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Accurate POI recommendation for random groups with improved graph neural networks and a multi-negotiation model

Xiaoyu Song[1], Zhizhong Liu[1]✉, Lingqiang Meng[1,5], Dianhui Chu[2,5], Jian Yu[3,5] & Quan Z. Sheng[4,5]

In recent years, the growing prevalence of group activities has brought increased interest in Point of Interest (POI) recommendations for groups. While significant progress has been made in recommending POIs for fixed groups, research on personality-aware recommendations for random groups has been still largely untouched. Moreover, existing works recommend a POI list for a group and the group makes further choice of the optimal POI, which results in poor user experience. To solve the above problems, this work proposes a model for Accurate POI Recommendation for Random Groups with improved Graph Neural Networks and a Multi-negotiation Model (termed as APRRGM). Specifically, APRRGM first produces the fitted feature of the random group based on group members' personalities and their POI interaction data. Then, APRRGM learns POIs' features from the bipartite graph of user and POI with an improved Graph Neural Networks (GNN) while considering members' personalities. Next, APRRGM recommends a POI sequence based on the fitted feature of the random group and the features of POIs. Finally, based on the recommended POI list and members' personalities, APRRGM determines the optimal POI for the random group with an improved multi-negotiation model. The extensive experiments conducted on three public benchmark datasets (Yelp, Gowalla, and Foursquare) have proved that APRRGM performs better than other baseline models.

Keywords Point-of-interest recommendation, Random group, Graph neural network, Multi-agent system, Multi-negotiation Model, User's personality

With the popularity of mobile networks and smart terminals, it becomes more convenient for people to gather together to carry out group activities, and the scale of group activities in human society is increasing rapidly[1–3]. For example, more and more people are inclined to travel in groups or watch movies they are interested in. Moreover, as the number of POIs is continuously increasing, the problem of information overload is becoming more and more serious, which makes it difficult for groups to find the optimal POI that can satisfy all members in a group. Therefore, it becomes a critical challenge to develop technology to find the suitable POI for groups from the massive POI data, so as to facilitate group activities[4–6] and improve user experience[7–9]. Over the last few years, some effective research has been conducted on group recommendations in several fields. For example, in the entertainment field, some works proposed methods for movie recommendation[10] and music recommendation[11] for groups. For smart tourism, the work in[12] studied tourist routes recommendation for groups.

In recent years, the rise of Location Based Social Networks (LBSNs) has sparked considerable attention in group POI recommendations[13–15]. Liu et al.[16], for instance, created an innovative POI recommendation framework for groups that leverages collaborative filtering while taking into account group divergence. Another approach by Sojahrood et al.[17] introduced a model that incorporates the geographical proximity of POIs relative to users' locations. Zhu et al.[18] presented a POI recommender system, enhancing its effectiveness through

[1]School of Computer and Control Engineering, Yantai University, Yantai 264005, China. [2]College of Computer Science and Technology, Harbin Institute of Technology (Weihai), Weihai 264209, China. [3]Department of Computer Science, Auckland University of Technology, Auckland 1142, New Zealand. [4]School of Computing, Macquarie University, Sydney, NSW 2109, Australia. [5]These authors contributed equally: Lingqiang Meng, Dianhui Chu, Jian Yu, and Quan Z. Sheng. ✉email: zhizhongliu@ytu.edu.cn

distance-based pre-filtering and ranking adjustments. Additionally, Schiaffino et al.[19] devised a multi-agent fusion method to tackle the group POI recommendation challenge.

There are two types of groups in our society, *fixed* groups and *random* groups[20,21]. A fixed group is a common form of group in our society, such as families, interest groups, and research groups. For fixed groups, strong social relationships usually exist between group members, and the preference differences between members are relatively small. Moreover, fixed groups usually exist for a long time, and these groups may have enough item interaction data. A random group, however, consists of individuals who come together for a common purpose or to engage in an activity at a particular time. Usually, there is no social relationship or other types of association between the members of the random group. The random group disbands once the purpose is achieved or the activity is completed[21], and there are few item interaction data for random groups.

Recently, some research efforts have been conducted on POI recommendations for fixed groups[17,22–25], but few work emphasizes POI recommendation for random group[21]. Because of the significant differences between random groups and fixed groups, existing POI recommendation methods for fixed groups are unsuitable for random groups. Furthermore, with the rapid development of information technology, more and more random groups are emerging and playing increasingly important roles in social development. How to realize POI recommendations for random groups becomes a critical issue that needs to be solved urgently.

