Socially-driven multi-interaction attentive group representation learning for group recommendation

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ABSTRACT

Group recommendation has attracted much attention since group activities information has become increasing available in many online applications. A fundamental challenge in group recommendation is how to aggregate individuals' preferences to infer the decision of a group. However, most existing group representation methods do not take into account the static and dynamic preferences of groups synchronously, leading to the suboptimal group recommendation performance. In this work, we propose a socially-driven multi-interaction group representation approach to learn static and dynamic group preference coherently. Specifically, we inject the social homophily and social influence into capturing static and dynamic preference of a group. Furthermore, we explore latent user-item and group-item multiple interactions with bipartite graphs for group representation. Extensive experimental results on two real-world datasets verify the effectiveness of our proposed approach.

Keywords: Social analysis; Multi-interaction learning; Representation learning; Group recommendation

1. Introduction

With the prevalence and rapid proliferation of social applications, it is becoming easier and more convenient for people to form a group. Therefore, group activities are dominating in people's social life, such as touring with friends, dining with partners, and watching movies with colleagues. This calls for an effective recommendation solution and group recommendation aims to maximize the utility of a group. It not only can facilitate group making decision and improve user engagement, but also can help service providers increase the profit (Yuan et al., 2014). Group recommendation is more challenging than the general recommendation to individual users. A good group recommendation method should be able to learn the preference of group members and drive the highly effective group recommendation (Felfernig et al.). However, most existing preference aggregation strategies are predefined (e.g., average, least misery and maximum satisfaction), and they cannot simulate complicated group making decision process better. Generally speaking, different users may exhibit static and dynamic social characteristics in different groups. Besides, a group has its own characteristics in the process of forming the group and we argue that it's group intrinsic preference. Therefore, inspired by the social homophily and social influence, we utilize them to capture static and dynamic group preference respectively. We further aggregate static social homophily-based and dynamic social influence-based group preference to obtain group representation for group recommendation.

To some extent, group members have certain similarities, leading to the appearance of group intrinsic preference. As show in Fig. 1(a), the social homophily (Aral et al., 2009; Mcpherson et al., 2001) emphasizes the inner similarity of a group that satisfies static group intrinsic preference mining. Meanwhile, users have similar preferences that contribute to the formation of a group, and group interactions could be influenced by shared preferences. As for the social influence, we take Fig.

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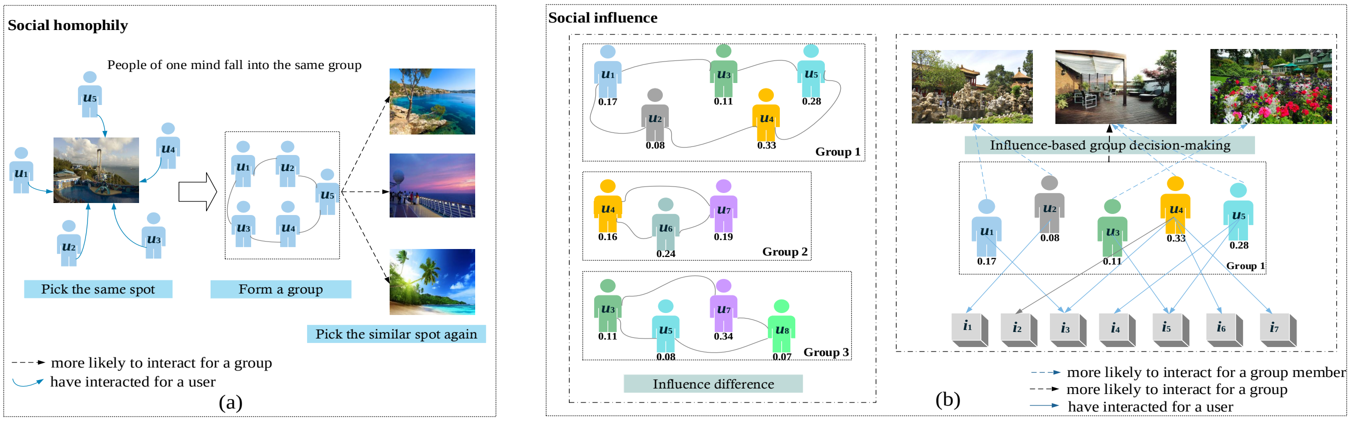


Fig. 1. Illustration of social homophily and social influence in our SGAGR group recommendation task. (a) Analysis of social homophily based on similar preference. Five different users form a group because they are all interacted with an attraction with water and trees, and then the group may again interact with a similar attraction with water and trees. (b) Analysis of social influence based on dynamic influence weight. Different users have different influence weights in different groups, and users with high weights play a more important role in group decision-making.

