

PEGA: Personality-Guided Preference Aggregator for Ephemerally Group Recommendation

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ABSTRACT

Recently, making recommendations for ephemeral groups which contain dynamic users and few historic interactions have received an increasing number of attention. The main challenge of ephemeral group recommender is how to aggregate individual preferences to represent the group's overall preference. Score aggregation and preference aggregation are two commonly-used methods that adopt hand-craft predefined strategies and data-driven strategies, respectively. However, they neglect to take into account the importance of the individual inherent factors such as personality in the group. In addition, they fail to work well due to a small number of interactive records. To address these issues, we propose a **Personality-Guided Preference Aggregator (PEGA)** for ephemeral group recommendation. Concretely, we first adopt hyper-rectangle to define the concept of *Group Personality*. We then use the personality attention mechanism to aggregate group preferences. The role of personality in our approach is twofold: (1) To estimate individual users' importance in a group and provide explainability; (2) to alleviate the data sparsity issue that occurred in ephemeral groups. The experimental results demonstrate that our model significantly outperforms the state-of-the-art methods w.r.t. the score of both Recall and NDCG on Amazon and Yelp datasets.

CCS CONCEPTS

- Information systems → Recommender systems;
- Computing methodologies → Neural networks.

KEYWORDS

Group Recommendation, Personality Traits, Data Sparsity

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1 INTRODUCTION

Humans, as social animals, inevitably participate in various group activities, including dining, entertaining, traveling, etc. Due to the

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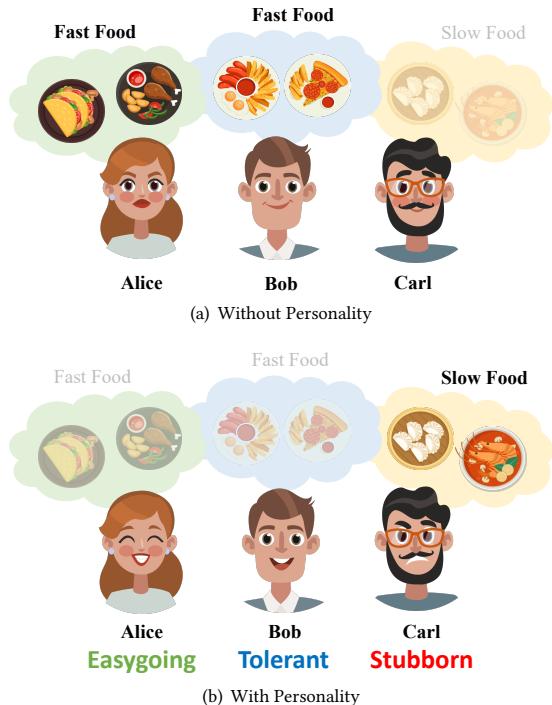


Figure 1: An example that illustrates the role of personality in ephemeral group recommendation.

diversity of group members' preferences, the traditional recommendation system for individuals cannot provide suggestions that satisfy all group members. Thus, the group recommendation system [27] has emerged, which simulates the group decision-making process and finally promotes group members to reach a consensus. Groups can be categorized into persistent and ephemeral groups [31]. Persistent groups have stable members and sufficient historical interactions, which can degenerate into a virtual individual and directly apply recommendation techniques for individuals [2, 9]. In this paper, we focus on the more challenging and realistic scenarios, that is, making recommendations for ephemeral groups which contain dynamic users and few interactions.

The main challenge of ephemeral group recommender is how to aggregate individual preferences to represent the group's overall preference. That is because members in ephemeral groups are unfamiliar with each other, and each group member may contribute differently to the final decision. To solve this problem, earlier studies mainly use heuristics and predefined score aggregate strategies

(e.g., least misery [3]), which fail to achieve satisfactory performance because they show less consideration for the interactions between group members. In recent years, some researchers turn to adopt some data-driven strategies, including attentive models [8, 39] and graph neural network models [20, 47]. In addition, some methods learn better user preference representation through regularization [36] and pre-training [48]. However, these methods are mainly guided by user preference information when simulating users' importance. In the real-world group decision-making process, estimating individual users' importance by using individual preference alone is not enough. It may also relate to individual inherent characteristics such as personality [30, 37]. Personality is described as "consistent behavior patterns and interpersonal processes originating within the individual", [7] which helps to infer one's behavior in an ephemeral group. Meanwhile, Ertac et al. [12] find that personality traits can affect group decisions by distinguishing the user roles, which makes personality a key factor in ephemeral group recommender. Figure 1 gives an example that illustrates the role of personality in group recommendation. Imagine that Alice, Bob, and Carl are dining out for the first time and aiming to find a restaurant. Alice and Bob are fond of fast food, while Carl prefers slow food. Following traditional preference-guided methods (Figure 1. a), fast food would be the final choice since most members are fond of fast food. However, the situation changes when considering personality (Figure 1. b). Carl is a stubborn person who persists in slow food, while Alice and Bob are easy-going and tolerant. Considering Carl's feelings, slow food would be the final choice. The group recommendation that combines personality and preference is undoubtedly more in line with the real scenario.

Personality can not only help estimate the importance of individuals in the group but also help alleviate the problem of data sparsity. In previous works [41, 42], personality has been proven to enhance the performance of Collaborative Filter (CF) under cold start. It also has the ability to play an essential role in ephemeral group recommendation. Contrary to diverse individual preferences, personality is relatively stable and will not frequently change in one's life [26]. Therefore, a proper amount of data can learn the multiple distribution patterns of individual personalities in the group, guiding the aggregation of individual preferences and giving robust group decision-making suggestions.

In this paper, we are motivated to propose a new solution for ephemeral group recommendation named **Personality-Guided Preference Aggregator** (PEGA). Firstly, we use Linguistic Inquiry and Word Count (LIWC) lexicon to implicitly capture users' personality traits from their review texts' linguistic features, laying the foundation for generating personality-enhanced group representation. Secondly, we employ hyper-rectangle to innovatively define the concept of *Group Personality* on the basis of individual personality. *Group Personality* not only reflects the fusion of individual personality in the group but also alleviates group-level data sparsity. Thirdly, we design a personality-guided preference aggregation module that aggregates group members' preferences and generates personality-enhanced group representation. It not only estimates individual users' importance in a group but also provides an explanation for group recommendation results. Finally, we apply the inner product of the representation of the group and candidate item as the prediction score. We conduct experiments on several

real-world datasets to verify the effectiveness of our model. The experimental results show that PEGA achieves significantly higher Recall and NDCC scores than state-of-the-art models.

