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Social dual-effect driven group modeling for neural group recommendation

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Abstract

Frequent group activities of human beings have become an indispensable part of human daily life. Group recommendation aims to recommend preferred items to a group of users in recommender systems. The existing solutions on group recommendation are to explore group modeling with or without the help of auxiliary information on social networks. However, we observe that the social factors can be explored directly in the group without employing social information on social networks. Towards this end, we study the social effect-based design guideline to drive group modeling. In this work, we propose a novel **S**ocial dual-**E**ffect driven **A**ttentive **G**roup **R**ecommendation method (SEAGR) that well utilizes social selection effect and social influence effect from sociology to explore group representation learning for neural group recommendation. Specifically, we construct the social selection-driven group inherent modeling from interaction-level and user-level. To mimic interaction-based dynamic group decision-making, we also design a social influence-driven attentive influence mining model in terms of users' influence distinction in different groups. Based on these two components, an aggregative group representation is obtained. Moreover, neural recommenda-

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tion for groups and users could be intensified reciprocally considering the impact of groups on users. The experimental results validate the effectiveness of the proposed method on three real-world datasets, and demonstrate its advantages over state-of-the-art methods in accuracy through extensive experiments.

Keywords: Group recommendation, Social analysis, Group modeling, Representation learning, Neural networks

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1. Introduction

With the ever-growing volume of available online information, the information overload problem is becoming increasingly serious and recommender systems could mitigate this issue effectively. Many traditional recommender systems focus on studying recommendations for individual users. However, the form of user groups is pervasive in human daily life, for example, social networks platform (Meetup[1]) where users are organized as groups to participate in some entertainment activities. There are some situations where items are recommended for groups of users, such as watching movies with family, traveling with friends, and dining with classmates. Therefore, group recommendation emerges as the times require and has gained increasing attention over the last years. An effective group recommendation method not only facilitates group decision making but also improves user participation in Web services (Yuan et al., 2014). A major challenge in group recommendation is how to adapt to the group as a whole, given information about the individual preferences of group members (Felfernig et al., 2018).

Prior works and limitations. Group recommendation task expands individual users into groups, and how to trade-off the preferences of different group members is a great challenge both academic and industry. Previous preference aggregation strategies mainly rely on predefined static strategies, such as average

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

(Baltrunas et al., 2010), least misery (Amer-Yahia et al., 2009), and maximum satisfaction (Boratto & Carta, 2009). However, these methods are hard to capture the complicated dynamic group decision-making process. Nowadays, the studies (Tran et al., 2019; Cao et al., 2018; Zhenhua et al., 2020) are proposed to alleviate this problem. Intuitively, we argue that these dynamic strategy-based studies lack sufficient design guideline study and inherent preference mining of how to achieve group modeling. In other words, existing methods are mostly patchworked models designed to improve accuracy. In essence, it may be subjective and arbitrary without a driving guide to a certain extent. Moreover, there are also some works (Yin et al., 2019; Cao et al., 2021) adding auxiliary information of social networks for group profile modeling. However, we observed that social factors can be explored without auxiliary information of the social networks. Based on this, we develop a novel dual social effects-driven group representation method, in this way, not only can social factors be taken into account without using social networks, but also group inherent preference can be discovered.

Motivations and rationales. In real life, group decision-making could be impacted by miscellaneous social factors, and a group's preference for one item is often the result of multifaceted causes. Intuitively, there is otherness (i.e. difference) as well as likeness (i.e. similarity) among group members. Clearly, people with likeness points fall into the same group, and people could be influenced in terms of individual otherness. For one thing, people tend to form relationships with others who are already similar to them, which is often termed as social selection, which has a long history of study in sociology (Crandall et al., 2008; Zhang & Pelechrinis, 2014). Analogously, people of a kind fall into the same group, and group members' certain similar preferences or attributes promote the formation of a group. For another, group members may have different influences in different groups, which is often called social influence (Zhang & Pelechrinis, 2014; Friedkin, 1998).

With the above intuitions, we probe into several social effects to assist group representation learning for group recommendation, namely social selection and

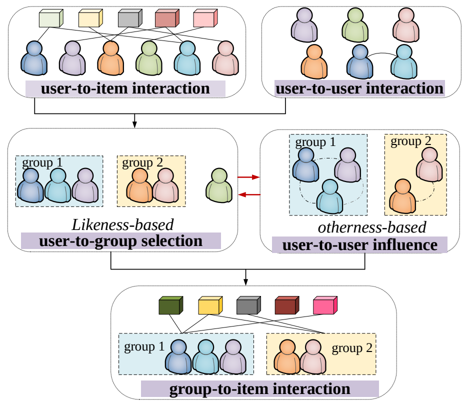


Figure 1: A schematic of the two-fold social effects, i.e., social selection effect and social influence effect. The two social effects jointly affect a group's decision on one item for group recommendation.

social influence. As illustrated in Fig. 1, users interact with items before forming a group respectively, and the likeness could be exhibited among users from user-to-item interaction and user-to-user interaction. Conventionally, the external likeness of group members stays unchanged of contexts in the user-to-group selection, which is inherent preferences or attributes of a group (Wu et al., 2019). Meanwhile, social influence contributes to internal otherness for group member preference which may change in a dynamic way with specific contexts. As shown in Fig. 1, there is an obvious interplay between the user-to-group selection and user-to-user influence. Therefore, the two-fold social effects may jointly impact a group's decision-making on one item, which motivates us to explore such social effects to improve group representation performance.

Methodologies and contributions. To these ends, in this work, we propose a novel social dual-effect driven attentive group recommendation method in the group decision-making process. Specifically, to improve group representation, we first construct social selection-driven group inherent modeling that capture likeness-based group inherent preferences or attributes. By this means, we achieve interaction-level and user-level group modeling. Also, we develop a social influence-driven attentive influence mining model that explores otherness-based on the expertise level of each group member. In our settings, we design a neural attention network to focus on or place a higher influence on representative group members in the group while placing less importance on other members who may be less influence dynamically. We then aggregate them to obtain more effective group representation. Finally, to further consider the impact of groups on users, neural recommendation for groups and users is intensified reciprocally.

In summary, the main contributions of this work can be outlined as follows:

- To the best of our knowledge, this is the first attempt that leverages social dual-effect from sociology to drive group modeling for neural group recommendation.
- We propose a novel social dual-effect driven attentive group recommendation method (SEAGR), a socially-driven deep architecture to unify the group inherent modeling and attentive structure to improve its performance.
- Extensive experiments are conducted on three real-world datasets. Comparisons with state-of-the-art methods demonstrate the effectiveness of the proposed method.

The remainder of this paper is organized as follows. The existing works are discussed related to our method in Section 2. The proposed method is shown in Section 3. In Section 4, experiments are executed to demonstrate the performance of our method. Finally, in Section 5, we draw conclusions and points to future work.