To solve the above problems, in our previous work[21], we proposed a novel POI recommendation model for random groups based on Cooperative Graph Neural Networks (named CGNN-PRRG), which can effectively complete POI recommendations for random groups while overcoming the cold start problem. Unfortunately, CGNN-PRRG does not consider the personalities of group members when conducting POI recommendations. The personalities of members have significant impacts on the choices of POIs. Thus, members' personalities also have an important influence on groups' POI selection. Moreover, existing methods for POI group recommendation just generate a POI list for the group and let the group to determine the optimal POI, which is inconvenient for the group and decreases the user experience.

Here, we use an example to illustrate our research motivation (see Fig. 1). A group of travelers from all over the world gather in a city and plan to choose a suitable POI to visit. These travelers form a typical random group. In this situation, it is expected that the recommender system can find the optimal POI for the group effectively. For this random group, different members may have different personalities, and members with different personalities always exhibit different behavioral patterns when selecting POIs. For example, if Member 3 of the group has an introverted personality, he may compromise with the group's decision. However, if Member 1 has an outgoing personality, he may be more persuasive and determined, thus influencing the group selection to favor his preference. In addition, various personalities of group members have a significant impact on achieving the final POI selection that can satisfy each member. Therefore, it is necessary to fully consider the members' personalities, which can help to meet the needs of the group more accurately, and thereby improve the overall user experience.

Despite the advancements in POI recommender systems for random groups, significant challenges remain to be overcome to attain accurate recommendations for such groups:

- **How to realize personality-aware POI recommendation for random groups.** Personality traits of group members have a significant impact on the decision-making of the group. Due to the absence of social connections among members in a random group, the personality of each member has a different influence on others. However, existing POI group recommendation methods always adopt the static strategies[4,20,26] or dynamic

Figure 1. An example of random group considering members' personalities.

strategies[27,28] to produce the fitted features of the groups, and few works consider generating the fitted features of random groups while considering members' personalities. Therefore, how to realize the personality-aware POI recommendation for random groups has been a primary issue.

- **How to implement accurate POI recommendation for random groups.** Existing POI group recommendation works usually perform the recommendation task by recommending the Top-K POIs for groups. However, the recommended results are not precise enough, and the group still needs to discuss and negotiate on the recommended results and then determine the optimal POI for the group, which always brings difficulty for the groups and decreases the user experience. Thus, how to determine the optimal POI for random groups has become another challenge.To overcome these challenges, we propose a model called APRRGM (**A**ccurate **P**OI **R**ecommendation for **R**andom **G**roup with improved Graph Neural Networks and a Multi-negotiation **M**odel). Specifically, based on members' personalities and their POI interaction data, APRRGM generates the fitted feature of the random group. Then, APRRGM learns POIs' features from the bipartite graph of users and POIs with an improved GNN by considering members' personalities. Next, APRRGM recommends a POI list based on the fitted feature of the random group and the features of POIs. Finally, based on the recommended POI list and members' personalities, APRRGM determines the accurate POI for the random group with an improved multi-negotiation model based on multi-agent system, which conducts the negotiation process for the random group. The main contributions of our work are as follows:
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- **We propose a novel method for accurate POI recommendation for random groups.** To tackle the issue that existing research on POI group recommendation did not consider members' personalities and failed to provide accurate POIs for random groups, we propose a method for accurate POI recommendation for random groups, which not only takes members' personalities into consideration, but also can determine the accurate POI for the random groups. To the best of our knowledge, this is the first work that can provide accurate POI for random groups through two models, where one model generates the recommended POI list and the other model determines the optimal POI.
- **We propose a personality-aware method to generate the fitted feature of a random group.** To fully explore the influence of members' personalities on group behavior patterns, we propose a method to generate the fitted features of random groups while leveraging members' personalities. This method calculates the impact of group members' personalities alongside their feature representations to generate fitted feature representations for random groups.
- **We propose improved graph neural networks for personality-aware POI feature learning.** Unlike traditional GNN-based methods for learning POI features, our enhanced graph neural networks learn both node-level and edge-level information influenced by graph features. By integrating members' POI preferences and members' personalities, our proposed improved graph neural networks can comprehensively excavate members' POI interaction preferences and produce more comprehensive features of POIs.
- **We propose a method for accurate POI determination based on an improved multi-negotiation model.** To find the accurate POI from the recommended POI sequence for random groups, so as to improve users' experience and enhance the intelligent level of POI recommendation, we propose a novel multi-negotiation method based on a multi-agent system that takes into account the user's personality to determine the accurate POI. It can automatically adjust the concession strategy based on members' personalities, conduct the steps of concession negotiation and consensus among group members, and finally select the accurate POI that can satisfy all the members.The remainder of this paper is organized as follows: "Related work" reviews the related work. Section "Problem statement" describes our studied problem and related definitions. Section "Methodology" introduces our proposed method in detail. Section "Experiments and analysis" presents the experimental results and analysis. Section "Conclusion and future work" summarizes this work and discusses our future work.