Specifically, the main contributions of our work are as follows:

- We have proposed an ephemeral group recommendation model based on implicit personality, where personality is used to guide the aggregation of individual preferences and more realistically simulate the group decision-making process.
- We have innovatively defined the concept of *Group Personality* to learn the distribution patterns of individual personalities in the group, which alleviates group-level data sparsity.
- We have designed a personality attention mechanism to learn the influence of individual personality in a specific group, which enhances group preference representation and gives an explainable recommendation result.
- We have conducted extensive experiments on three public datasets, and experimental results demonstrate that our model produces superior recommendation performance than state-of-the-art methods.

2 RELATED WORK

2.1 Group Recommendation

In general, group recommenders can be divided into two categories: persistent group recommenders and ephemeral group recommenders [31]. Earlier studies mainly focused on making recommendations for persistent groups which have stable members and sufficient historical interactions. As mentioned before, a common approach was to consider persistent groups as virtual users [2, 9] and directly apply individual recommenders. However, such methods cannot handle ephemeral groups which contain sparse group-level interactions.

The studies on ephemeral group recommendations can be further divided into score aggregation methods and preference aggregation methods. Score aggregation methods straightforwardly aggregated users' scores to obtain group prediction scores by hand-craft predefined strategies. Among the strategies, average [3, 5, 32], least misery [3], and maximum pleasure [6] were the three most popular ones. However, these methods were gradually replaced by preference aggregation methods since they ignored the real-world interactions between group members.

Unlike score aggregation methods, preference aggregation methods adopted data-driven strategies to model group preference representation. Probabilistic methods (e.g., COM [46] and PIT [25]) modeled the group generative process by considering both the personal preferences and relative influence of members, but they assumed that users have the same influence in different groups. Attentive methods (e.g., AGREE [8] and MoSAN [39]) employed attention networks to model group interactions. However, they ignored the impact of candidate items. SIGR [44] and GroupSA [16] exploited users' social networks as external side information to tackle interaction sparsity. Yet, the individual's previous social roles became invalid in the ephemeral group. GAME [20] and Zhang et al. [47] employed graph neural networks to learn the adaptive weights of users through high-dimensional interactive information. GroupIM [36] and GBERT [48] used regularization and pre-training

strategies, pushing the group recommendation performance to a new level. However, the above methods are either rule-based or data-driven. For one thing, they lack consideration of other influencing factors in the real group decision-making process; for another, they achieve suboptimal performance in the case of few group-level interactions in the ephemeral group and lack explainability.

2.2 Personality-based Group Recommendation

In recommendation systems, personality can be considered a context-independent and domain-independent user profile [26, 38]. Many studies have applied the user’s personality traits in recommendation systems. Wu et al. [41] used personality to solve the cold start problem in recommendation systems and presented a personality-based greedy reranking algorithm [42] where the personality is used to estimate the users’ diversity preferences. Ferwerda et al. [13] studied the influence of users’ personality traits on music genre preferences.

With the development of group recommendations, some earlier works discussed the importance of users’ personality traits in group decision-making. Zheng et al. [50] collected users’ Big-Five traits through Ten-Item Personality Inventory (TIPI) [15] to divide ‘Dominators’ and ‘Followers’ in the group and used predefined score aggregation methods to aggregate ‘Dominators’ scores. Recio-Garcia et al. [33] combined the Conflict Mode Weight(CMW) calculated by Thomas-Kilmann Conflict Mode Instrument (TKI) [21] with predefined score aggregation methods, which enhanced the influence of assertive users in the group. Kompan et al. [23] constructed influence graphs for groups and directly used TKI scores as the weight of edges to represent the influence between users.

However, the above work had two significant drawbacks: (1) The psychological questionnaire cannot be applied to large ephemeral groups in social media, which were time-consuming and impractical. Moreover, through questionnaires, users tended to show their desirable personalities rather than actual ones [17]. (2) They were mainly based on pre-defined heuristics strategies that failed to dynamically model the group decision-making process and lacked generalization capability. To solve these limitations, we implicitly capture personality traits from written review texts from online social media [4, 14, 43] and are thus interested in exploring whether personality traits can be incorporated in large-scale ephemeral groups and guide the aggregation of user preferences.

3 PRELIMINARIES

To facilitate understanding, we present the definition of the group recommendation task in this section. We use $\mathcal{U} = \{u_1, u_2, \dots, u_M\}$, $\mathcal{V} = \{v_1, v_2, \dots, v_N\}$ and $\mathcal{G} = \{g_1, g_2, \dots, g_L\}$ to represent the sets of M users, N items and L groups, respectively. The ℓ -th group $g_\ell \in \mathcal{G}$ is consisted of a set of users $\mathcal{U}_{g_\ell} = \{u_{\ell,1}, u_{\ell,2}, \dots, u_{\ell,|g_\ell|}\}$, where $u_{\ell,*} \in \mathcal{U}$. The binary user-item and group-item interaction matrices are denoted by X_U and X_G . In our work, user reviews are introduced as side information. We denote $\mathcal{R} = \{R_{u_1}, R_{u_2}, \dots, R_{u_M}\}$ as the set of M users’ reviews set. Here, $R_{u_i} = \{r_{i,1}, r_{i,2}, \dots, r_{i,|u_i|\}$ is the reviews set of user u_i , where $r_{i,j}$ is j -th review of user u_i . Then, given a target group g_t , our goal is to generate a ranked list of items that g_t may be interested in, which is formally defined as:

Table 1: The strongly correlated LIWC word categories of Big-Five personality traits.