2. Related work

2.1. Group recommendation

In recent years, group recommendation has been widely concerned and deployed in various fields, such as movies, tourism, restaurants, music, and so on. Existing group recommendation methods can be roughly categorized into memory-based and model-based methods (Felfernig et al., 2018). Memory-based methods can be further divided into two categories, namely preference aggregation and score aggregation. The preference aggregation strategy is to first create a group profile by combining all users' preferences, and then generate recommendations for groups (Yin et al., 2019; Li et al., 2018). On the contrary, the score aggregation strategy first predicts the score of each group member for the item and then combines the individual scores of group members to generate recommendation (Baltrunas et al., 2010). Both aggregation strategies are based on predefined strategies (e.g., average, least misery, maximum satisfaction, etc.) and cannot simulate dynamic interactions of preferences between group members.

Many model-based methods have also been proposed by learning the generative process of group decision-making (Zan et al., 2021). Probability models are widely applied to group recommendation task, (Liu et al., 2012) proposed a PIT model and it assumed that the group members with the greatest influence play an important role in group decision-making. Group modeling is implemented by considering the personal preferences and influences of the group members. Besides, (Yuan et al., 2014) proposed a COM model to simulate the group decision-making process and generate recommendation results for groups. (Tran et al., 2019; Cao et al., 2018; Zhenhua et al., 2020; He et al., 2020; Zan et al., 2021) are typical dynamic strategy-based group recommendation examples. (Tran et al., 2019; Cao et al., 2018; He et al., 2020; Zan et al., 2021) are attention-based methods. Similar to ours, they also do not consider social information on social networks and we compare with these methods in our experiments. For example, (Tran et al., 2019) proposed AGREE model that utilizes attention network to learn different weights among group members. Based on AGREE, (He et al., 2020; Zan et al., 2021) explored the multi-view group modeling and the information of comparisons respectively. Although existing methods are effective, they pay less attention to group inherent modeling and lack sufficient design guideline study. Therefore, in this work, our goal is to explore a socially-driven group representation without the help of auxiliary information on social networks.

2.2. Recommendation using social analysis

Social analysis has made massive strides in many research presenting new opportunities to recommender systems. In our work, it can be divided into two categories: one (Yin et al., 2019; Zhenhua et al., 2020; Cao et al., 2021) is an approach that utilizes information of social networks as an auxiliary, and the other (Arazy et al., 2010) is a theory-driven modeling approach. In general individual recommendation, (Li et al., 2017) employed the information of location-based social networks to study point-of-interest recommendations. (Fan et al., 2019) designed the user-item and user-user social graph to achieve social recommendation. (Zhu et al., 2021) exploited long-term and short-term social behaviors by using attention mechanisms. In the group recommendation task, (Yin et al., 2019; Zhenhua et al., 2020; Cao et al., 2021) utilize social influence to discover social features of social networks for effective group recommendation. These studies add more available auxiliary information to improve the model.

In essence, we observed that we are freed to infer them when lacking social features of social networks and so to focus on exploring social effects directly without the help of auxiliary information. Therefore, in contrast to these examples, we aim to infer group inherent modeling without adding side information of social networks. Based on this, we develop a novel dual social effects-driven group representation model, in this way, not only can social factors be taken into account, but also interaction-level and user-level group modeling can be learned without using social networks. In terms of socially-driven study, (Arazy et al., 2010) proposed a framework to merge sociological behavioral theory and social recommender systems design. Inspired by the successful application of sociology, we emphasize that group recommender systems should take into account design guideline studied to drive group modeling. Therefore, we consider social dual-effect from sociology to drive group modeling in process of group recommendation.

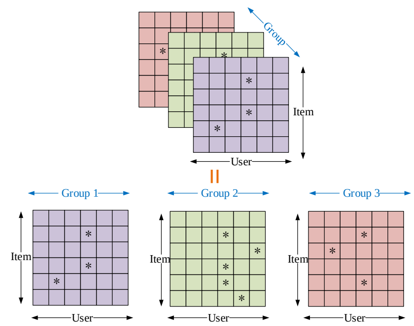


Figure 2: Illustration of the data representation for group recommendation task. If user u as a member in group g shows his/her preference on item i, then the cell is assigned with "$*$", on the contrary, the cell is empty.

3. The proposed method

3.1. Preliminaries

Assumed that there are a set of users $\mathcal{U} = \{u_1, u_2, ..., u_E\}$, a set of items $\mathcal{V} = \{v_1, v_2, ..., v_F\}$, and a set of groups $\mathcal{G} = \{g_1, g_2, ..., g_R\}$ in group recommendation. Two kinds of interactions among these data are considered, namely user-item interaction P, group-item interaction Q. For real-world group-item interaction data, we assume that there is a specific actor in process of group decision-making, and when the user switches to the actor role, this actor will execute the group's decision. Fig. 3 (a) illustrates the input data of our group recommendation task. Given a target group g_l, our task is to generate the recommended item scores for a group that may be interested in, and the problem of group recommendation can be defined as follows:

Input: A set of users $\mathcal{U}$, a set of items $\mathcal{V}$, a set of group $\mathcal{G}$, user-item interactions P, group-item interactions Q.

Output: Two personalized ranking functions that maps an item to a ranking score for target group $f_g : \mathcal{V} \to \mathbb{R}$ and each user $f_u : \mathcal{V} \to \mathbb{R}$.

Fig. 2 illustrates the data representation of a group recommendation task. Assumed that each column denotes a user, each row indicates an item and each matrix represents a group. In our recommendation task, each user belongs to

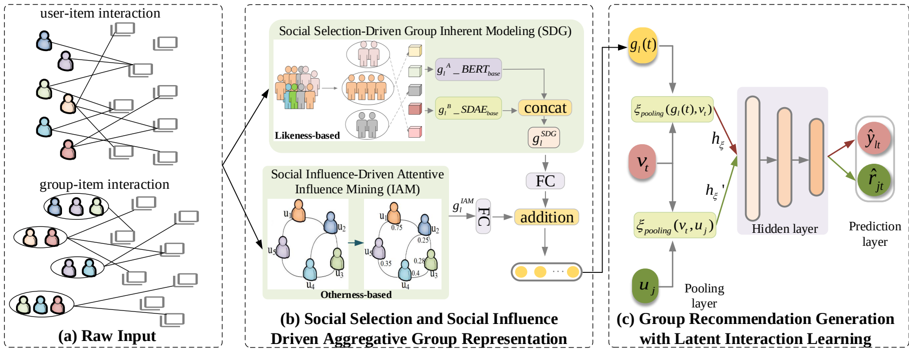


Figure 3: Overview of social dual-effect driven attentive group recommendation. (a) Illustration of the input data for group recommendation task. (b) Social selection and social influence driven aggregative group representation. The first part is SDG that achieves group inherent modeling from two levels in terms of likeness among group members. The second part is IAM that assigns different influence weights in terms of otherness among group members. (c) Group recommendation generation with latent interaction learning.

at least one group. For instance, user 2 belongs to group 1 and group 3, while user 4 belongs to group 1, group 2, and group 3. In this paper, we aggregate the preference of group members to model group representation and obtain prediction scores.