Related work

Recommendation methods for random groups

In human society, random groups are an important form of collective activities. However, due to the large differences between random groups and fixed groups, the existing recommendation methods for fixed groups cannot be directly applied to random groups. Guo et al.[22] introduced a movie recommender system targeted at random groups that initially establishes preference relationships using multi-attribute utility theory to predict unknown preferences, and then employs a boundary voting rule for random group recommendation. However, the model overlooks the social influence of group members and fails to consider users' interaction preferences. Ding et al.[23] considered members' rating information in their research and devised a recommendation model of movies for random group (called GRMFC). GRMFC converts random groups into virtual users and uses personalized recommendation methods to suggest suitable movies, but it overlooks member influence in group representations. Pujahari et al.[24] proposed a movie recommendation approach for random groups that employs preference-based matrix factorization to generate unknown ratings and aggregates group members' preferences through a graph aggregation strategy. Wang et al.[29] proposed a recommendation model (named MCS) for recommending travel destinations to random groups. MCS creates recommendations for random groups based on the contribution of each member. In our previous work, Liu et al.[21] proposed a random group POI recommendation model based on a hybrid graph neural network, called CGNN-PRRG. CGNN-PRRG learns the user's POI comprehensive preferences through the labeled bipartite graph network integrated with edge learning, which enhances the recommendation performance.

For POI group recommendation, existing studies mainly focus on fixed groups to start POI recommendation, and there is a lack of POI recommendation methods for random groups. Random groups are characterized by their short duration, lack of historical check-in records, and absence of social relationships among group members, making it difficult to directly apply the existing fixed group-oriented POI recommendation methods to random group POI recommendation. Along with the increasing demand for random group POI recommendations, there is an urgent need for more targeted and better performance recommendation methods for random group POI recommendations.

Recommendation methods with consideration of user personality

User's personality has been gradually emphasized by the researchers of recommender systems in the past few years. A person's personality not only influences her behavioral patterns, but also affects her preferences. User personality-based recommender systems are a class of recommender systems that consider the character and personality traits of the user when making recommendations.

Gwendolyn et al.[25] proposed a new method for automatically extracting user personality traits from publicly available product review texts based on natural language processing techniques and utilized these traits to improve the performance of context-aware recommender systems. Kendra et al.[30] studied and compared four personality-aware recommender systems based on different personality models and proposed a hybrid personality model for recommender system based on personality traits and type model hybrid personality model for recommendation. Wu et al.[31] proposed a generalized dynamic greedy rearrangement method for personalized recommendation diversity based on user's personality, which is capable of generating recommendation lists based on the user's diversity preferences. Alper et al.[32] used five basic personality traits (*Openness, Likability, Neuroticism, Dutifulness* and *Extraversion*)[33] to determine the degree of influence of each member of the group on the final decision and used these traits to weight the aggregation of the user's preferences. Yazidi et al.[34] utilized a matrix decomposition method with paired preference scores to generate user and item latent factors. They constructed an influence diagram based on users' assertiveness and cooperativeness to represent each member's impact on the final decision. By weighting user preferences and applying an opinion dynamics model, group consensus can be reached. The study showed that the final opinion relates to the steady state distribution of the Markov chain tied to the influence diagram. Chen et al.[35] applied a recommender system based on users' personality and individuality to Facebook, and proposed a method to predict users' personality traits based on their online interaction behaviors on Facebook, using the theory of *Dominance, Induction, Submissiveness* and *Cooperation* (DISC)[36] to determine user's personality type, and using data mining and machine learning techniques to extract user's personality information from the user's network interaction behavior, and a predictive model is built to provide a more effective communication strategy for enterprises.

Recommendation methods based on multi-negotiation model

Multi-negotiation is a relatively popular topic in the research of recommender systems. Multi-negotiation recommender systems aim to consider multiple user preferences and needs, and to introduce multiple stakeholders into the recommendation process to improve recommendation accuracy and user satisfaction. Sarit et al.[37] proposed a cooperative negotiation-based group recommender system. The authors propose a negotiation process in which an agent engages in direct (alternating offers) or mediated (merging rankings) negotiations, and this negotiation produces group recommendations based on personalized recommendations and user preference models. However, this approach has been tested in simulations only in contexts involving two agents and cannot be better adapted to large-scale groups. Garcia et al.[38] developed an agent-based negotiation model using alternating offers, in which agents negotiate preferences for the whole group. Moreover, Garcia et al.[39] further proposed a multi-intelligent body system in which user agents conduct negotiations aiming to create group profile that satisfy users' needs. The whole negotiation process is managed by a mediator to facilitate the agreement.