Trait	Level	LIWC word Categories
O	High	Cogproc, Insight, Cause, Tentat, Death, Percept, Hear, See, Anx, Space
	Low	Netspeak, Family, Affect, Posemo, Reward, Affiliation, Focusfuture, Home, Relativ, Time
C	High	Acheiv, Reward, Affiliation, Relativ, Time, Motion, Posemo, Work, Focusfuture Negemo, Anger, Sad, Bio, Sexual, Body, Swear, Death, Percept, Hear
	Low	
E	High	Posemo, Affiliation, Reward, Netspeak, Social, Friend, Family, Leisure, FocusFuttrue, Bio
	Low	Death, Work, Cogproc, Tentat, Insight, Differ, Cause, Risk, Negemo, Anx
A	High	Drives, Affiliation, Reward, Achiev, Relativ, Time, Motion, FocusFuture, Relig
	Low	Negemo, Anger, Anx, Death, Swear, Bio, Sexual, Body, Death, Money, Risk
N	High	Negemo, Anger, Sad, Anx, Death, Cogproc, Discrep, Tentat, Body, Sexual
	Low	Posemo, Affiliation, Reward, Achiev, Leisure, Relig, Netspeak, Relativ, Time, Motion

Input: Users \mathcal{U} , items \mathcal{V} , groups \mathcal{G} , U-I interactions X_U , G-I interactions X_G and user reviews sets \mathcal{R} .

Output: A personalized ranking function that maps an item to a real value for a given group: $f_{g_t} : \mathcal{V} \rightarrow \mathbb{R}$.

4 PEGA FRAMEWORK

As shown in Figure 2, the proposed PEGA framework includes four components: (1) The **Review-based Personality Extraction Module**, which captures users’ implicit personality traits from review texts; (2) The **Group Personality Generation Module**, which takes individual personalities captured from (1) as input to generate group personality by using hyper-rectangle; (3) The **Personality-Guided Preference Aggregation Module**, where we first adopt a personality attention mechanism to learn the user’s weight from group personality. We then fine-tune the weight by the user’s preference and use the weight to aggregate group members’ preferences to get personality-enhanced group representation; (4) The **Model Optimization Module**, which applies the inner product to calculate the prediction score of the candidate item and uses a two-stage optimization scheme to optimize both user and group representations. We unfold the details of PEGA in the following.

4.1 Review-based Personality Extraction

In our paper, the Big-Five personality model [28] is selected to represent personality traits as it is one of the most authoritative personality models. In the Big-Five framework, personality traits can be described by five dimensions: **Openness (O)** describes a person’s

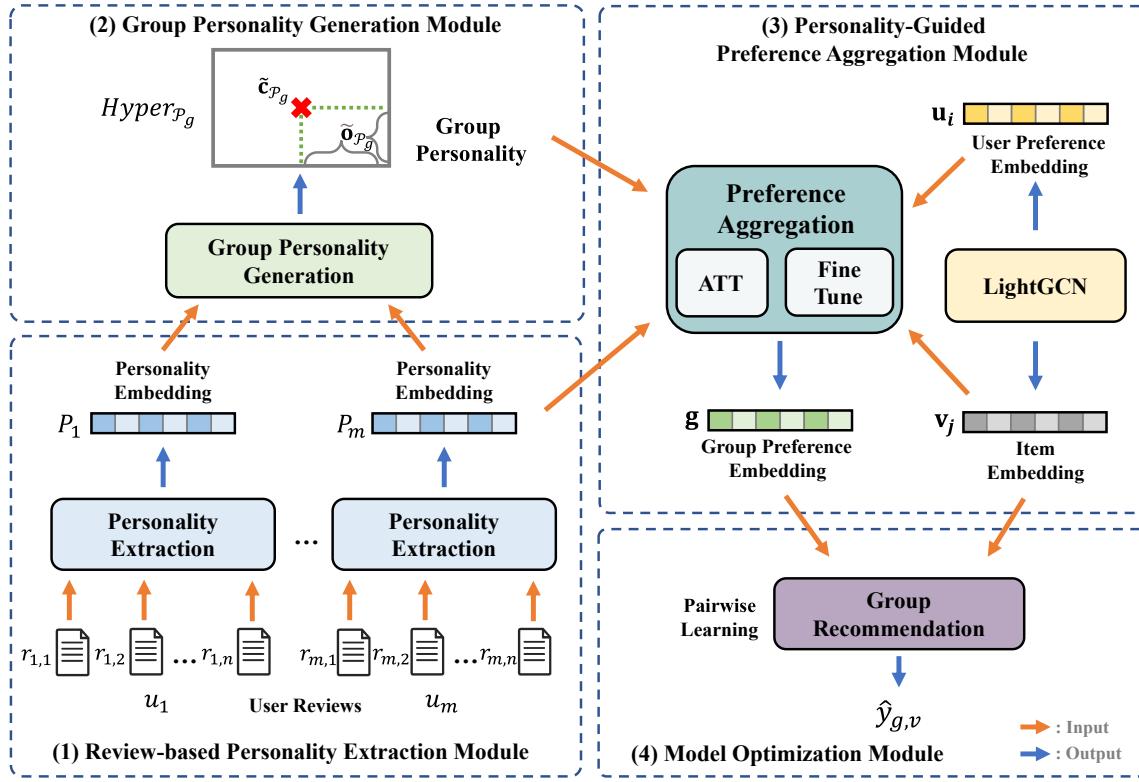


Figure 2: The framework of our proposed Personality-Guided Preference Aggregator (PEGA).

cognitive style and attitude towards exploring new things. **Conscientiousness (C)** refers to controlling, managing, and regulating our impulses. **Extraversion (E)** is displayed through a higher degree of sociability, assertiveness, and talkativeness. **Agreeableness (A)** measures the individual's attitude toward others. **Neuroticism (N)** indicates the degree of emotional stability, impulse control, and anxiety [49].