The overview of our SEAGR is shown in Fig. 3. As mentioned before, the multifaceted social effects contribute to group decision-making. In our SEAGR, we first model interaction-level ($g_l^A\_BERT_{base}$) and user-level ($g_l^B\_SDAE_{base}$) group representation respectively. We then conduct concatenation operation to obtain social selection-driven group inherent modeling (SDG), including SDG-A features and SDG-B features. SDG-A and SDG-B achieve interaction-level and user-level group high-order feature coding respectively. We then develop a social influence-driven attentive influence mining model (IAM) to explore the expertise level of each group member dynamically. On this basis, we aggregate them to model group representation using a simple addition operation. Lastly, we suggest the group recommendation items in the general neural recommendation framework.

3.2. *Social selection-driven group inherent modeling*

Driven by social selection, people tend to form a group with others who are already similar to them (Crandall et al., 2008; Zhang & Pelechrinis, 2014). When similar people gather together, they will present a global feature that enables to reflect group inherent preferences as introduced in Section 1. Therefore, a social selection-based group inherent modeling (SDG) module is designed to model group inherent preferences or attributes. Considering the similarity of interaction among group members in the same group, we learn the group representation from two aspects. SDG-A and SDG-B achieve interaction-level and user-level group modeling separately. SDG integrates SDG-A features and SDG-B features. This design conforms to the intuition that the social selection effect contributes to group modeling with intrinsic preferences mining, so we term it as a static inherent preference factor. Fig. 4 provides an overview of our SDG and we refine group inherent modeling as follows:

$$g_l^{SDG} = \{g_l^A, g_l^B\} = Concat\{\prod_{BERT}(g_l^{emb1}), \prod_{SDAE}(g_l^{emb2})\}. \tag{1}$$

where g_l^A and g_l^B denote group representation based on SDG-A and SDG-B separately. g_l^{SDG} contains g_l^A and g_l^B. $\prod$ is the implementation way (BERT and SDAE). *Concat* denotes concatenation operation. g_l^A and g_l^B are combined to construct social selection-driven group inherent modeling using concatenation operation. After that, we apply an element-wise mean-pooling operation to obtain final group representation. Next, the implementation of SDG-A and SDG-B is introduced in detail.

3.2.1. *Interaction-level group modeling*

Generally, a group has several users (i.e. group members) and historical user-item interactions exist within the group. Therefore, the modeling of a group is the high-order interaction coding of intra group. As introduced before, SDG-A aims to achieve interaction-level group modeling. We argue that the modeling of a group can be regarded as an interaction model among internal group members, and it is analogous to the language model. Thus, we construct a

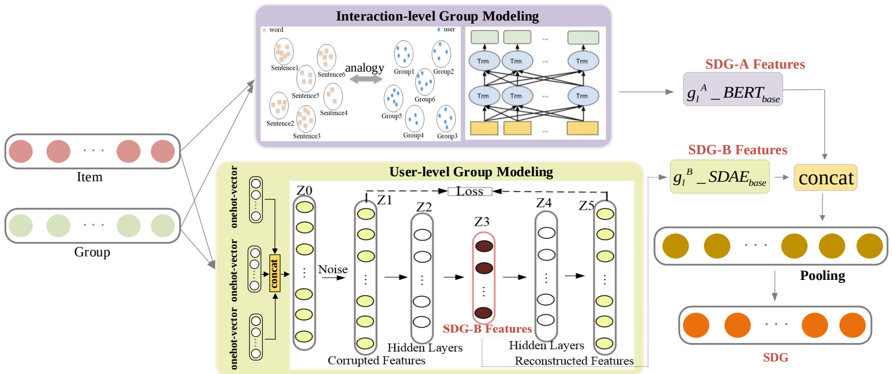


Figure 4: Illustration of social selection-driven group inherent modeling (SDG). It contains the two-fold features with SDG-A features and SDG-B features. SDG-A adopts the idea of deep bidirectional BERT model to learn interaction-level group modeling. SDG-B employs five-layer SDAE to achieve user-level group modeling.

deep bidirectional interaction model to achieve interaction-level group modeling. Inspired by the success of BERT (Devlin et al., 2019), BERT4Rec (Sun et al., 2019) is proposed to model user behavior sequences. Analogously, in our SDG-A part, we adopt the idea of BERT to obtain group representation. The encoder is based on $BERT_{base}$, an interaction-level group modeling as follows:

$$g_l^A = BERT_{base}(g_l^{emb1}). \tag{2}$$

As illustrated in the purple block of Fig. 4, we make the resemblance analysis between group and sentence and regard the group as a sentence and a sentence is composed of words. It contains the features of words, then just as the features of group members are included in a group. What is worth mentioning, a word is not a group member, and the contextual interaction of a group is consistent regardless of the order. 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 bidirectional context information and avoid the information loss caused by global pooling in each layer. Hence we use BERT to model the deep bidirectional interaction as the group vectors. By this means, it reflects likeness-based group inherent preferences from interaction-level adequately.

3.2.2. User-level group modeling

As we all know, there is an inclusion relationship between users and groups. It is crucial to account for the user-level group modeling, especially in an unsupervised learning way. Thus, we investigate how to employ an unsupervised learning model called stacked denoising auto-encoder (SDAE)(Vincent et al., 2010) to obtain user-level group modeling. SDAE is a feedback neural network that learns clean representations from corrupted input data. It is worth mentioning that since the interactions between users and items are undirected, the proposed user-level group modeling in this section also applies to the item-level to a certain extent. We develop a novel SDG-B part by using five-layer SDAE to achieve user-level group modeling for group inherent modeling as follows:

$$g_l^B = SDAE_{base}(g_l^{emb2}). \tag{3}$$

As illustrated in the pale yellow block of Fig. 4, we obtain one-hot vectors for each group members and then concatenate these vectors for constructing a group feature training sample. On this basis, SDG-B trains a five-layer SDAE to achieve user-level group modeling. The following loss function is defined:

$$\mathrm{L} = \theta \sum_{i \in K} (Z_1[i] - Z_5[i])^2 + \eta \sum_{i \notin K} (Z_1[i] - Z_5[i])^2. \tag{4}$$

where $Z_1 - Z_3$ act as the encoder and $Z_3 - Z_5$ act as the decoder respectively. The embedding vector in the middle layer Z_3 is the final group user-level feature vector. θ and η are two hyper-parameters, and K is the set of indexes of entries that are corrupted. The pale yellow block of Fig. 4 shows the neural network structure with five-layer SDAE and we employ a stochastic gradient descent algorithm to minimize the loss function. Equation (4) is the pre-training process and once the training of SDG-B is finished, the feature vectors are fixed.