Endriss et al.[40] proposed the multilateral Monotonic Concession Protocol (MCP), which aims to mimic in a simplified way of the negotiation process that humans perform when trying to reach an agreement on a subject. Agents negotiate and each agent is required to make proposals which are evaluated by the other agents until an agreement is reached or negotiated. Agents follow pre-specified rules that define the agreed actions that each agent can take at various stages of the negotiation process. These rules include: **(i)** The agreement criterion. **(ii)** Which agent proposes the next concession (in case no agreement is reached in a round). **(iii)** How much the agent should concede. Silvia et al.[41] proposed a multi-intelligentsia approach (PUMAS-GR) using MCP, where each user is represented by an agent as a delegate in the negotiation process, and each agent owns all the user's profiles. The MCP-based multi-agent multilateral negotiation strategy is used to obtain recommendation results that can more evenly satisfy the group user's preferences compared to the traditional group recommendation. In addition, Silvia et al.[42] proposed the MAGReS model, and proposed a Willingness to Risk Conflict (WRC) strategy, which aims at selecting the agent that makes a concession during the negotiation process, and the Desires Distance (DD) concession strategy, which selects the next proposal of the agent that needs to make a concession. Furthermore, Silvia et al.[19] applied the MAGReS model to POI group recommendations in Location-Based Social Networks (LBSNs) to investigate how the geographic relationships of group members provided by LBSNs affect the process of neighbor selection and other additional information to provide better POI recommendations for groups.

Problem statement

In this section, we first introduce some important definitions about the problem studied in this work, then we present the problem statement.

Definition 1: Users set. Consider the set of users $U = \{u_1, u_2, \ldots, u_m\}$, where *m* represents the number of users. Each user in *U* has a unique user ID.

Definition 2: POIs set. A POI, defined as a location such as a mall or an attraction, serves specific functions to meet user needs. There are three attributes for each POI: a unique *id*, category *c*, and geographic information

$d = (\text{long}, \text{lat})$, where long and lat represent the longitude and latitude, respectively. Let $P = \{p_1, p_2, \ldots, p_n\}$ be the set of POIs, and *n* be the number of POIs.

Definition 3: Random Group. Given a set *U* of users, in our work, we randomly divide the users in the set *U* into a number of groups according to the predefined group size. Let $RG = \{u_i, u_j, \ldots, u_r\}$ denote a random group and *r* denote the number of members of the random group. In our research, it is assumed that members in each random group do not have social relationships with each other.

Definition 4: User's personality traits. According to the Big Five personality model[43], we generate a five-dimensional vector PER_i in which the value of each dimension represents the user's assessment score in a certain personality. Let $PER_i = \{per_1, per_2, ..., per_5\}$ denote the user's personality traits, and *i* denotes the number of users.

Definition 5: Check-in. Consider $S = \{S_i, S_j, \ldots, S_r\}$ as the set of POI check-in sequences for all members of *RG*. Here, $S_i = \{s_1, s_2, \ldots, s_i\}$ represents the check-in sequences of member u_i, and $s_i = \{p_1, \ldots, p_k\}(k \in [0, n])$ denotes the *i*th POI check-in sequence for member u_i.

Problem Statement: Given a random group $RG = \{u_i, u_j, \ldots, u_r\}$, POI check-in data of similar users $S_i = \{s_1, s_2, \ldots, s_i\}$, members' personality profiles $PER_i = \{per_1, per_2, ..., per_5\}$. The problem studied in this research centers on how to find the accurate POI from the POIs set for the random group that can satisfy all members.

Methodology

To address the challenges of accurate POI recommendation for random groups, we introduce APRRGM, a new method that leverages improved graph neural networks and a multi-negotiation model for precise POI recommendations for random groups. Figure 2 illustrates the overall design of APRRGM. There are four modules in APRRGM: the fitted feature learning module, the POIs' features learning module, the POI sequence generation module, and the accurate POI generation module. Briefly, in Module I, APRRGM generates the fitting features of random groups according to the user influence under the influence of personality. Then, in Module II, we identify users with similar characteristics and use their POI interaction data as a learning dataset to learn POI features with user interaction preferences, taking into account the personalities of group members. Subsequently, Module III generates a random group of recommended POI sequences. Module I, Module II and Module III complete POI sequence recommendations for random groups. These three modules constitute APRRGM's random group POI recommendation sub-model (named PRRG). Finally, Module IV uses the modified multiple negotiation model to determine the most accurate POIs for the random group and Module IV constitutes the accurate POI determination sub-module of the APRRGM (named APDMN). Each module of APRRGM is described in detail in the rest of this section.

Module I: learning the fitted feature of a random group

In random group POI recommendations, due to the randomness of the groups, interaction data between the group and POIs is often not directly available. An important indirect approach to acquiring group preferences is by simulating multiple members within a group into a virtual user. The fitted features of a group are typically derived from the representations of its members along with their respective weights.