The personality score of Big-Five has been proven to be related to LIWC features [24]. Therefore, we adopt the LIWC lexicon to capture users' implicit personality traits. Similar to [40], we pick the top 20 LIWC word categories which are strongly correlated with the corresponding personality trait, where 10 categories of them are correlated to the high-level personality trait, while the other 10 categories are correlated to low-level ones. As shown in Table 1, we collect 100 lexicon categories for 5 Big-Five dimensions. Then, we employ $P = \{p_1, p_2, \dots, p_{100}\}$ as the embedding of Big-Five personality traits, where p_i is the Term Frequency-Inverse Document Frequency(TF-IDF) value [1] of lexicon words for the i -th lexicon category calculated over the user's reviews set. Given a user u and her/his reviews' set R_u , u 's Big-Five personality traits P_u is calculated as:

$$P_u = \{p_{u,1}, p_{u,2}, \dots, p_{u,100}\} = \frac{1}{N} \sum_i^N t_{fi} \times \log \left(\frac{N}{df_i} \right), \quad (1)$$

where $t_{fi} = \{t_{fi,1}, t_{fi,2}, \dots, t_{fi,100}\}$ is the frequency of each LIWC lexicon in i -th review of R_u , $df_i = \{df_{i,1}, df_{i,2}, \dots, df_{i,100}\}$ is the

number of reviews containing words of each LIWC lexicon, and N is the total number of reviews.

4.2 Group Personality Generation

To overcome group interaction sparsity, we propose the concept of *Group Personality*, which exhibits the personality distribution of the group. Specifically, inspired by Chen et al. [10], which uses the hypercube to represent group preference, we adopt the hyper-rectangle to carry the rich information in the group personality since each dimension of the hyper-rectangle covers a range of values of personality traits rather than a fixed value. Hyper-rectangle [34] is the high-dimensional form of the rectangle where each edge of the hyper-rectangle represents a real value closed interval on each personality dimension. Given a group g and its members' Big-Five personality traits set $\mathcal{P}_g = \{P_1, P_2, \dots, P_{|g|}\}$, we define the group personality of g as:

$$\text{Hyper}_{\mathcal{P}_g} \equiv \{\mathbf{v} \in \mathbb{R}^{100} : C(\mathcal{P}_g) - O(\mathcal{P}_g) \leq \mathbf{v} \leq C(\mathcal{P}_g) + O(\mathcal{P}_g)\}, \quad (2)$$

where $C(\mathcal{P}_g) \in \mathbb{R}^{100}$ is the center of the hyper-rectangle, and $O(\mathcal{P}_g) \in \mathbb{R}_{\geq 0}^{100}$ is the positive offset of the hyper-rectangle. The dimension of $C(\mathcal{P}_g)$ and $O(\mathcal{P}_g)$ is the same as with the individual personality vector P , which is set as 100. To be more intuitive, we combine the center embedding with the offset embedding to further express the hyper-rectangle:

$$\text{Hyper}_{\mathcal{P}_g} = \mathbf{c}_{\mathcal{P}_g} \parallel \mathbf{o}_{\mathcal{P}_g}, \quad (3)$$

$$\mathbf{c}_{\mathcal{P}_g} = \frac{\mathcal{P}_g^{\max} + \mathcal{P}_g^{\min}}{2}, \quad (4)$$

$$\mathbf{o}_{\mathcal{P}_g} = \frac{|\mathcal{P}_g^{\max} - \mathcal{P}_g^{\min}|}{2}, \quad (5)$$

where \parallel is the concatenation operation, $\mathcal{P}_g^{\max} = \max(P_1, P_2, \dots, P_{|g|})$ and $\mathcal{P}_g^{\min} = \min(P_1, P_2, \dots, P_{|g|})$ are element-wise boundary of group personality. In this way, the boundary of group personality can be regarded as an extreme individual personality, while the geometric center reveals the main personality tone of the group. However, taking $\text{Hyper}_{\mathcal{P}_g}$ as the final representation of group personality straightforwardly lies a problem. That is, excessively diverse individual personalities will generate a group personality that covers too much information and leads to low generalization. To shrink the representing area of group personality, we introduce two projection matrices into $\text{Hyper}_{\mathcal{P}_g}$, and then $\text{Hyper}_{\mathcal{P}_g}$ is computed as the following:

$$\text{Hyper}_{\mathcal{P}_g} = \tilde{\mathbf{c}}_{\mathcal{P}_g} \parallel \tilde{\mathbf{o}}_{\mathcal{P}_g} = \mathbf{W}_c \mathbf{c}_{\mathcal{P}_g} \parallel \mathbf{W}_o \mathbf{o}_{\mathcal{P}_g}, \quad (6)$$

where \parallel is the concatenation operation, $\mathbf{W}_c \in \mathbb{R}^{100 \times 100}$ and $\mathbf{W}_o \in \mathbb{R}_{\geq 0}^{100 \times 100}$ are learnable projection weights for the center and offset, respectively.

4.3 Personality-Guided Preference Aggregation

In this section, we first propose the personality attention mechanism to capture the influence of individual personality in a specific group. Then, we design the preference-based fine-tuning module to fine-tune users' weight based on users' preferences.

4.3.1 Personality Attention Mechanism. As mentioned before, PEGA focuses on aggregating individual preferences under the guide of personality traits. In our paper, we employ LightGCN [18] to learn user and item embedding, which uses the message-passing mechanism to facilitate modeling higher-order collaborative signals. The embeddings are as follows:

$$U, V = \text{LightGCN}(X_U), \quad (7)$$

where X_U is user-item interaction metric, LightGCN is the functional training process of the model LightGCN, $U = \{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_M\}$, $\mathbf{u}_i \in \mathbb{R}^{M \times d}$ and $V = \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_N\}$, $\mathbf{v}_i \in \mathbb{R}^{N \times d}$ are d -dimensional embedding sets of user and item, respectively. Given a group g , we use the personality attention mechanism to calculate the influence weight of g 's member $u_t \in \mathcal{U}_g$, where \mathcal{U}_g contains all user indexes of the group g . The group personality $\text{Hyper}_{\mathcal{P}_g}$ is employed as query vector Q , the individual personality P_t of u_t is employed as key vector K , and user u_t 's embedding \mathbf{u}_t is employed as value vector V . Intuitively, the personality attention mechanism aims to calculate group attention levels to different personalities. Since the dimension of Q and K are different, we use an MLP layer to estimate the influence of the user u_t in the group g with Q and K as the input:

$$\alpha(g, t) = \mathbf{H}^T \text{Tanh}(\mathbf{W}_q Q + \mathbf{W}_k K + \mathbf{b}), \quad (8)$$

$$\tilde{\alpha}(g, t) = \text{Softmax}(\alpha(g, t)) = \frac{\exp \alpha(g, t)}{\sum_{t' \in \mathcal{U}_g} \exp \alpha(g, t')}, \quad (9)$$

where $\mathbf{W}_q \in \mathbb{R}^{200 \times 200}$ and $\mathbf{W}_k \in \mathbb{R}^{100 \times 100}$ are trainable weight matrices that convert group personality traits and user personality traits to the hidden layer, respectively, and $\mathbf{b} \in \mathbb{R}^{100}$ is the bias vector. Tanh is the activation function of our personality attention network, and $\mathbf{H} \in \mathbb{R}^{100}$ is the weight vector that projects the hidden layer to the score $\alpha(g, t)$. Then, we adopt the Softmax function to get normalized attention weight $\tilde{\alpha}(g, t)$.