1(b) as an example. A group member may have different social influence weights in different groups (Tang et al., 2009; Yin et al., 2019) in terms of their own interactions, resulting in different contribution for group making decision. To this end, we probe into the social homophily and social influence for group preference aggregation in group recommendation task.

Specifically, we utilize sentence-level embedding and graph-based group embedding based on social homophily to model group profile in view of static group intrinsic preference. In addition, inspired by the recent advancement of representation learning (Xie et al., 2016; Wu et al., 2019; Yin et al., 2019), we propose a multi-interaction attentive group representation based on social influence and attention mechanism in terms of dynamic group making decision. The dual graph attention networks was proposed to learn representations for two-fold social effects (Wu et al., 2019). The attention mechanism and the bipartite graph representation were combined for group recommendation(Yin et al., 2019). Discriminatively, to obtain an optimal embedding, we consider fully the user-item and group-item multiple interactions in the embedding construction, and we adopt the bipartite graph embedding to represent these multiple interactions. Furthermore, we design a neural attention network to assign different influence weight for a group member in different groups in a learnable way. After that, we aggregate the static social homophily-based group embedding and dynamic social influence-based group embedding to complete the final group representation. Through this way, we can obtain the optimal group representation and simulate the complex group making decision process better.

Our main contributions are threefold. First, we propose a novel socially-driven multi-interaction graph-based attentive group representation approach (SGAGR), which can model group profile in social homophily and social influence coherently for group recommendation. To the best of our knowledge, this is the first work that considers social homophily and social influence for group preference aggregation synchronously in group recommendation task. Second, we propose a multi-interaction representation model to yield optimal embeddings by using group-item and user-item multiple interactions. Finally, we demonstrate the effectiveness of the proposed approach on two real-world datasets.

The remainder of this paper is organized as follows. We discuss related work in Section 2, and we introduce our proposed approach in Section 3. Next, experiments are reported in Section 4. Finally, Section 5 draws conclusions and provides future work directions of this study.

2. Related work

The significance of group recommendation has attracted the great attention in various fields, such as music (Crossen et al., 2002), movies (Pera and Ng, 2013) and tourism (McCarthy et al., 2006). Existing studies (Tran et al., 2019; Baltrunas et al., 2010; Hu et al., 2014) on group recommendation focus on aggregation preference strategies. These strategies mainly include that aggregate individual preferences and aggregate group members' recommendation results as the group preferences. Hence, all of these aggregation-based group recommendation approaches can be categorized into late aggregation and early aggregation (Yin et al., 2019). As for the late aggregation-based approaches, these approaches first generate the recommended results of individual preferences, and then aggregate the results to complete the group recommendations. For example, average pleasure (Baltrunas et al., 2010), least misery (Amer-Yahia et al., 2009) and maximum satisfaction (Boratto and Carta, 2011) have been proposed. Taking the average pleasure as an example, it obtains the average scores of group members as the final recommendation scores. Meanwhile, it assumes that each group member has equal contributions to group making decision and it may return results that are favorable to some group members and unfavorable to others. In reality, these predefined strategies cannot simulate the dynamic group making decision, and it may not perform best on all datasets.

