategy is more suitable for the sparse group-item interaction graph than the classic degree-based negative sampling strategy.

6.4 Impact of Tuning Hyper-parameters (RQ4)

Tables 2 – 6 show the results of Experiment 4. Due to the space limitation, we only show the experimental results on Yelp dataset, and similar results are also achieved on Douban-Event dataset.

Both the size of model dimension $d$ (e.g., the size of user and group embeddings) and the number of heads $h$ are important to balance between the model size and the expressiveness. Moreover, the model can enjoy a higher degree of parallelization with increasing $h$. To study their impacts, we test the performance of CAGR by varying the values of $d$ from 16 to 512 and varying the values of $h$ from 1 to 32. Their results are presented in Tables 2 and Table 3. From the results, we observe that CAGR achieves the best performance when $d = 128$ and $h = 16$. Another pattern we observe from both results is that the recommendation accuracy of CAGR first increases with the increasing $d$ (or $h$), and then begins to decrease. The reason is that there may be excessive parameters in the model if $d$ or $h$ is too large, which can introduce noise to the model and lead to overfitting eventually.

Similarly, we investigate the converging performance of our CAGR model with increasing number of iterations $N$ (i.e., the number of stochastic gradient steps) and number of negative samples $M$ drawn for each positive sample. Table 4–5 presents the performance of our CAGR model w.r.t. the number of iterations.

![Fig. 4: Effect of Different Network Embedding Methods.](image1)

![Fig. 5: Comparison of Different Model Optimization Approaches.](image2)
When $N$ is larger than 4 millions, our model converges quickly and its performance becomes very stable. Table 5 shows the performance of CAGR w.r.t. the number of negative examples $M$. From the table, we observe that when the number of negative examples is larger than 6, the performance becomes very stable. Therefore, for each positive example, we do not need to sample many negative examples and just need to sample a few, which ensures the training efficiency of our CAGR model.

Finally, we study how the number of neighbors for each user $i$ in Algorithm 1 $(|\mathcal{N}_i|)$ affects the model performance. Specifically, we evaluate the model performance w.r.t. different settings of $|\mathcal{N}_i|$ (i.e., 1, 2, 4, 6, 8 and 10) and then show the results in Table 6. From the experimental results, we observe that our model achieves the peak results when $|\mathcal{N}_i| = 4$, and then the results remain stable as the number increases. This observation validates our intuition of the GraphCSC component that only a small number of important neighbors are sufficient to facilitate the learning of target node’s representation.

### 7 Related Work

There are two lines of research on group recommendation based on the group types [4]. Groups with stable members and rich historical interactions are often referred to as persistent groups (also called established groups) while groups formed by users ad-hoc are dubbed as occasional groups. As a persistent group can be treated as a virtual user, conventional personalized recommendation techniques can be straightforwardly adopted for making recommendation to persistent groups [6]. In this paper, we focus on making recommendations to occasional groups.

Making recommendations to occasional groups is much more challenging due to the lack of sufficient group-item interactions. Existing studies on occasional group recommendations focus on aggregation approaches that aggregate individual preferences or recommendation results of the group members as the group preferences or group recommendations. All these aggregation-based group recommendation approaches can be divided into two categories: late aggregation and early aggregation.

The late aggregation-based approaches [5, 12, 13] first generate the recommendation results or lists for each group member, and then aggregate these individual recommendation results to produce the group recommendations. A variety of aggregation strategies [4, 10, 12, 13, 45] have been proposed, such as average satisfaction, least misery and maximum pleasure, and most of them come from the social choice theory [46]. For example, average satisfaction assigns equal importance to each group member and assumes that each group member contributes equally to the group decision-making. However, these aggregation strategies are heuristic and manually predefined rather than data-driven or learned from data. [47] does a systematic evaluation of all existing predefined aggregation strategies. Their conclusion is that the best-performing aggregation strategy does not exist and their performances depend on the datasets. In other words, there does not exist a predefined fixed aggregation strategy which can perform best on all datasets.