3.3. Social influence-driven attentive influence mining

Since social influence among group members often impacts on group's decision on one item, for example, a cinephile may provide some insightful decisions

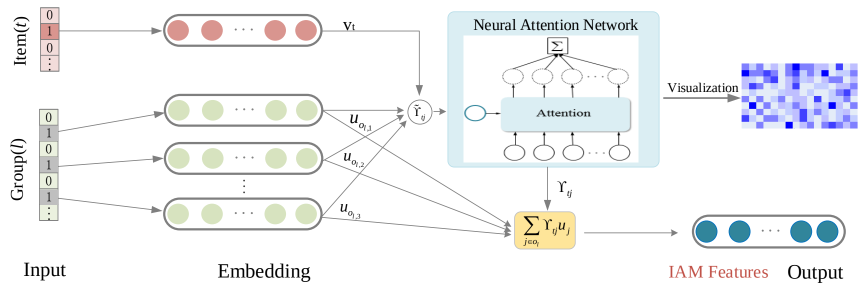


Figure 5: Illustration of social influence-driven attentive influence mining(IAM). Group members of group are assigned different weights by designing neural attention network.

in the choosing process of a movie, but may not have any contributions in terms of choosing a restaurant. We develop social influence-driven attentive influence mining (IAM) to explore fully the expertise level of each group member. As illustrated in Fig. 3(b), we provide an example from our experimental cases and use different numerical values to show the influence weight differences of different members in the group. Generally, a group's embedding is generated by aggregating the embeddings of group members as follows:

$$g_l^{IAM} = \sum_{j \in o_l} \Upsilon_{tj} \mathrm{u}_j. \tag{5}$$

Technically speaking, inspired by the success of the attention mechanism (He et al., 2020; Xu et al., 2021), we design a neural attention network to learn the weight Υ of group members, and it is different from the general way of weighting. During its interaction process, each group member is assigned different weights in this dynamic way. Furthermore, it can simulate the complex process of group decision-making.

In IAM part, $\mathrm{u}_j, \mathrm{v}_t$ are the encoders of the user's historical preference and target item's property respectively, A is a weight vector. Specifically, we use the softmax activation function to obtain the final attention weights and it makes the neural attention network have a probabilistic interpretation. We compute the attention score as:

$$\tilde{\Upsilon}_{tj} = \mathrm{A}^T \mathrm{ReLU}(v, u),$$
$$\Upsilon_{tj} = \mathrm{softmax}(\tilde{\Upsilon}_{tj}) = \frac{exp(\tilde{\Upsilon}_{tj})}{\sum\limits_{j' \in o_l} exp(\tilde{\Upsilon}_{tj'})}. \tag{6}$$

As shown in Fig. 3(b) and Fig. 5, with the attention neural networks, each group member contributes to the group decision making and we can capture the influence distinction of members in different groups. Through our model, group members' different influences can also reflect clearly.

3.4. Social dual-effect driven aggregative group representation

As have mentioned before, SDG captures group inherent preferences or attributes, and IAM explores the expertise level of each group member by considering the different influences of group members. In this subsection, we further aggregate the attention-based representation and group inherent modeling. With the aggregative representation learning, the final group representation captures group inherent preferences and places the higher influence weight in representative group members of the group. In the general group modeling task, it obtains an embedding vector for each group to predict its preference on items. We learn the dynamic aggregation strategy from data in our work, which can be defined as follows.

$$\mathrm{g}_l(t) = AF(\mathrm{v}_t, \{\mathrm{u}_j\}_{j \in o_l}). \tag{7}$$

where $\mathrm{g}_l(t)$ denotes the embedding of group g_l , o_l contains the group member indexes of group g_l and AF presents the aggregation function.

As shown in Fig. 3(b), we aggregate the SDG features and IAM features to achieve the final group representation. Our final group representation modeling consists of two components, namely social influence-driven attentive representation and social selection-driven group inherent modeling, which can be shown as:

$$\mathrm{g}_l(t) = \sum_{j \in o_l} \Upsilon_{tj} \mathrm{u}_j + \mathrm{g}_l^{SDG}. \tag{8}$$

3.5. Model prediction and optimization

In the previous section, we perform the group modeling based on dual social effects by aggregating the attention-based representation (IAM) and group inherent modeling (SDG). Based on our proposed group representation, we next describe how to generate the final group recommendation.

From the work (He et al., 2017), neural collaborative filtering (NCF) is a general multi-layer neural network for item recommendation and has been successfully extended to group recommendation (Cao et al., 2018; He et al., 2020). As shown in Fig. 3(c), we feed the obtained group representation, item representation, and user representation into a dedicated neural network to learn group-item interaction and user-item interaction. First, given group-item pair $(\mathrm{g}_l, \mathrm{v}_t)$ or user-item $(\mathrm{u}_j, \mathrm{v}_t)$, the representation can be obtained by our above representation learning. And then the embeddings vectors are fed into a pooling layer and shared hidden layers and the prediction results are obtained at last. We elaborate on each layer and model optimization in our framework below.

3.5.1. Pooling layer

We take group-item pair $(\mathrm{g}_l, \mathrm{v}_t)$ as a input instance, and pooling layer first makes element-wise product $\mathrm{g}_l(t) \odot \mathrm{v}_t$. To avoid information loss, we then concatenate them to the original embedding and form a matrix:

$$\mathrm{h}_0 = \xi_{\ pooling}(\mathrm{g}_l(t), \mathrm{v}_t) = concat(\mathrm{g}_l(t) \odot \mathrm{v}_t, \mathrm{g}_l(t), \mathrm{v}_t). \tag{9}$$

3.5.2. Hidden layer

The hidden layer is a stack of fully connected layers, which can capture nonlinear and high order dependencies among users, groups, and items. f is activation function ReLU. D_ε , b_ε and h_ε denote the weight matrix, bias vector and output neurons of the ε-th hidden layer respectively.

$$\mathrm{h}_\varepsilon = f(\mathrm{h}_{\varepsilon-1}) = \mathrm{ReLU}(D_\varepsilon h_{\varepsilon-1} + \mathrm{b}_\varepsilon). \tag{10}$$

3.5.3. Prediction layer

The output of last hidden layer h_ε is transformed to the prediction layer. The prediction score of group g_l on item v_t can be computed as:

$$\hat{y}_{lt} = f_{score}(h_\varepsilon) = d^T h_\varepsilon,\ when\ h_o = \xi_{\ pooling}(g_l(t), v_t). \tag{11}$$

where d represents the weights of the prediction layer. (g_l, v_t) denotes group-item pair. Similarly, the prediction score of user u_j on item v_t is as follows:

$$\hat{r}_{jt} = f_{score}(h_\varepsilon) = d^T h_\varepsilon,\ when\ h_o = \xi_{\ pooling}(u_j, v_t). \tag{12}$$

where (u_j, v_t) denotes user-item pair. It's worth pointing out that we specifically designed the prediction to share the same hidden layer for both tasks. Since group embedding is aggregated from user embedding, this puts them in essentially the same semantic space. In addition, the user-item interaction data can also be used to increase the training of group-item interaction function, and vice versa, to facilitate the mutual reinforcement of the two tasks.