Distinct from the late aggregation-based approaches, the early aggregation-based approaches first build user profiles of the each group member, and then aggregate these use profiles as a group profile or group representation to produce the group recommendations. A surge of this type of works (Yuan et al., 2014;

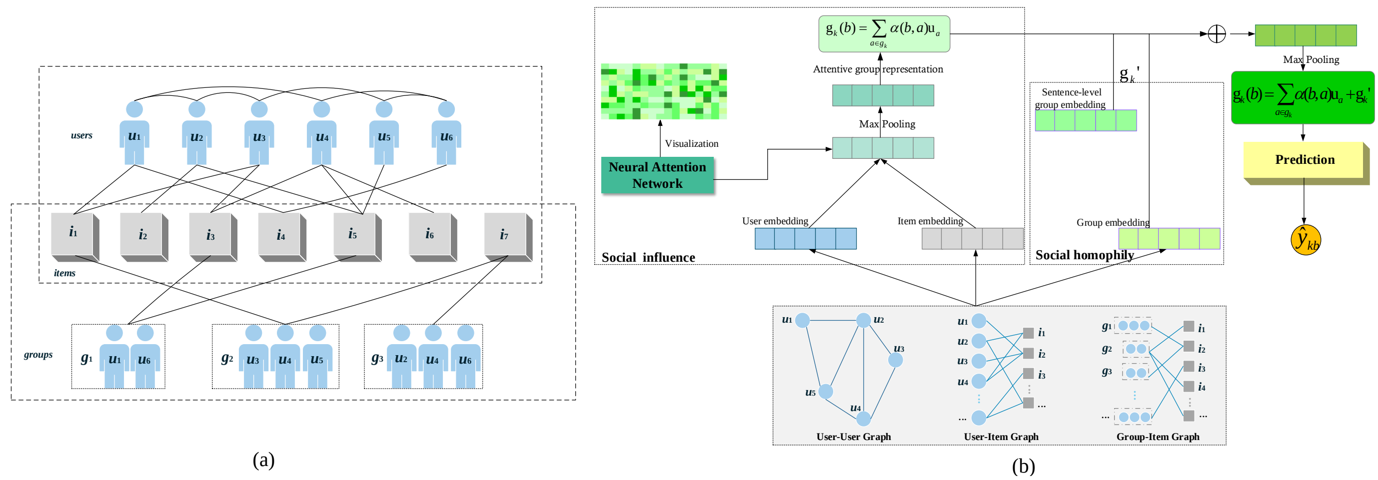


Fig. 2. Overview of socially-driven multi-interaction attentive group representation approach. (a) an illustration of the input data of our SGAGR group recommendation task. (b) an illustration of our group recommendation, which contains group representation and recommendation prediction.

Liu et al., 2012) are based on probability model, which represent the groups by capturing group members' preferences with different influence in the group. Besides, MoSAN (Tran et al., 2019) shares the similar technology by using attention mechanism with our SGAGR. Despite the idea of attention mechanism is similar to it, our approach emphasizes that social influence effect is always context-aware, and the model needs to output different influence weights in the different groups for each group member. In this way, we capture dynamic preferences of a group, and then achieve aggregation representation learning by combining group static intrinsic preferences. In other words, MoSAN (Tran et al., 2019) does not consider group intrinsic preference and the user-item and group-item multiple interactions in the embedding construction. Thus, it leads to the suboptimal embedding in the process of group recommendation. More importantly, we adopt the bipartite graph embedding to obtain representation from user-item and group-item multiple interactions data. Moreover, we employ social homophily analysis to discuss static group intrinsic preference, and we utilize social influence analysis to consider dynamic group preference in terms of group representation. Our SGAGR not only can produce the optimal embedding by using multi-graph embedding and sentence-level embedding, but also can adjust group members' influence dynamically in different groups by designing a neural attention network. All in all, several novel technologies are proposed in our work to address the above limitations and drive better group recommendation performance.

3. Proposed approach

3.1. Preliminaries

Let $U = \{u_1, u_2, \cdots, u_m\}$, $I = \{i_1, i_2, \cdots, i_n\}$ and $G = \{g_1, g_2, \cdots g_t\}$ be the sets of users, items and groups, respectively. The k-th group $g_k \in G$ consists of a set of users. We consider three kinds of observed interactions data among U, I and G, that is, user-user interaction, user-item interaction and group-item interaction in Fig. 2(a). Particularly, we employ bipartite graphs $\mathbf{G}_{UI}$ and $\mathbf{G}_{GI}$ to denote user-item interactions and group-item multiple interactions, and we build a general graph $\mathbf{G}_{UU}$ to represent user-user interactions. Our group recommendation task is to recommend a list of items in terms of a given group g_k. The frequently used symbols are shown in Table 1.