In contrast, the early aggregation-based approaches, such as [9, 11, 48], first aggregate either explicit or implicit user profiles into a group profile or representation, and then produce the group recommendations based on the group profile or representation. The explicit user profiles refer to users’ interaction records on items, and the implicit user profiles refer to the latent representations of users’ preferences, such as user embedding. A line of this type of work is based on probabilistic generative models or more precisely topic models [3, 11, 49, 50], which model groups by capturing both personal preferences of group members and their impacts in the group. The basic assumption of these models is that users should be treated differently and the notion of influence is introduced to quantify the contribution of each group member to the group decision making and implement the data-driven aggregation. Although these models share the similar intuitions with our proposed CAGR model, they do not consider the sparsity issue of the group-item interaction data. Moreover, our CAGR model is technically different from them such as PIT and COM. Compared with our proposed CAGR that takes the bipartite graph embedding model BGEM as the foundation, these topic model-based group recommender models have limited modeling and expressive abilities, since they constrain the key parameters (e.g., users’ personal preferences) to be a probability distribution. Moreover, these models are not as flexible as our CAGR, and they
are incapable of seamlessly integrating the user activity data to improve the estimation of users’ personal preferences.

Recently, [2] developed an Attentive Group Recommendation system (AGREE) by combining a standard attention network with the neural collaborative filtering method (NCF). Compared with our CAGR, AGREE has two serious drawbacks. First, it does not consider the data sparsity issue of the group-item interaction data in learning user weights. Second, its good performance heavily depends on the direct learning of group preference embedding from the group’s interaction data and cannot make good recommendations for cold-start groups without any interaction record.

In our previous work [14], we proposed Social Influence-based Group Recommender (SIGR) that represents groups by aggregating the members’ preferences based on the social influences. Compared with SIGR, CAGR makes the following significant improvements. **End-to-end:** SIGR is a two-stage method that cannot be trained in an end-to-end manner, and CAGR addresses this limitation by introducing a single optimization criterion to enable end-to-end training. **Expressiveness:** SIGR uses the plain linear weighted sum to aggregate raw user embeddings to represent the group, but it ignores the complex interactions among them. To address this problem, our CAGR handles this problem with a self-attention mechanism that can better model the intra-relations in the group. **Mitigating user data sparsity:** SIGR learns user embeddings using the pure BGD framework from the user-item interaction data, which is too sparse to support accurate estimation of user representations. CAGR mitigates the user data sparsity problem and enhances the user embedding learning by additionally considering the user social network data and incorporating the node centrality information in the network.

Our work can be categorized as early aggregation-based approaches and we focus on overcoming the sparsity issue and limitations of the group-item and user-item interaction data in learning both users’ personal and groups’ preferences.

8 CONCLUSIONS AND FUTURE WORK

In this paper, we focused on the problem of making recommendations to occasional groups. We proposed an end-to-end Centrality-Aware Group Recommender (CAGR) model to enhance the group and user representation learning by overcoming the bottleneck data sparsity problems. Specifically, to mitigate the sparsity of data generated by occasional groups, we proposed to represent a group by aggregating its member representations based on a novel and end-to-end self-attention mechanism. To learn centrality-aware user embeddings, we developed a graph convolution operation on the user social network data in order to overcome the user-item interaction data sparsity problem. We also proposed two model optimization approaches to leverage the user embedding learning procedure to help improve the parameters estimation. To evaluate the performance of group recommender systems in making recommendations to occasional groups, we created three large-scale benchmark datasets and conducted extensive experiments on them. The experimental results validated the superiority of our solutions by comparing with the state-of-the-art techniques.

Having alleviated the data sparsity problem in group recommendation to a great extent, we plan to further investigate another rarely explored problem in group recommendation: the propensity problem [51]. This problem arises because the probabilities of different ratings being observed in most datasets are not the same. More specifically, users tend to only rate an item that they like and thus the ratings of a lower value are more likely to be missing [52]. This type of bias commonly existing in the dataset would lead to inaccurate user preference modeling results, and hence eventually harm the group representation learning. To this end, in the future, we intend to employ the state-of-the-art techniques, such as [51], in our CAGR model to address the propensity problem and further improve the group recommendation performance.

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