4.3.2 Preference-based Fine-tuning. Considering that individual preference may enhance the influence of personality under certain circumstances, PEGA further considers individual preference on candidate items. For example, a vegetarian fanatic may try her/his best to persuade others to choose vegetarianism while s/he often keeps silent in other contexts. We introduce the preference-based fine-tuning module to balance relatively stable personality and variable preference. Specifically, we use the similarity calculated between the user and the candidate item to properly enhance the user's influence. Firstly, we incorporate the user u_t 's personality traits into his/her preference embedding to get a more complete embedding \mathbf{u}'_t of user u_t as follows:

$$\mathbf{u}'_t = \mathbf{u}_t \parallel P_{u_t}, \quad (10)$$

where \parallel is the concatenation operation, \mathbf{u}_t is user u_t 's embedding, and P_{u_t} is the personality traits of u_t . For i -th candidate item v_i , user u_t 's, preference can be calculated as:

$$\beta(i, t) = \mathbf{v}_i^T \mathbf{w} \mathbf{u}'_t, \quad (11)$$

$$\tilde{\beta}(i, t) = \text{Softmax}(\beta(i, t)) = \frac{\exp \beta(i, t)}{\sum_{t' \in \mathcal{U}_g} \exp \beta(i, t')}, \quad (12)$$

where $\mathbf{v}_i \in \mathbb{R}^d$ is the embedding of candidate item v_i and $\mathbf{w} \in \mathbb{R}^{d \times |\mathcal{U}_t'|}$ is a trainable matrix that project \mathbf{u}'_t into the same dimensional space as \mathbf{v}_i . Finally, a weighted sum is performed on the embeddings of group g 's member users U , and the group preference \mathbf{g} is abstracted as follows:

$$\mathbf{g} = \sum_{t \in \mathcal{U}_g} \gamma(g, t, i) \mathbf{u}_t, \quad (13)$$

$$\gamma(g, t, i) = \tilde{\alpha}(g, t) + \lambda \tilde{\beta}(i, t), \quad (14)$$

where $\gamma(g, t, i)$ is the overall influence weight of the user u_t in the group g towards candidate item v_i , and λ is a fixed coefficient that balances the importance of an individual's personality and preference.

4.4 Model Optimization

We leverage a two-stage training strategy to alleviate the sparsity issue of group-item interaction. Since a ranked list of top-K items is required in both stages, Bayesian Personalized Ranking (BPR) [35] pairwise learning is adopted to optimize the parameters of PEGA. BPR pairwise learning aims to maximize the score difference between positive and negative items. Specifically, we obtain the user and the item embeddings by minimizing the user-level BPR pairwise loss \mathcal{L}_{user} :

$$\mathcal{L}_{user} = - \sum_{(u, v_p, v_n) \in O} \log \sigma(\hat{y}_{u, v_p} - \hat{y}_{u, v_n}), \quad (15)$$

where O is the set of user training instances. Each instance (u, v_p, v_n) contains a positive item v_p that the user u has interacted with and

a negative item v_n that the user u hasn't interacted with yet. σ is the sigmoid function, \hat{y}_{u,v_p} and \hat{y}_{u,v_n} are the predicted score for v_n and v_p which are calculated from:

$$\hat{y}_{u,v} = \mathbf{u}^T \cdot \mathbf{v}, \quad (16)$$

where element-wise dot product \cdot is adopted on user u 's embedding \mathbf{u} and item v 's embedding \mathbf{v} . Similarly, we optimize the group preference representation and the rest of the parameters in PEGA in the second stage by minimizing the group-level BPR pairwise loss \mathcal{L}_{group} :

$$\mathcal{L}_{group} = - \sum_{(g, v_p, v_n) \in O'} \log \sigma(\hat{y}_{g, v_p} - \hat{y}_{g, v_n}), \quad (17)$$

where O' is the set of group training instances, each instance (g, v_p, v_n) contains a positive item v_p that the group g has interacted with and a negative item v_n that group g hasn't interact with yet. σ is the sigmoid function, \hat{y}_{g, v_p} and \hat{y}_{g, v_n} are the predicted score for v_n and v_p which are calculated from:

$$\hat{y}_{g,v} = \mathbf{g}^T \cdot \mathbf{v}, \quad (18)$$

where element-wise dot product \cdot is adopted on group g 's embedding \mathbf{g} and item v 's embedding \mathbf{v} . Both \mathcal{L}_{user} and \mathcal{L}_{group} are optimized by the Adam optimizer [22], and the entire training process is repeated until the \mathcal{L}_{user} and \mathcal{L}_{group} are sufficiently small.

5 EXPERIMENTS

In this section, we aim to answer the following research questions (RQs):

- **RQ1:** Does our proposed PEGA approach outperform state-of-the-art models?
- **RQ2:** What are the benefits of PEGA's major components?
- **RQ3:** What is the impact of the hyper-parameters of PEGA?
- **RQ4:** How does PEGA perform with different group sizes?
- **RQ5:** Can personality traits in PEGA help explain the results of group recommendation?

5.1 Datasets

We conduct experiments on two public datasets, including **Yelp**¹ and **Amazon**². Yelp is a real-world dataset that covers users' check-in and comment data on local businesses. Amazon is a classical dataset in the domain of recommendation systems that records users' explicit ratings and comments data on various merchandise categories.