Table 1. Frequently used symbols.

Symbol	Description
U	a set of users
I	a set of items
G	a set of groups
$\mathbf{G}_{UI}$	user-item interaction
$\mathbf{G}_{GI}$	group-item interaction
η_{UI}	a set of edges between users and items
η_{GI}	a set of edges between groups and items
eu_a	the embedding of user a
ei_b	the embedding of item b

Input: A set of users U, a set of items I, a set of groups G, user-user interactions $\mathbf{G}_{UU}$, user-item interactions $\mathbf{G}_{UI}$, and group-item interactions $\mathbf{G}_{GI}$.

Output: A personalized ranking function that maps an item to a ranking value for each group $f_g : \mathrm{I} \rightarrow \mathbb{R}$.

Fig. 2(a) illustrates the input data of our group recommendation, which includes user-user interactions, user-item interactions and group-item multiple interactions. The overview of our SGAGR is shown in Fig. 2(b). On the whole, our SGAGR includes social homophily-based global module and social influence-based local module. Based on social homophily and social influence, we capture static and dynamic preference of a group coherently. To achieve multiple interactions, we first use multi-graph embeddding to represent user-user interactions, user-item interactions and group-item multiple interactions respectively. By this way, we obtain the graph-based embeddings of each user, item and group, which considers the interactions data sufficiently in the embedding construction. Next, we argue that each group member has different social influence in different groups. On this basis, we design a neural attention network to learn the social influence of each group member in a dynamic way. Meanwhile, we hold that each group has its own group intrinsic preference in the process of a group formation. Therefore, we utilize sentence-level embedding to model group profile, and then aggregate the multi-interaction graph-based group embedding to complete group intrinsic preference modeling based on social homophily. At last, we aggregate the social influence-based group embedding and social homophily-based group embedding to obtain the optimal group representation for group recommendation.

3.2. Analysis of social homophily and social influence

In the real world, a group's behaviors could be influenced by various factors, and group making decision is always the results of multifaceted causes. As social animals, social effects are glutted with people's daily life, and they have been studied in group recommendation task. In this paper, we consider mainly two important social effects, namely, social homophily and social influence. In this section, we distinguish the social homophily and social influence in view of group intrinsic preference and group dynamic preference. We will introduce the detailed technologies for capturing them in Section 3.3.

For one thing, to a certain extent, each group member may have similar preferences, and it may contribute to form a group. Intuitively, social homophily emphasizes the similarity of group members, and it usually stays unchanged and independent of certain group members' preferences. Accordingly, we analyze and mine group intrinsic preference based on social homophily, which is the fundamental group preference. Fig. 1(a) visualizes the social homophily of a group. As you can see, different five users have a similar preference item, leading to the formation of a group. Thus, we call the similarity preference as group intrinsic preference, and this group is more likely to interact with the similar items. As such, we exploit an effective approach to capture social homophily for group representation, which combines the sentence-level embedding and graph-based group embedding. In other words, we model the group intrinsic preference to obtain global group representation by using different technologies.

For another, generally, each group member has often different influence in different groups, and a group member with high influence plays more important role for group making decision. Hence, social influence occurs when one's opinions, emotions, or behaviors are affected by others, intentionally or unintentionally[1]. Fig. 1(b) illustrates the social influence of several groups. Specifically speaking, the left of Fig. 1(b) shows the influence of different users in group 1, group 2 and group3. The right of Fig. 1(b) exhibits that the group members with high social influence weight contribute to group making decision greatly. In some detail, individuals have their own preferences, which result in the value of social influence. Putting it another way, we assign the social influence weight of each group member in terms of interaction. Based on social influence, we adopt attention mechanism and graph embedding to assign influence weight for each group member.

[1] http://en.wikipedia.org/wiki/Social_influence

3.3. Attentive group representation learning

Fig. 2 provides an overview of our SGAGR. We will go into the details of each part in order.