3.5.4. Model optimization

Following the previous work (Cao et al., 2018; He et al., 2020), pair learning is used to optimize model parameters and we opt for the regression-based pairwise loss in our recommendation task, which is a general approach for item recommendation (Wang et al., 2017). Because of the sparsity of group-item interactive data, we adopt a two-stage training strategy. In the first stage, the preferences of users are learned by minimizing the pair loss function of user-item interaction instances in Equation (13) :

$$\Gamma_u = \sum_{(j,t,z)\in O} (\hat{r}_{jt} - \hat{r}_{jz} - 1)^2. \tag{13}$$

where O denotes the user training set. (j, t, z) indicates that user u_j has interacted with item v_t but does not interact with v_z before. Similarly, in the second stage, the pair loss function of the group-item interaction instance in Equation (14) is minimized:

$$\Gamma_g = \sum_{(l,t,z)\in O'} (\hat{y}_{lt} - \hat{y}_{lz} - 1)^2. \tag{14}$$

where O' represents the group training set for group recommendation task. (l, t, z) denotes that group g_l has interacted with item v_t, but has not interacted with v_z before. These two functions are optimized by Adam optimizer (Kingma & Ba, 2015).

4. Experiments

In what follows, we first introduce the experimental setup, including datasets, evaluation metrics, and comparison methods. We conduct extensive experiments on three datasets with the aim of answering the following research questions. The codes are ready for public download.

RQ1: How does our proposed SEAGR perform as compared with state-of-the-art group recommendation methods?

RQ2: Do the key components (i,e., SDG and IAM) of SEAGR contribute to group recommendation performance?

RQ3: How is the convergence of our SEAGR?

RQ4: Can the attentive influence of group members in different groups be mined?

4.1. Experimental setup

Datasets. In reality, there are two types of groups. One is the persistent group (or similar group), the other is the occasional (or random) group (Baltrunas et al., 2010; Tran et al., 2019). Hence, to better simulate different group types in the real world, random groups and groups with high inner group similarity are distinguished. Our experiments are conducted on three real-world datasets. Table 1 denotes the basic statistics of the three datasets. The detailed descriptions of the dataset are as follows.

The first dataset is CAMRa2011[2], which is a public dataset containing the movie rating records of individual users and households (persistent group). Following the work (Cao et al., 2018, 2021), each household is treated as a group

[2]http://2011.camrachallenge.com/2011

Table 1: Basic statistics of the datasets.

Dataset	#Groups	#Users	#Items	Avg.Group Size
CAMRa2011	290	602	7710	2.08
Yelp2018	24,103	34,504	22,611	4.45
MovieLens	30,426	5,987	2,795	5.00

and movies are recommended for each household. The users without group information are filtered and users who have joined a group are kept.

The second dataset is Yelp2018[3]. It allows users to share their check-ins about the local businesses, such as restaurants, bars, and so on. Following the work(Yin et al., 2019), we focus on the restaurants located in the Los Angles area. If a set of users visit a restaurant or participate in the same event at the same time, they are considered group members of a group (random group) and the common activity they participate in is the corresponding group activity. This dataset is used in recent group recommendation tasks (Yin et al., 2019; Sankar et al., 2020).

The third dataset is MovieLens[4] and following existing work (Yuan et al., 2014; Tran et al., 2019), users in our MovieLens dataset are assigned into the same group when they have high inner group similarity. Thus, it contains groups (similar group) with high similarity between user-user. The similarity is calculated with the Pearson correlation coefficient and the top 33% of all possible pairs are selected to form groups.

Evaluation metrics. Our final goal is to obtain the item scores. To match the recommendation better, we use the evaluation index generated by item lists to evaluate the performance of our proposed method for group recommendation. The performance of the top-N recommendation is evaluated in our experiment by the widely used metric, namely Hit Ratio (HR) and Normalized Discounted

[3]http://www.yelp.com/dataset/challenge

[4]http://grouplens.org/datasets/movielens/

Cumulative Gain (NDCG). HR measures whether the test item is in the top-N list (1 for yes, 0 for No), while NDCG measures the hit position by giving a high score. Here N is the number of recommendations and we evaluate the performance with $N = \{5, 10, 20\}$. NDCG and HR metrics are used in (Yuan et al., 2014; Yin et al., 2019; Cao et al., 2018, 2021). The higher value is, the better performance is.

Comparison methods. As mentioned before, the general aggregation methods include the least misery (LM) strategy, maximum satisfaction (MS) strategy, and average(AVG) strategy. Existing social recommendations focus on social networks and regard social information as an auxiliary to better recommendation quality. Distinct from these studies, we observe that the social factor can be explored without auxiliary information of social networks. Based on this, our method does not take into account auxiliary information from social networks but explores social dual-effect driven group modeling. Therefore, the proposed method does not compare against social recommendations based on social networks (Yin et al., 2019; Zhenhua et al., 2020). NCF has superior performance compared to the traditional recommendation model such as factorization machines, which has been adopted by some advanced work (Cao et al., 2018; Sankar et al., 2020; Cao et al., 2021), and we compare the NCF with static LM and AVG strategies. AGREE, MoSAN, GAME and UDA are similar to our method in terms of attention mechanism, however, we employ the more effective aggregation representation to model the group profile. PIT and COM are probabilistic models and the comparison to show the effectiveness of our attentive weights. The comparison methods are described in detail below.

- **LM (Amer-Yahia et al., 2009)**: We take the minimum score of all group members as the group's score in the framework of neural collaborative filtering. This method assumes that the least satisfied members have a high influence on group decision-making.

- **AVG (Baltrunas et al., 2010)**: We average the preference scores of all group members as the group's score in the framework of neural collaborative filtering. This method assumes that the influence of group members is equal.

- **PIT (Liu et al., 2012)**: Personal Impact Topic (PIT) is an author-topic model and it assumes that each group member has an influence weight. PIT regards the relatively high influence member as the representatives of a group. This representative user selects a topic based on her (his) preference, and the topic generates a recommendation result for the group.

- **COM (Yuan et al., 2014)**: COM is the state-of-the-art group recommendation method and it is a probabilistic model that models the group activity generation process for a group.

- **NCF (He et al., 2017)**: This method regards a group as a virtual user and it does not consider the information of group members. And then users and virtual users are embedded into the NCF [5] framework.

- **AGREE (Cao et al., 2018)**: AGREE [6] employs attention mechanism to learn the group-item interaction and user-item interaction. Besides, in (Cao et al., 2021), AGREE is presented without considering social information. However, this model ignores group inherent modeling.

- **MoSAN (Tran et al., 2019)**: MoSAN designs sub-attention module for each group members to model users' preference. However, it is insufficient to explore latent interaction for group representation.

- **GAME (He et al., 2020)**: It mainly targets the occasional group recommendation and learns graphical and attentive multi-view embeddings of users, items, and groups. GAME is implemented based on AGREE.

- **UDA (Zan et al., 2021)**: UDA [7] is short for user-difference attention model for group recommendation. This model uses user-difference attention to cap-

[5] https://github.com/hexiangnan/neural_collaborative_filtering
[6] https://github.com/LianHaiMiao/Attentive-Group-Recommendation
[7] https://github.com/zanshuxun/User-Difference-Attention

ture the comparisons between group members. UDA is also implemented based on AGREE.