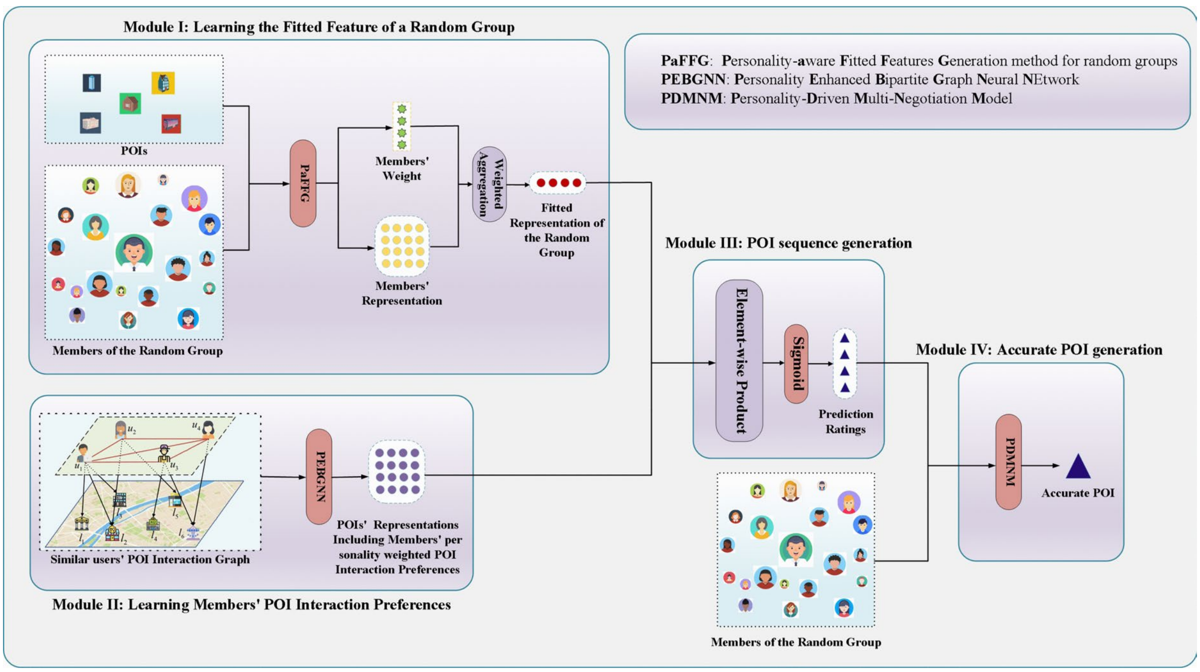

Figure 2. The overall flowchart of the APRRGM model.

However, existing approaches often calculate these weights solely from members' interaction records[44], neglecting comparisons between different group members. The weights of members computed by existing methods are essentially relative weights that cannot reflect the true importance of a member in a group[45]. In fact, when a member is more important than other members, this member should have a higher weight. In addition, comparisons between different members provide more information to reflect the internal relationships among members in a group[44]. However, when performing POI recommendations for random groups, members with different personalities tend to have different influences on the final decision of the group. For example, a member with a outspoken personality may be more persuasive and determined, thus dominating the group and making the choices more favorable to his preferences. Therefore, when computing the fitted features of a random group, different influence weights should be assigned to different members according to their personalities as well as other factors.

Moreover, some research has identified that each user's personality has five characteristics, which are <Openness, Conscientiousness, Extraversion, Agreeableness, Emotional Stability>, called Big Five personality[46]. Next, we present the influence of each characteristic on a user's behavioral in decision-making.