Multi-interaction representation learning. We take user-item interaction as an example to state how to learn representation from the multiple interaction data. Also, Its superiority has been verified in Section 4. As shown in Fig. 2(b), we adopt a bipartite graph to represent the user-item interactions, i.e., $\mathbf{G}_{UI} = (U \cup I, \eta_{UI})$. η_{UI} denotes the set of edges between users and items. Given a user u_a, if he interacts with i_b, an edge will exist between them. In such case, we define the interaction probability of user u_a and item i_b as follows:

$$p(i_b\,|u_a) = \frac{\exp(eu_a \cdot ei_b)}{\sum\limits_{i_{b'} \in I} \exp(eu_a \cdot ei_{b'})}, \tag{1}$$

where eu_a and ei_b denote the embeddings of user u_a and item i_b respectively.

In this paper, we try to minimize the KL-divergence between the estimated neighbor probability distribution of each user and empirical distribution. The empirical distribution can be expressed as:

$$\hat{p}(i_b\,|u_a) = \frac{\varpi_{ab}}{d_a}, \tag{2}$$

where ϖ_{ab} is the weight on the edge R_{ab}, and d_a is the outdegree of user node u_a. The outdegree can be computed:

$$d_a = \sum_{i_b \in I} \varpi_{ab}. \tag{3}$$

By omitting some constants, the objective function is defined as:

$$\varphi_{UI} = -\sum_{R_{ab} \in \eta_{UI}} \varpi_{ab} \log p(i_b\,|u_a). \tag{4}$$

With minimizing the above objective function, we can learn the graph embedding of each user and each item in the latent space. Analogously, the group-item multiple interactions can also be represented by a bipartite graph $\mathbf{G}_{GI} = (G \cup I, \eta_{GI})$. We use same object function to learn the group embedding of each group. As shown in Fig. 2(b), based on the multi-graph, we are able to obtain the graph embedding of each user, item and group. More importantly, we employ them to assist the following dynamic group aggregation representation.

Attention-based social influence learning. As discussed in section 3.1, we consider that social influence effect is always context-aware, and the model needs to output different influence weights in the different groups for each group member. To tackle this problem, as show in Fig. 2(b), we design a neural attention network to assign weights for each group member of a group. Attention mechanism (Guan et al., 2019; Ji et al., 2018; He et al., 2018) allows one to focus on or place a higher influence on some group members in a group. On the contrary, the other group members of a group may be placed less importance. Following the above graph embedding, eu_a encodes the group member's preference and ei_b encodes the item's property. We parameterize $\alpha(b,a)$ as a neural attention with eu_a and ei_b as the input, it can be formulated as follows:

$$z(b,a) = A^T \mathrm{ReLU}(\mathrm{H}_i \mathrm{i}_b + \mathrm{H}_u \mathrm{u}_a + c),$$
$$\alpha(b,a) = \mathrm{Softmax}(z(b,a)) = \frac{\exp z(b,a)}{\sum_{a' \in g_k} \exp z(b,a')}, \tag{5}$$

where H_i and H_u are weight matrices of the attention network, and c is the bias vector. Besides, we use ReLU as the activation function and normalize the scores, leading to a probabilistic interpretation and handle different group sizes in our case. Fig. 2(b) illustrates the mentioned design. By such an attention network, we allow each group member with different influence weight to contribute for group making decision in a dynamic way.

Group aggregation representation. As mentioned in section 3.1, social homophily can give expression to group intrinsic preference. In order to capture social homophily, we combine two global-based models, which are BERT-based sentence-level embedding and the graph embedding of a group. BERT (Devlin et al., 2019) is short for bidirectional encoder representation from transformers and it can obtain directly sentence-level embedding. Specifically, we regard a group as a sentence and the sentence consists of several words. However, a word is not equal to a group member and group member may be composed of some words. Different from other linguistic models, BERT could consider the context well and obtain directly a unique vector representation of an entire sentence. Also, it can get the better global semantic information and avoid the information loss caused by global pooling in each layer. Hence we use BERT to obtain the sentence vectors as the group vectors. To some degree, group members' similar preferences may be incarnated by the sentence-level embedding. As shown in Fig. 2(b), we complete the social homophily-based global group representation.