Implementation and setting details. Our SEAGR is implemented on PyTorch [8]. Each dataset is randomly split into training and testing sets with the ratio of 80% and 20% respectively. Each setting is repeated 5 times and the average result is reported. 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]. Moreover, we employ the "masking noise" corruption strategy in the SDAE training process, and SDAE consists of five fully connected layers with ReLU activation. Besides, we adopt dropout on the hidden layer of the neural attention network and the NCF interaction learning component. Note that the results of baselines take the best values of the existing results and the results we implemented. For efficiency, we have recorded the running time of SEAGR and AGREE in our equipment (2080Ti, 64G). When K=10, epoch=30, the running time (including training and testing) interval of AGREE was 870 to 880 seconds, and our SEAGR was 880 to 890 seconds.

4.2. Overall performance comparison: RQ1

Since we propose the innovations in group representation learning, we compare the performance of our SEAGR with the relevant state-of-the-art methods in the group recommendation task. Note that since PIT, COM, MoSAN, GAME, UDA, and score aggregation methods are specially designed for group recommendation, they don't consider the recommendation for individual users. Table 2 to Table 4 show the results of different methods on the three datasets receptively. We have the following observations:

(1) Generally, our SEAGR achieves the best performance over baseline methods. UDA and GAME are better than MoSAN and AGREE, and most of the

[8] https://pytorch.org

Table 2: Top-N overall performance comparison for users and groups on CAMRa2011 Dataset.

	N=5				N=10				N=20			
	User		Group		User		Group		User		Group	
	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG
LM (Amer-Yahia et al., 2009)	-	-	0.5593	0.3788	-	-	0.7648	0.4455	-	-	0.8874	0.4729
AVG (Baltrunas et al., 2010)	-	-	0.5683	0.3819	-	-	0.7641	0.4452	-	-	0.8845	0.4718
PIT (Liu et al., 2012)	-	-	0.4987	0.2878	-	-	0.6488	0.3325	-	-	0.7829	0.3956
COM (Yuan et al., 2014)	-	-	0.5798	0.3785	-	-	0.7695	0.4385	-	-	0.8746	0.4612
NCF (He et al., 2017)	0.6119	0.4018	0.5803	0.3896	0.7894	0.4535	0.7693	0.4448	0.8894	0.4807	0.8895	0.4725
AGREE (Cao et al., 2018)	0.6223	0.4118	0.5883	0.3955	0.7967	0.4687	0.7807	0.4575	0.8951	0.4856	0.8926	0.4792
MoSAN (Tran et al., 2019)	-	-	0.5894	0.3971	-	-	0.7823	0.4591	-	-	0.8947	0.4836
GAME (He et al., 2020)	-	-	0.5914	0.3963	-	-	0.7851	0.4606	-	-	0.8963	0.4872
UDA (Zan et al., 2021)	-	-	0.5922	**0.4027**	-	-	0.7848	0.4598	-	-	0.8959	0.4866
SEAGR-M	0.6184	0.4120	0.5803	0.3950	0.7923	0.4668	0.7792	0.4569	0.8930	0.4815	0.8921	0.4762
SEAGR-DA	0.6233	0.4176	0.5888	0.3940	0.7987	0.4727	0.7952	0.4610	0.9076	0.4972	0.9014	0.4843
SEAGR-DB	0.6237	0.4152	0.5849	0.3961	0.7979	0.4710	0.7918	0.4579	0.9092	0.4932	0.9045	0.4875
SEAGR-D	0.6427	0.4215	0.5944	0.3981	0.8066	0.4723	0.7968	0.4612	0.9095	0.5093	0.9100	0.4902
SEAGR (ours)	**0.6452**	**0.4221**	**0.5956**	0.3997	**0.8107**	**0.4796**	**0.7992**	**0.4615**	**0.9139**	**0.5101**	**0.9126**	**0.4951**

*Note that empty results with "-" because some methods are designed specifically for group recommendation. The best results are bold.

results show that our SEAGR achieves the improvement of performance compared with all baselines.

(2) More specifically, the optimal improvement over AGREE is 17.55% for HR and 12% for NDCG on the Yelp2018 dataset. Besides, compared to MoSAN, the proposed SEAGR gains 5.88% and 8.32% improvement maximally for HR and NDCG respectively.

(3) For maximum improvement, our SEAGR improves 4.61% than GAME on Yelp2018 dataset in terms of HR@10 and 6.16% than UDA on Yelp2018 dataset in terms of NDCG@10.

As mentioned before, our SEAGR for neural group recommendation is similar to AGREE, MoSAN, GAME, and UDA at a technological level. AGREE just uses an attention network to get the representation of a group, while MoSAN designs a sub-attention module for each group member. GAME and UDA are implemented based on AGREE. Distinct from them, our SEAGR models the group inherent preferences. On the one hand, we adopt a deep bidirectional model to obtain interaction-level group modeling. On the other hand, a deep SDAE model is employed to achieve user-level group modeling. Therefore, our method is better than UDA, AGREE, and MoSAN on three datasets.

Although SEAGR is 0.75% lower than GAME on the CAMRa2011 dataset

Table 3: Top-N overall performance comparison for users and groups on Yelp2018 Dataset.

	N=5				N=10				N=20			
	User		Group		User		Group		User		Group	
	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG
LM (Amer-Yahia et al., 2009)	-	-	0.1052	0.1994	-	-	0.1594	0.2051	-	-	0.2362	0.2220
AVG (Baltrunas et al., 2010)	-	-	0.1064	0.2035	-	-	0.1663	0.2090	-	-	0.2402	0.2249
PIT (Liu et al., 2012)	-	-	0.0981	0.1530	-	-	0.1494	0.1620	-	-	0.2387	0.1730
COM (Yuan et al., 2014)	-	-	0.1090	0.2040	-	-	0.1630	0.2120	-	-	0.2512	0.2260
NCF (He et al., 2017)	0.1389	0.2052	0.1264	0.1987	0.2016	0.2253	0.1959	0.2094	0.2454	0.2539	0.2084	0.2295
AGREE (Cao et al., 2018)	0.1914	0.2206	0.1583	0.2183	0.2712	0.2415	0.2125	0.2342	0.3105	0.2636	0.2735	0.2621
MOSAN (Tran et al., 2019)	-	-	0.1698	0.2257	-	-	0.2376	0.2438	-	-	0.2843	0.2603
GAME (He et al., 2020)	-	-	0.1718	0.2357	-	-	0.2388	0.2498	-	-	0.2893	0.2799
UDA (Zan et al., 2021)	-	-	0.1703	0.2341	-	-	0.2379	0.2451	-	-	0.2888	0.2770
SEAGR-M	0.1824	0.2186	0.1579	0.2141	0.2694	0.2351	0.2101	0.2294	0.3024	0.2620	0.2680	0.2589
SEAGR-DA	0.1957	0.2239	0.1586	0.2188	0.2774	0.2485	0.2235	0.2451	0.3175	0.2701	0.2770	0.2634
SEAGR-DB	0.1928	0.2264	0.1621	0.2251	0.2693	0.2468	0.2252	0.2390	0.3140	0.2692	0.2782	0.2597
SEAGR-D	0.2011	0.2321	0.1724	0.2310	0.2798	0.2518	0.2401	0.2499	0.3251	0.2850	0.2901	0.2711
SEAGR (ours)	**0.2114**	**0.2405**	**0.1798**	**0.2445**	**0.2842**	**0.2647**	**0.2498**	**0.2602**	**0.3362**	**0.2908**	**0.2990**	**0.2819**