Since Yelp and Amazon do not contain explicit group interactions, we follow two widely adopted approaches [36, 44, 45] to construct group interaction datasets. For Yelp, each group interaction data consists of a group of users who are friends in the social network and check into the same business within 15 minutes. For Amazon, we extract two datasets, including Amazon-Simi and Amazon-Rand, from Amazon books, a subset of Amazon where the merchandise category is the book. For Amazon-Simi, the members of groups share similar interests, and we adopt Pearson correlation (PCC) [11] to calculate the similarity between them. Specifically, we set the threshold value of PCC as 0.27, following [3], which means the PCC

¹<https://www.yelp.com/dataset>

²<https://jmcauley.ucsd.edu/data/amazon/>

Table 2: Dataset Statistics.

Dataset	Yelp	Amazon-Simi	Amazon-Rand
# Users	19,007	33,589	44,843
# Items	38,665	24,806	26,588
# Groups	33,782	13,145	13,332
# U-I interactions	330,956	191,366	207,777
# G-I interactions	34,830	15,053	152,282
Avg. # reviews per user	18.68	18.37	18.07
Avg. # items per user	17.41	5.70	4.63
Avg. # items per group	1.03	1.15	1.15
Avg. group size	4.47	5.55	9.03

between each pair of users in the same group is higher than 0.27. As for Amazon-Rand, the groups are structured randomly without any restrictions. Meanwhile, for both Amazon-Simi and Amazon-Rand, the premise of a ground-truth item is that every member in the group gives a rating to the item higher than 3.

Besides constructing the group-item interactions, we collect users' review texts to capture their implicit personality traits. Specifically, for a given user, we collect at least 5 content-rich reviews with a minimum text length of 1000. Table 2 shows the key statistics of three datasets.

5.2 Baselines

We compare our proposed PEGA model with the following state-of-the-art models, which can be broadly divided into predefined score aggregation methods (i.e., NFC-AVG, NCF-LM, and NCF-MAX) and data-driven preference-guided aggregation methods (i.e., AGREE, CubeRec, and GroupIM).

- **NCF-AVG, NCF-LM, and NCF-MAX** are based on the state-of-the-art individual recommendation model NCF [19], which replaces the inner product with a neural architecture to complete the recommendation task. We combine NCF with three predefined score aggregation strategies, including average (AVG), least misery (LM), and maximum satisfaction (MAX).
- **AGREE** [8] is an attention-based neural group recommender that calculates item-specific attention weight of use by jointly training user-item and group-item interactions.
- **CubeRec** [10] is an ephemeral group recommender that uses hypercube vector space to replace point embeddings of user's preference to represent group preference.
- **GroupIM** [36] is a recommender architecture-agnostic framework that maximizes user-group mutual information when regularizing the representation space of users and groups.

5.3 Experimental Setup

5.3.1 Evaluation Metrics. Following [36, 48], we use two widely adopted evaluation metrics to evaluate the performance of PEGA: recall at rank K(R@K) and normalized discounted cumulative gain (NDCG) at rank K(N@K) where K={10, 20, 50}. In addition, we use

Table 3: Overall performance comparison on three datasets. (Note: * denotes the statistical significance for p -value < 0.05 compared to the best baseline, the boldface indicates the best model result of the dataset, and the underline indicates the second best model result of the dataset.)

Dataset	Yelp						Amazon-Simi						Amazon-Rand						
Metric	N@10	N@20	N@50	R@10	R@20	R@50	N@10	N@20	N@50	R@10	R@20	R@50	N@10	N@20	N@50	R@10	R@20	R@50	
Predefined Score Aggregator																			
NCF+AVG	0.116	0.143	0.183	0.210	0.319	0.518	0.221	0.234	0.248	0.322	0.376	0.446	0.154	0.169	0.184	0.248	0.305	0.384	
NCF+LM	0.095	0.102	0.167	0.186	0.225	0.396	0.255	0.278	0.302	0.402	0.492	0.613	0.175	0.201	0.227	0.305	0.404	0.539	
NCF+MAX	0.104	0.129	0.187	0.203	0.263	0.454	0.244	0.259	0.287	0.352	0.397	0.521	0.167	0.189	0.206	0.269	0.326	0.443	
Preference-Guided Aggregators																			
AGREE	0.210	0.214	0.358	0.556	0.573	0.632	0.280	0.289	0.502	0.555	0.613	0.692	0.369	0.383	0.530	0.610	0.669	0.729	
CubeRec	0.057	0.073	0.101	0.113	0.174	0.318	0.462	0.478	0.494	0.588	0.654	0.734	0.403	0.422	0.440	0.528	0.602	0.694	
GroupIM	0.358	0.388	0.412	0.579	0.711	0.835	0.630	0.642	0.649	0.811	0.854	0.886	0.582	0.597	0.606	0.747	0.827	0.874	
Personality-Guided Aggregator																			
PEGA	0.387* 0.421* 0.447* 0.585* 0.721* 0.851*						0.657* 0.670* 0.683* 0.819* 0.874* 0.936*	0.601* 0.620* 0.634* 0.766* 0.841* 0.914*											
VIP	8.10%	8.51%	8.50%	1.03%	1.41%	1.92%	4.29%	4.18%	5.24%	0.99%	2.34%	5.64%	3.26%	3.85%	4.62%	2.54%	1.69%	4.58%	

Value Improvement Percentage (VIP) to measure the value improvement percentage of our method against other compared methods.

$$VIP = \frac{Value_{ourmethod} - Value_{comparedmethod}}{Value_{comparedmethod}} \quad (19)$$

The datasets are split into training, validation, and testing sets according to the proportion of 8:1:1. We performed 5-fold cross-validation for each dataset to avoid any biases. As the data are not normally distributed, we adopted the permutation test [29] for significance tests.

5.3.2 Implementations. We reproduce the models mentioned above and use the grid search method to obtain optimal hyperparameters. Specifically, we search the learning rate and dropout rate in $\{0.01, 0.001, 1e-4\}$ and $\{0, 0.3, 0.5, 0.7\}$, respectively. In PEGA, the latent dimension d , the number of MLP attention layers L and the balance coefficient λ are fixed as 256, 2 and 0.3, respectively. We adopt the Adam optimizer for all models and sample 5 negative items for each ground truth item.