Next, we aggregate the social homophily-based and social influence group embeddings, which are basic representation blocks in our SGAGR.

In group representation task, our target is to obtain an embedding for each group to estimate its group preference on an item. It can be abstracted as:

$$\mathrm{g}_k(b) = f_s(\mathrm{i}_b, \{\mathrm{u}_a\}_{a \in g_k}), \tag{6}$$

where $\mathrm{g}_k(b)$ is the embedding of group g_k tailored for predicting its preference on item i_b, f_s denotes the aggregation function to be specified. In our SGAGR, we exploit the group embedding as consisting of two components, namely, social homophily-based global embedding aggregation g_k and social influence-based user embedding aggregation. It can be expressed as:

$$\mathrm{g}_k(b) = \sum_{a \in g_k} \alpha(b,a)\mathrm{u}_a + \mathrm{g}_k{}'. \tag{7}$$

Note that by aggregating the above social effect features coherently, we are able to capture social homophily and social influence in group making decision process. Different from previous work, our multi-interaction group representation yields the optimal embedding because of considering the multiple interaction data in the embedding construction.

Group recommendation using SGAGR. Once we have obtained the group representation, a ranking score for each item i_b can be computed according to the dot product of the embedding of g_k and i_b. Finally, we generate the predicted group recommendation results $\hat{y}_{kb}$ with highest scores by ranking the scores of items. Meanwhile, we use a common pairwise loss function (Wang et al., 2017) to optimize model for group recommendation task:

$$\delta_{group} = \sum_{(k,b,x) \in O'} (y_{kbx} - \hat{y}_{kbx})^2 = \sum_{(k,b,x) \in O'} (\hat{y}_{kb} - \hat{y}_{kx} - 1)^2, \tag{8}$$

where O' denotes the training set for group recommendation task, and (k,b,x) represents that group g_k has interacted with item i_b but has not interact with item i_x.

4. Experiments

To comprehensively evaluate our SGAGR, we preform extensive experiments on two real-world datasets. In general, we aim to answer the following research questions:

- **RQ1**: How does SGAGR perform as compared with state-of-the-art methods?
- **RQ2**: Are the key components in SGAGR, such as multi-interaction embeddding and aggregation method, necessary for improving performance?
- **RQ3**: How is the effectiveness of our social influence-based attention network? Are the dynamic influence weights learned by SGAGR more preferable than the other fixed weights learning methods?

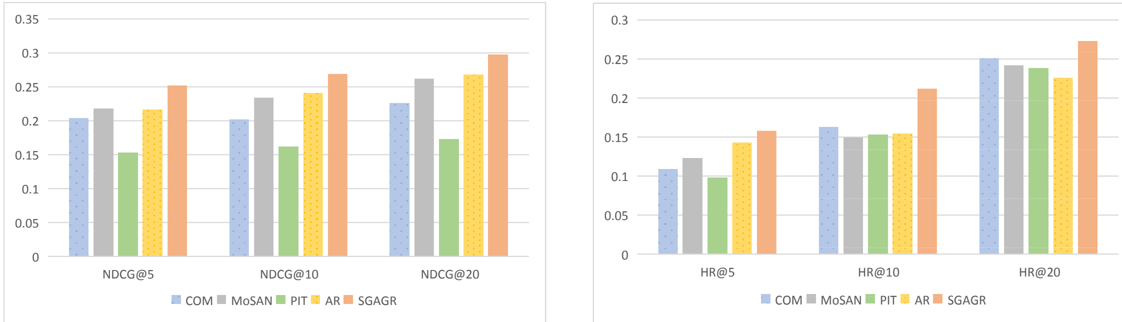
4.1. Experimental settings

This subsection consists of datasets description, evaluation metrics and compared baselines.

Datasets description. We conduct our experiments on two real-world datasets, which are Yelp2018[2] and MovieLens[3]. Yelp allows users to share their check-ins about the local businesses, such as restaurants, bars and so on. Each user can create social connections with the others users. The final Yelp2018 dataset contains 34,504 users, 24,103 groups and 22,611 items, and average group size is 4.45. In this paper, to verify our proposed social homophily in group recommendation task, we extract from the MovieLens 1M Data one dataset that contains groups with high similarity between user-user. Therefore, users in our MovieLens dataset are assigned into the same group when they have high inner group similarity. The final MovieLens dataset contains 5,987 users, 30,426 groups and 2,795 items, and average group size is 5.00. Table 2 denotes the basic statistics of the two datasets.