*Note that empty results with "-" because some methods are designed specifically for group recommendation. The best results are bold.

at NDCG@5, SEAGR beats GAME on the other evaluations. The possible reason is that the characteristics of CAMRa2011 dataset are small in scale and there is less learning interaction information, the useful information is directly and simply obtained through multi-view embedding of GAME. Besides, if we don't consider the impact of groups on users and lack mutual reinforcement, NCF has unsatisfactory results. As an upstream task, the effectiveness of our SEAGR in group preference modeling is justified. Meanwhile, our SEAGR compares the performance with the COM, AVG, and LM, the results have a better improvement.

AGREE, MoSAN, GAME, UDA, and our SEAGR employ dynamic aggregation strategies based on attention mechanisms and can simulate the group's dynamic decision-making. Thus, it has better results than others. More importantly, in contrast to AGREE, MoSAN, GAME and UDA, SEAGR learns jointly interaction-level and user-level group modeling to capture group inherent preferences and it has more accuracy for group recommendation. Moreover, we can see that our SEAGR outperforms obviously other comparison methods on the Yelp2018 and MovieLens. They have a larger average group size compared with CAMRa2011 and our proposed method has more accuracy in the larger group. The deep latent interaction among group members in the larger groups is

Table 4: Top-N overall performance comparison for users and groups on MovieLens Dataset.

	N=5				N=10				N=20			
	User		Group		User		Group		User		Group	
	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG
LM (Amer-Yahia et al., 2009)	-	-	0.1158	0.2355	-	-	0.1394	0.2684	-	-	0.2301	0.2834
AVG (Baltrunas et al., 2010)	-	-	0.1204	0.2476	-	-	0.1401	0.2761	-	-	0.2339	0.2876
PIT (Liu et al., 2012)	-	-	0.1134	0.0781	-	-	0.1595	0.0843	-	-	0.2481	0.0918
COM (Yuan et al., 2014)	-	-	0.1262	0.1297	-	-	0.1695	0.1687	-	-	0.2574	0.2071
NCF (He et al., 2017)	0.1628	0.3495	0.1297	0.2586	0.1824	0.3254	0.1448	0.2847	0.2584	0.3412	0.2375	0.2950
AGREE (Cao et al., 2018)	0.1748	0.3621	0.1376	0.2648	0.1904	0.3492	0.1542	0.2975	0.2734	0.3571	0.2476	0.3140
MoSAN (Tran et al., 2019)	-	-	0.1459	0.2735	-	-	0.1667	0.3083	-	-	0.2539	0.3252
GAME (He et al., 2020)	-	-	0.1479	0.2782	-	-	0.1689	0.3106	-	-	0.2579	0.3299
UDA (Zan et al., 2021)	-	-	.01485	0.2768	-	-	0.1677	0.3099	-	-	0.2564	0.3286
SEAGR-M	0.1704	0.3458	0.1303	0.2143	0.1834	0.3352	0.1441	0.2570	0.2574	0.3389	0.2314	0.3083
SEAGR-DA	0.1789	0.3710	0.1416	0.2714	0.2011	0.3537	0.1641	0.3018	0.2831	0.3642	0.2526	0.3217
SEAGR-DB	0.1792	0.3691	0.1431	0.2730	0.1999	0.3541	0.1612	0.3046	0.2793	0.3655	0.2520	0.3197
SEAGR-D	0.1801	0.3733	0.1498	0.2800	0.2053	0.3611	0.1664	0.3073	0.2813	0.3695	0.2612	0.3215
SEAGR (ours)	**0.1821**	**0.3735**	**0.1506**	**0.2861**	**0.2100**	**0.3663**	**0.1693**	**0.3130**	**0.2897**	**0.3699**	**0.2622**	**0.3306**

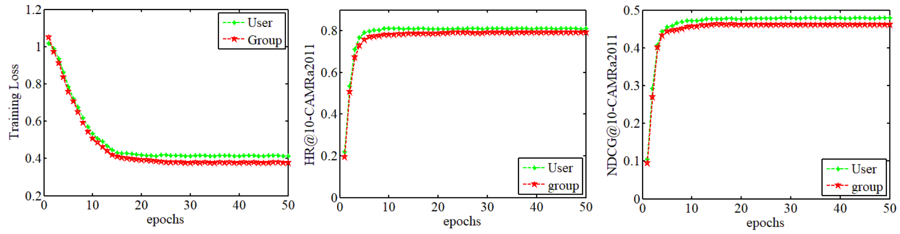
*Note that empty results with "-" because some methods are designed specifically for group recommendation. The best results are bold.

obvious, and it reflects the advancement of our method for group representation.

4.3. Ablation study: RQ2

To further understand the importance of aggregation the group inherent modeling and attention-based representation, the ablation study is conducted. SEAGR-D represents the social selection-driven group inherent modeling, SEAGR-M denotes the social influence-driven attention-based representation, and SEAGR is our attentive aggregation representation. In SEAGR-D, SEAGR-DA only achieves interaction-level group modeling, and SEAGR-DB only achieves user-level group modeling. Table 2 to Table 4 show the results of four simplified components and our SEAGR on three datasets.

As shown in Table 2 to Table 4, SEAGR-D has more accuracy than SEAGR-M on the three datasets. Technically speaking, the key difference between SEAGR-D and SEAGR-M is the way of group representation. Specifically, SEAGR-D obtains the group representation by combining interaction-level model and user-level model to obtain group representation. SEAGR-M is to learn group representation based on attention mechanism and it is similar to AGREE (Cao et al., 2018, 2021) at a technical level. Moreover, SEAGR-DA has bet-



(a) Training Loss **(b) HR@10** **(c) NDCG@10**

Figure 6: Training loss and group recommendation performance of SEAGR w.r.t. the number of epochs on CAMRa2011. (a) Training Loss. (b) HR@10 with different epochs on CAMRa2011 dataset. (c) NDCG@10 with different epochs on CAMRa2011 dataset.

ter results than SEAGR-B on both datasets. The experimental results show that our group representation has a better performance than attention-based representation. Above all, our SEAGR aggregates the SEAGR-D (SDG features) and SEAGR-M (IAM features) as the representation for group modeling, which considers the influence difference of group members and the group inherent modeling of two levels. Therefore, the performance of our SEAGR is better than the two components, and SEAGR demonstrates significant improvements over SEAGR-D and SEAGR-M.