- **Influence of openness on individuals' behavior**: Individuals with stronger openness are more receptive to new concepts and ideas and are likely to consider and incorporate the perspectives of others. For a group, these individuals may contribute to a broader range of options and be more open to exploring diverse suggestions, which can enrich the group's decision-making. Conversely, individuals with weak openness tend to be more conservative and fixed in their viewpoints, which might limit the variety of recommendations they are willing to entertain and reduce the group's exposure to novel ideas.
- **Influence of conscientiousness on individuals' behavior**: Individuals with stronger conscientiousness are usually well-organized and goal-oriented. They tend to be firm in their opinions, particularly when these align with group objectives. For group recommendations, these individuals might push for structured and goal-aligned suggestions, thereby ensuring that the group's recommendations are practical and purposeful. Those with weak conscientiousness may display spontaneity and greater flexibility, which can introduce adaptability and a wider range of options into the recommendation process, but might also lead to less consistent contributions.
- **Influence of extraversion on individuals' behavior**: Individuals with stronger extraversion are generally more socially adept and assertive in expressing and defending their opinions within groups. In the context of group recommendation, these individuals might drive discussions and influence group decisions more strongly, often leading to their preferences being more prominently represented. Individuals with weaker extraversion may be more introverted and struggle to voice their preferences and assert their choices, possibly leading to their recommendations being underrepresented despite their potential value.
- **Influence of agreeableness on individuals' behavior**: Individuals with stronger agreeableness always exhibit cooperative behavior and a propensity for compromise, readily accepting others' perspectives. For group recommendation, these individuals are instrumental in facilitating consensus and promoting harmonious decision-making, thereby mitigating conflicts and integrating diverse viewpoints. Conversely, individuals with weaker agreeableness are more inclined to assert their own opinions and exhibit resistance to compromise. This can introduce friction into the recommendation process and reduce group cohesion.
- **Influence of emotional stability on individuals' behavior**: Individuals with emotional stability stability tend to remain composed under pressure and assert their viewpoints with confidence. For group recommendation, these individuals may contribute to maintaining system stability and ensuring consistent input, which supports a steady and reliable decision-making process. In contrast, individuals with weaker emotional stability are more vulnerable to stress and may struggle to assert their preferences. This susceptibility can result in their preferences being underrepresented, potentially destabilizing group dynamics.For group recommendations, based on the lens of these five personality traits, we can better understand and balance the diverse behaviors and preferences of their members, thus leading to more effective and inclusive recommendations. To better utilize individual's five personality traits and to generate more accurate fitted features of random groups, we propose a personality-aware fitted features generation approach for random groups (PaFFG). First, PaFFG calculates members' relative influence weights based on their personalities and historical POI interaction data. Next, PaFFG selects a representative member and compares the weights of other members to determine their absolute influence weights. Finally, PaFFG generates the fitted feature of the random group by aggregating group members based on these absolute influence weights. The PRGRF group feature fitting process is shown in Fig. 3.

Calculating the relative influence of each group member

First, for any two group members u_m, u_n and a POI p_i, the contrast difference vector of two group members over p_i is calculated according to Eq. (1):

$$\overrightarrow{C_{mn}^{i}} = [\overrightarrow{u_m} - \overrightarrow{u_n}] \cdot \overrightarrow{p_i} \tag{1}$$

where $\overrightarrow{C_{mn}^{i}}$ denotes the contrast difference vector, $\overrightarrow{u_m}$ and $\overrightarrow{u_n}$ denote the feature vectors of the group members, $\overrightarrow{p_i}$ denotes the feature vectors of the POIs. The calculation of $\overrightarrow{C_{mn}^{i}}$ is useful for filtering out the members who are more familiar with $\overrightarrow{p_i}$ and have a stronger preference for $\overrightarrow{p_i}$ from the group, and will not assign them higher influence weights against $\overrightarrow{p_i}$.

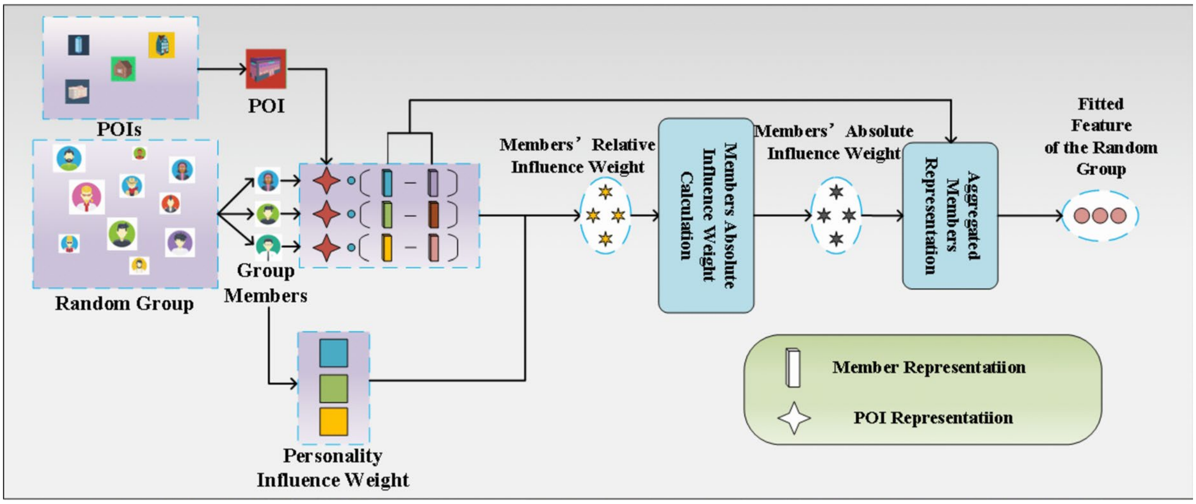

Figure 3. PaFFG group feature fitting flowchart.