Evaluation metrics. We evalute our SGAGR and baselines using two metrics in terms of hit ratio (HR) and normalized discounted cumulative gain (NDCG). In leave-one-out evaluation, HR is to measure the accuracy of recommendation results,

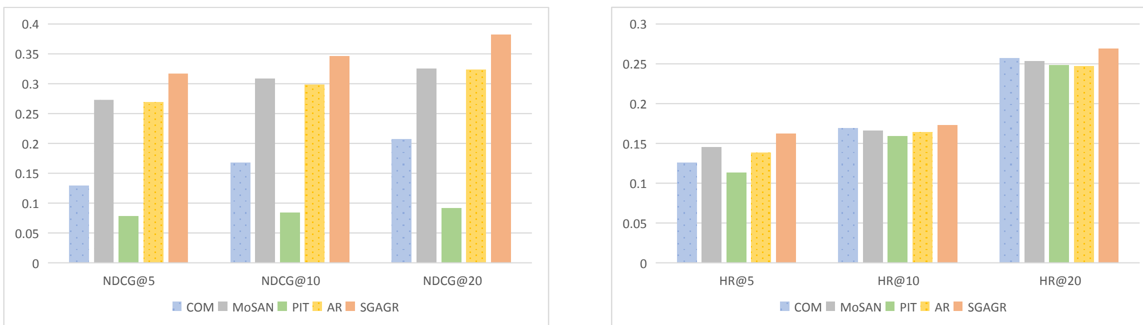
[2]http://www.yelp.com/dataset/challenge
[3]http://grouplens.org/datasets/movielens/



(a) NDCG@K

(b) HR@K

Fig. 3. Performance of group recommendation methods in terms of NDCG@K and HR@K on Yelp2018.



(a) NDCG@K

(b) HR@K

Fig. 4. Performance of group recommendation methods in terms of NDCG@K and HR@K on MovieLens.

Table 2. Basic statistics of the two datasets.

Dataset	#Groups	#Users	#Items	Avg.Group Size
Yelp2018	24,103	34,504	22,611	4.45
MovieLens	30,426	5,987	2,795	5.00

while NDCG can explain the position of the hit by assigning higher score to hit at top positions. The larger the value, the better the performance. The two evaluation metrics have been widely used in most existing work (Tran et al., 2019; Yin et al., 2018; Sun et al., 2019; Wang et al., 2019).

Compared baselines. To demonstrate the effectiveness of our proposed SGAGR, we compared the performance of the following methods.

- **MoSAN (Tran et al., 2019)**: MoSAN designs sub-attention module for each group members to model users' preference. However, it is not sufficient to yield satisfactory embeddings for group recommendation. Our method is different from this method in the embedding construction. We employ multi-graph embedding technology to consider fully the interaction of user-user, user-item, and group-item.

- **AR**: AR is short for attentive representation. This baseline is a simplified version of our SGAGR. It just utilizes the attentive group representation based on social influence, and it does not consider social homophily to capture group intrinsic preference.

- **PIT (Liu et al., 2012)**: As an author-topic model, PIT regards the relatively high influence score as the representation of a group. It chooses the topic based on the preference, and the topic generates the recommendation results.

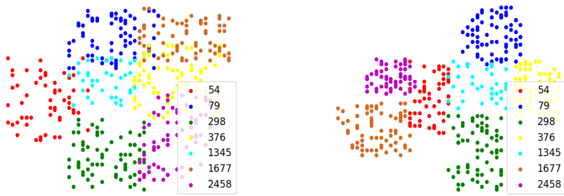
- **COM (Yuan et al., 2014)**: COM is the state-of-the-art group recommendation method. It uses probabilistic model to recommend some activities for a group.

- **BPRMF**: This is matrix factorization (MF) optimized by the Bayesian personalized ranking (BPR) based on average users' embedding aggregation strategy.