5.4 Overall Performance Comparison (RQ1)

The overall comparison results of PEGA against state-of-the-art baselines are shown in Table 3. We have some key observations from the table:

Our proposed PEGA consistently outperforms all baselines on three datasets in terms of both R@K and N@K metrics. Compared with the strongest baseline GroupIM, our method shows a significant improvement (p -value < 0.05 via permutation test).

Our model obtains the greatest advantage against predefined score aggregators on all datasets in terms of both metrics. For instance, when measured by R@10, the improvements against NCF-BEST³ are 178.6% in Yelp, 103.7% in Amazon-Simi and 151.1% in Amazon-Rand. It is possibly because PEGA adopts a data-driven

strategy that dynamically models the group decision-making process and aggregates robust group preference representation rather than simply using hand-craft predefined strategies, which cannot adapt diversified scenarios in ephemeral groups.

By comparison, PEGA's advantages against preference-guided aggregators are slightly smaller, but the improvements are still significant. Specifically, it can be seen in Table 3 that compared with the strongest preference-guided aggregator GroupIM, our proposed model PEGA achieves higher performance w.r.t. both N@K (e.g., VIP of N@10: 8.10% in Yelp vs. 4.29% in Amazon-Simi vs. 3.26% in Amazon-Rand) and R@K (e.g., VIP of R@10: 1.03% in Yelp vs. 0.99% in Amazon-Simi vs. 2.54% in Amazon-Rand). The reason is that PEGA simulates users' importance not only by their history preferences but also by considering the influence of personality when they integrate into a new ephemeral group.

All models achieve relatively lower abstract values of evaluation metrics on Yelp relative to Amazon-Simi and Amazon-Rand. As shown in Table 2, the Yelp dataset owns the largest number of candidate items. Thus, more diverse individual preferences will lead to more complex group decision-making results, further exacerbating the group-level sparsity problem. However, our method still shows a significant improvement (e.g., average VIP of N@K: 8.37% and average VIP of R@K: 1.45%). The possible reason is that, unlike preference-guided methods, our model aggregates diverse preferences with the guidance of consistent personality, which alleviates this problem and keeps stable superiority in such a challenging dataset.

Another interesting observation from Table 3 is that all models perform better in Amazon-Simi than Amazon-Rand in both R@K and N@K. For example, the average values of R@10 and N@10 in Amazon-Simi are 0.550 and 0.393, while the values in Amazon-Rand are 0.496 and 0.350. It is reasonable since groups in Amazon-Simi consist of individuals with similar preferences, while groups in Amazon-Rand are structured randomly.

³NCF-BEST represents NCF-based methods with the best performance in different datasets, i.e., NCF+AVG in Yelp, NCF+LM in Amazon-Simi and Amazon-Rand.

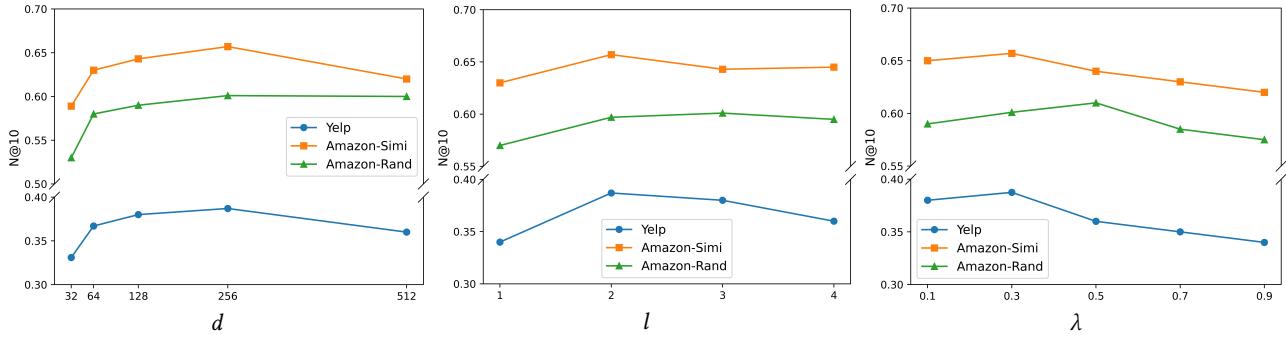


Figure 3: The influence of different model hyperparameters.

Table 4: Comparison between PEGA and its variants.

Dataset	Yelp		Amazon-Simi	
	N@10	R@10	N@10	R@10
BASE	0.3382	0.5419	0.6037	0.7857
PEGA-nATT	0.3433	0.5482	0.6198	0.7977
PEGA-nPRE	0.3805	0.5805	0.6534	0.8154
PEGA	0.3875*	0.5854*	0.6573*	0.8193*

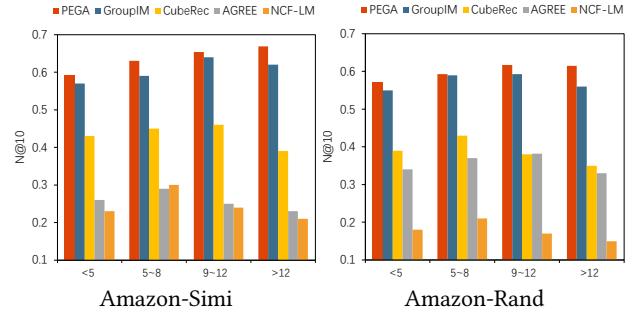


Figure 4: Performance across group size ranges.

5.5 Ablation Study (RQ2)

To verify the effectiveness of the main components of PEGA, we conduct ablation studies to evaluate several variants of PEGA. Due to limited space and similar results, Table 4 only depicts the results on Yelp and Amazon-Simi datasets with N@10 and R@10 as the metric.

We remove different components of PEGA mentioned in section 4.2 and present three variants below: (1) **PEGA-nATT** replaces the $\tilde{\alpha}(g, t)$ in Eq. (14) with 0 to remove the personality attention mechanism; (2) **PEGA-nPRE** sets the coefficient λ in Eq. (14) as 0 to remove the preference-based fine-tuning model (i.e., without considering users' preference for candidate items); (3) **BASE** gives the same weight $\gamma(g, t, i) = 1$ to each group member t in group g .