Secondly, the difference vector of member u_m against other members' pairs of p_i is fused, and the calculation process is described as Eq. (2):

$$\overrightarrow{C_m^i} = \sum_{n=1,n\neq m}^{|U_g|} \overrightarrow{C_{mn}^i} = \sum_{n=1,n\neq m}^{|U_g|} [\overrightarrow{u_m} - \overrightarrow{u_n}] \cdot \overrightarrow{p_i} \tag{2}$$

where $\overrightarrow{C_m^i}$ denotes the fused contrast difference vector of Group member u_m to p_i, which is equal to the sum of the contrast difference vectors of Group member u_m and other Group members to p_i.

After that, the fused contrast difference vectors are fed into a Multilayer Perceptron (MLP) model constructed by a three-layer neural network to compute the relative influence weights of the members, which is illustrated as Eq. (3):

$$\begin{aligned} h_1 &= [C_m^1, C_m^2, ..., C_m^k, ..., C_m^{|P|}] \\ \vec{h_2} &= Relu(\vec{W_2}h_1 \vec{+} b_2) \\ w_m &= soft\max(\vec{W_3}h_2 \vec{+} b_3) \end{aligned} \tag{3}$$

where w_m denotes the relative influence weight of group member u_m, $[\cdot]$ presents the splicing operation of u_m to the contrast difference vectors of all POIs, $Relu(x) = \max(0, x)$ indicates the activation function used in the hidden layer, and the Softmax function is adopted to perform the normalization operation on the influence weights of random group members.

Calculating the absolute influence of each group member
The relative influence weight w_m' is calculated by comparing two group members. However, the relative influence weight cannot reflect the absolute influence of the members in the group. To calculate the absolute influence weight of a group member, PaFFG randomly selects a representative member u_k from the group and compares the relative influence weight of other members with the representative member to get the absolute influence weight of the member, as defined in Eq.(4):

$$w_m^{'} = abs(w_m - w_k), m \neq k \tag{4}$$

Then, the absolute influence weights obtained for each group member are fused with their personality influence to obtain the absolute influence weights based on the personality of the group users, described as Eq. (5):

$$w_m^{''} = w_m^{'} * Q_m, m \neq k \tag{5}$$

where $w_m^{''}$ means the absolute influence weight based on the personality of the members in the group, $*$ denotes the number multiplication operation, Q_m indicates the influence degree of the user's personality based on the user's personality score, and Q_m is calculated using Eq. (6):

$$Q_m = MinMaxScaler\left(\sum_{i=1}^{n}[-1,1,1,-1,1]\cdot PER_m\right) \quad (6)$$

where $[-1, 1, 1, -1, 1]$ denotes the proportion of user's ratings on the adherence of her preferences to each dimension under the Big Five personality model. Subsequently, the ratings of the user's personality were converted to their personality influence by using the $\mathrm{MinMaxScaler}(\ )$ normalization function.

Generating the fitted feature of a random group

Finally, the fitted feature of the random group is generated by aggregating members' representations and members' absolute influence weights, defined as Eq. (7):

$$\vec{g} = \sum_{m=0}^{|RG|} \vec{w_m''}\vec{u_m} \quad (7)$$

where $\vec{g}$ represents the fitting feature of the random group, which is the manifestation of a complex group decision process.

Module II: learning members' POI interaction preferences

A user's POI interaction preference significantly impacts on the recommendation effect. For the problem of POI recommendation for random groups, in our earlier work[21], we proposed a novel neural network model called EBGNN, which leverages edge learning to enhance the learning of members' interaction preferences with POIs. Although EBGNN considers node-level and edge-level information learning, it does not consider learning of members' personalities. To tackle this issue, we improve EBGNN to get a new graph neural network (termed PEBGNN) by integrating members' personalities into edge-level learning. Moreover, since random groups form stochastically and are non-repetitive, there are no POI interaction records for any new random group, leading to a cold start problem in POI recommendation[47]. To address the problem, in our previous work[21], we proposed learning members' POI interaction preferences based on similar users' POI interaction to train the model. This approach is also used in PEBGNN.

Similar users selection

In this work, we take users with the similar representations to the fitted feature of random group as similar users, and we argue that the preferences of similar users can approximate that of random groups[48–51]. After finding the similar users, we collect the POI interaction data of similar users to learn members' POI interaction preferences. In this work, we adopt the cosine similarity function to calculate the similarities between users' representations and the fitted feature of the random group, which can be characterized as Eq. (8):

$$\mathrm{similarity}(\theta) = \frac{\vec{\mathrm{u}}\cdot\vec{\mathrm{g}}}{\|\vec{\mathrm{u}}\|\|\vec{\mathrm{g}}\|} = \frac{\sum_{i=1}^{K}\vec{\mathrm{u}}_i\cdot\vec{\mathrm{g}}_i}{\sqrt{\sum_{i=1}^{K}\vec{\mathrm{u}}_i^2}\cdot\sqrt{\sum_{i=1}^{K}\vec{\mathrm{g}}_i^2}} \quad (8)$$

where K denotes the dimension of the representation, the coefficient $similarity(\theta)$ measures the degree of similarity between users and the random group, the representation of the random group is denoted by $\vec{\mathrm{g}}$, and the representation of user u_i is given by $\vec{\mathrm{u}}_i$.