4.4. Convergence analysis: RQ3

The training loss is shown in Fig. 6(a). We can see clearly that SEAGR converges fast and it reaches optimal results when the epoch is about 14. Besides, as shown in Fig. 6(b) and 6(c), we also present the value of HR@10 and NDCG@10 with the increasing number of epochs on the CAMRa2011 dataset. Through our experiments, the convergence on Yelp2018 and Movielens dataset is similar to the CAMRa2011 dataset, so to save space, we only report convergence on the CAMRa2011 dataset.

As we all know, deep neural networks are with great representation learning ability. However, it is easy to overfit the trained model. In order to prevent SEAGR from overfitting, a dropout strategy is adopted to alleviate effectively the overfitting and achieve regularization to a certain extent. Fig. 7 exhibits

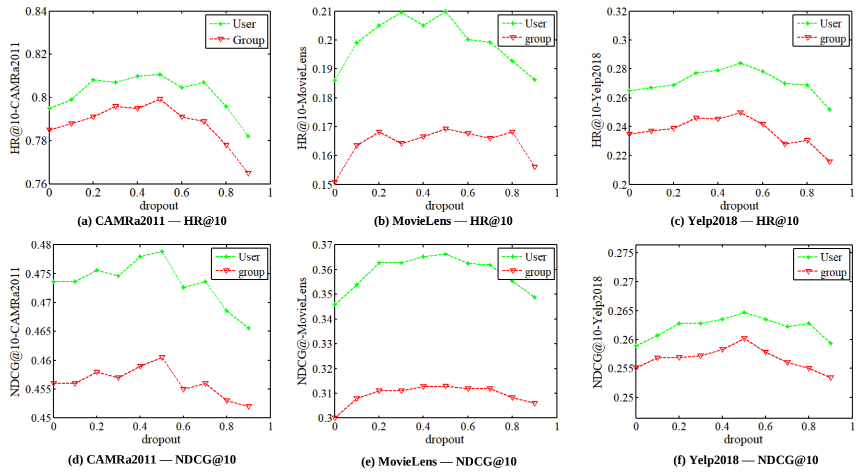


Figure 7: Performance of SEAGR w.r.t. the dropout ratio. (a) HR@10 with different dropout ratio on CAMRa2011 dataset. (b) HR@10 with different dropout ratio on MovieLens dataset. (c) HR@10 with different dropout ratio on Yelp2018 dataset. (d) NDCG@10 with different dropout ratio on CAMRa2011 dataset. (e) HR@10 with different dropout ratio on MovieLens dataset. (f) NDCG@10 with different dropout ratio on Yelp2018 dataset.

the performance of SEAGR w.r.t and the dropout ratio on the CAMRa2011, Yelp2018, and MovieLens datasets when N=10. As illustrated in Fig. 7, the optimal settings for the dropout ratio are 0.4 to 0.6 on both datasets.

4.5. Effect of attentive influence mining: RQ4

To visualize the validity of the attention mechanism in our attentive influence mining model, we show some sample groups in Fig. 8. These samples were randomly selected from our datasets. The darker the color is, the more influential group members have. As shown in Fig. 8, users 1 and 12 have the largest attention weights or the largest influence as representative group members in group 6, which are indicated by their darkest cells.

As noted previously, group members have different influences on the group decision making and representative group members of the group have a higher influence. Our idea is similar to PIT in this view, whereas we adopt a different technology. So we choose PIT as a comparison method to verify the effectiveness

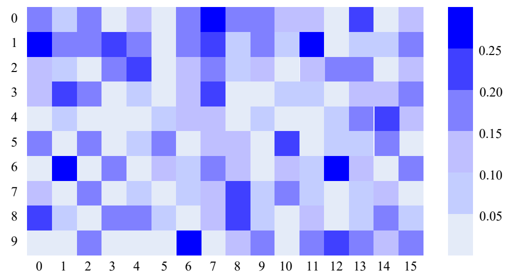


Figure 8: Visualization for the sampled 10 groups w.r.t. attention weights, where x-axis denotes the group member-ID and the y-axis denotes the group-ID.

of our method in this section. Fig. 9 visualizes that the influence weight using PIT and SEAGR in randomly-chosen groups from our datasets. We can see clearly that the two methods learn both the influence weight for each group member.

As shown in Fig. 9, in Group A, user-332 of four users has a large weight and is the representative group member of group A. However, PIT continues to consider that user-332 has a large weight in group B. In fact, user-119 has a large weight in group B and SEAGR can determine the representative group member of the group effectively for group decision-making. Since PIT's influence parameter cannot differentiate the roles of one user in different groups and it may fail to identify representative group members of the group. Therefore, our attentive influence mining model based on attention mechanism can capture the dynamic influence weight in the process of group decision-making.

4.6. Discussion

Overall, the advantages and limitations of the proposed method in this paper are summarized as follows.

Advantages: The proposed SEAGR has the following two advantages. (1) Our method is driven by social dual-effect from sociology and provides sufficient design guideline study. Meanwhile, the social effects can be explored without the help of side information on social networks. (2) Our group representation modeling captures group inherent preferences or attributes by aggregating fea-

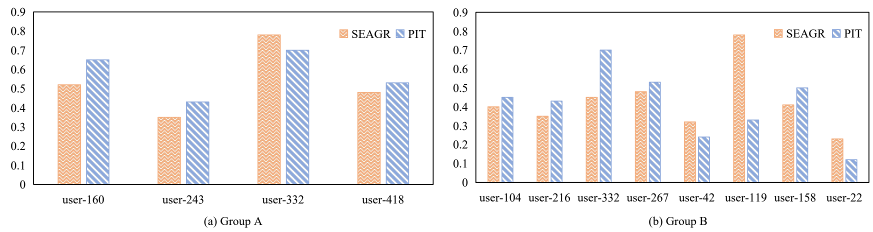


Figure 9: Visualization for the influence weight by PIT and SEAGR. (a) Group A. The user-332 of four users has a large weight and as the expert of group A. (b) Group B. The user-119 has a large weight in group B and as the expert of group B.

tures of two levels and the optimal improvement over AGREE is 17.55% in accuracy.

Limitations: We identify two limitations of our work. (1) Our model takes 10 to 20 seconds longer to run compared to the main baselines in efficiency. We plan to explore a lightweight model to reduce time costs. (2) In real life, there are some heterogeneous groups, and it is difficult for people to reach a consensus in such situations. Therefore, they are less likely to participate in group activities together. The proposed method follows the principle of homophily and is not applicable to heterogeneous groups to some extent.

5. Conclusion and future work

In this work, we focus on the issue of group modeling with social effects. To the best of our knowledge, this is the first work to adopt social selection and social influence simultaneously for group aggregation representation. We propose a novel social dual-effect driven attentive group modeling for neural group recommendation, which aggregates the group inherent modeling and attention-based representation for group representation. Our proposed method demonstrates impressive performance in the experimental results than the comparison methods. In the future, we would like to explore more social effects in recommender systems or extend them to other downstream tasks.

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