Implementation and setting details. We randomly split each dataset into training and testing sets with the ratio of 80% and 20% respectively. We carry out the experimental evaluation on the PyTorch and employ the Adaptive Moment Estimation (Adam) optimizer. We perform mini-batch training, and each mini-batch includes user-to-item interaction and group-to-item interaction. We test the mini-batch size of [128, 256, 512], and the learning rate of [0.001, 0.005, 0.01, 0.05, 0.1]. We repeat each setting for 10 times and report the average results. Besides, we set dropout=0.5. Specifically, we adopt dropout on the hidden layer of the neural attention network.

4.2. *Experimental results and discussion*

In this subsection we discuss the results of several experiments on three aspects of our SGAGR given the two real-world datasets.



(a) BPRMF (b) SGAGR

Fig. 5. Visualization for the t-SNE transformed representations derived between BPRMF and SGAGR on Yelp2018 and MovieLens.

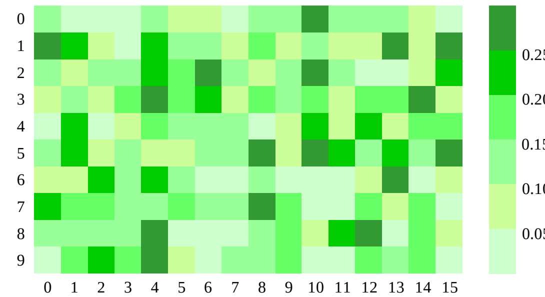


Fig. 6. Visualization for the sampled 10 groups w.r.t. attention weights, where x-axis denotes the group member-ID and the y-axis denotes the group-ID.

Overall performance comparison. We compare the recommendation results from our SGAGR to those from the baselines methods on Yelp2018 and MovieLens datasets. Fig. 3 and Fig. 4 report the NDCG@K and HR@K values $K = \{5, 10, 20\}$ for two datasets. We have the following observations: SGAGR consistently achieves the best performance across baselines, including dynamic aggregation approach MoSAN and probabilistic model approaches (COM, PIT). Specially, the average improvements over MoSAN are 14.28% on Yelp2018 and 15.34% on MovieLens. Although MoSAN uses a dynamic aggregation strategy based on attention network, our SGAGR considers the global group preference and adopts multi-interaction graph embedding to gain better results than it. Moreover, AR as a simplified version of our SGAGR, it just is an attentive group representation based on social influence without considering social homophily. Therefore, AR does not have better performance than our SGAGR.

Importance of exploiting multi-interaction representation. Fig. 5 provides a visualization of the representations derived from BPRMF and our proposed SGAGR. Nodes with the same color indicate all the item embeddings from a user's multiple interaction data. These users are selected typically from the above datasets. Jointly analysing the same users(e.g.,79 and 1677) arcoss Fig. 5, we find that both BPRMF and SGAGR have the avail to encode the items. However, our SGAGR generates more tighter clusters than BPRMF, and multi-interaction embedding technology contributes to the optimal embedding acquirement from the interaction data.

Effect of designing attention network. As shown in Fig. 6, we visualize the sampled 10 groups attention weights of group members. The x-axis denotes the group member-ID in a group and the y-axis represents the sampled group-ID. We take group 2 as an example in Fig. 6, and group member 6 and group member 10 have the largest attention weights or highest social influences. Therefore, these two users are represented by darkest cells. Meanwhile, we also find clearly that different users may have different social influence in different groups. To simulate this process, our SGAGR employs attention network to adjust influence weights well in a dynamic way.

5. Conclusions

In this paper, we have presented a novel SGAGR approach for group recommendation that incorporates multiple interactions to excavate deeply user-item and group-item relationships. More importantly, we analyze social effects of group making decision based on social homophily and social influence. In this way, we capture the static and dynamic group preference respectively. Therefore, our SGAGR not only learns dynamically social influence weights of each group member, but also considers group intrinsic preference from a global perspective. The experimental results clearly show the effectiveness of our proposed approach. In the future, we would like to explore more social effects in recommender systems or extend them to other downstream tasks (Al-Molegi et al., 2018). We believe this work is beneficial to more effective and interpretable recommendation.

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