It can be seen from Table 4 that **PEGA** performs significantly better than the three variations in all datasets. Due to the similar experimental results of the two datasets, we take the Yelp dataset as an example, and the key observations are as follows: (1) **PEGA** obtains the greatest advantage against **BASE** (i.e., VIP of N@10: 14.6% and VIP of R@10: 8.0%). This is reasonable because **BASE** equally aggregates users' preferences without any guidance; (2) PEGA performs slightly higher than **PEGA-nPRE** (i.e., VIP of N@10: 1.8% and VIP of R@10: 0.8%) but obviously higher than **PEGA-nATT** (i.e., VIP of N@10: 12.9% and VIP of R@10: 6.8%), implying that the weight of personality is more important than the weight of preference. Thus, it can be proved that personality would be more efficient in simulating users' importance than preference, while preference would be more suitable to play a supporting role that fine-tunes the weight calculated by personality.

5.6 Hyperparameter Analysis (RQ3)

We answer RQ3 by evaluating the latent dimension d , the number of MLP attention layers L and the balance coefficient λ of Eq. (14) on three datasets. We adjust each hyperparameter while others remain unchanged, and the results are reported in Figure 3, where N@10 is used for benchmarking.

Impact of d . We tune d in $\{32, 64, 128, 256, 512\}$. In general, PEGA benefits a larger latent dimension d on all datasets. However, the performance decreases when d is set too large (i.e., 512 in our case) due to overfitting.

Impact of L . To investigate whether PEGA can benefit from the number of MLP layers, the MLP layers' number L is set among $\{1, 2, 3, 4\}$. PEGA performs the best when $L = 2$ while the worst performance occurs when $L = 1$. The model's performance is sub-optimal when L equals 3 or 4. The possible reason is that when $L = 1$, the MLP may not capture the importance of various personalities. When L is set higher than 2, the model will be trapped in overfitting.

Impact of λ . The parameter λ is used for balancing the weight of the user's personality and preference. When the value of λ varies in $\{0.1, 0.3, 0.5, 0.7, 0.9\}$, the best performance can be observed when $\lambda = 0.3$. In addition, the performance decreases as λ increases in most scenarios, which testifies to our assumption that personality is more important than preference in the group decision-making process. It is noteworthy that personality and preference enjoy the same weight (i.e., $\lambda=0.5$) in Amazon-Rand. The possible reason is

that groups in Amazon-Rand are too random (refer to the descriptions in section 5.1), which weakens the importance of the user's personality.

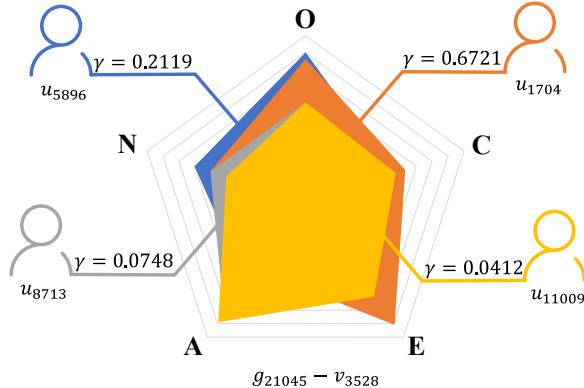


Figure 5: A visualized example of different weights of group members with different personality traits in the group decision-making process.

5.7 Effect of Group Sizes (RQ4)

To further investigate the impact of different group sizes on the recommendation performance, we divide group size into four levels (<5, 5~8, 9~12, >12), which is similar to [36, 48]. Figure 4 depicts the recommendation results of N@10 scores on Amazon-Simi and Amazon-Rand due to the limitation of space.

The results show that PEGA has strong robustness against different group sizes since it outperforms other models on both datasets, which is consistent with the overall performance in Table 3. An important observation is that the performances of most methods rise with the increase of the group size and the best performance mainly occurs when the group size is 5~12. It indicates that the group decision-making process in medium-sized groups is more regular and more learnable for group recommenders. Meanwhile, most models suffer a noticeable performance decrease when the group size is too large (>12 here), except our model. This is primarily associated with the preference noise caused by too diverse preferences of group members. However, PEGA studies users' weights from their personalities which alleviates the impact of preference noise, indicating that our proposed PEGA method has the potential to perform well among different group sizes.

5.8 Case Study (RQ5)

To intuitively show the influence of personality on group decision-making, we visualize the recommendation result of a randomly selected group g_{21045} interacting with the item v_{3528} on the Yelp dataset. We map the implicit personality trait embeddings into Big-Five radar charts for clarity. As shown in Figure 5, the *Group Personality* of g_{21045} can be described as high-level openness (O), high-level extroversion (E), and high-level Agreeableness (A). Under this personality contribution, our proposed model PEGA gives the user u_{1704} the largest influence weight which is 0.6721, and sets u_{5896} as the second place with a weight of 0.2119 while other

users' influence weights are less than 0.1. Thus, the preference of g_{21045} is primarily contributed by u_{1704} and u_{5896} . An important observation is that u_{1704} and u_{5896} have higher values in Openness, Extraversion, and Neuroticism which means they are outgoing and confident. As a result, they would be more willing to express their preference. Meanwhile, other users' value of Agreeableness is relatively higher, which means they are easygoing and tend to follow others' suggestions. The example explicitly explains that when the group consists of aggressive and easygoing individuals, the aggressive ones will dominate the group decision-making process.

6 CONCLUSION

Existing preference-guided methods lack consideration of other influencing factors in the real group decision-making process and suffer the group-level data sparsity problem. In this paper, we propose a personality-guided preference aggregator for ephemeral group recommendation. Specifically, we design the personality attention mechanism to aggregate group members' preferences from the perspective of individual personality, which gives explainable recommendation results. Moreover, to alleviate the issue of data sparsity of ephemeral groups, we define the concept of *Group Personality* by hyper-rectangle, which reflects the process of individual integration into the group in a generalizable way. We evaluate our model on three real-world datasets (i.e., Yelp and Amazon). The experimental results show the superiority of our model against other state-of-the-art methods and verify the contribution of the main components.

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