POI interaction preferences learning

After selecting the similar users, we learn the POI interaction preferences of similar users based on their POI interaction data. Assume that the similar users set is $SU = \{u_i, u_j, ..., u_r\}$, the POI set is $P = \{p_1, p_2, ..., p_n\}$, and the similar users' POIs check-in data is $I =< u_i, p_j > (i \in [0, m], j \in [0, n])$. Based on the similar users' POI check-in data, we first construct a user and POI interaction bipartite graph $G =< user - POI >$ (which is shown in Fig. 4a). The corresponding adjacency matrix of the bipartite graph can be constructed according to the graph, and the element $M_{i,j}$ of the matrix indicates the visiting frequencies of similar users u_i to POI p_j. Moreover, considering the influence of users' personalities, based on the interaction bipartite graph, we construct the personality-aware bipartite graph of users and POIs, and the construction process is described as follows.

For a similar user u_i and a POI p_j, If u_i has visited p_j, a positive edge is established between u_i and p_j. Otherwise, a negative edge is established between them. If u_i and u_m have links with same sign on p_j, a positive edge is constructed between u_i and u_m. Otherwise, a negative edge is constructed between these two similar users. Similarly, when u_i has links with same sign on p_k and p_f, a positive edge is constructed between p_k and p_f. Otherwise, a negative edge is constructed between these two POIs. For a positive edge between u_i and p_j,

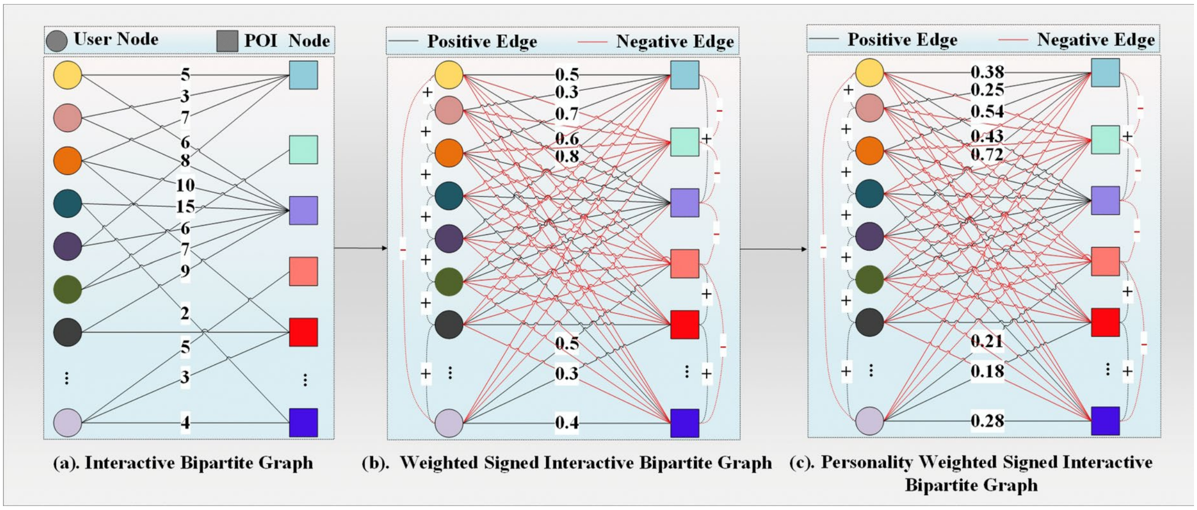

Figure 4. The heterogeneous bipartite graph of similar users interacting with POIs.

the weight w_{ij} of the edge is obtained according to the user's access frequency to p_j, as shown in Fig. 4b). And the specific calculation is shown in Eq. (9):

$$w_{ij} = MinMaxScaler(W_{i,j}), 0 \leq |U|, 0 \leq |P|, 0 \leq |Q_i| \tag{9}$$

where $W_{i,j}$ means the initial interaction frequency and the normalization operation is denoted by $MinMaxScaler(\cdot)$. By normalizing the user's interaction frequency, a weighted user POI interaction bipartite graph can be constructed.

Then, considering the importance of user's personality traits for learning POI interaction preferences, the influence degree of the user's personality is obtained according to Eq. (6) and is used to update the weight w_{ij} of the edge. The weight calculation method considering the influence of user personality is defined as Eq. (10):

$$\begin{aligned} w_{ij} &= w_{ij} \otimes \vec{Q}_i, 0 \leq |U|, 0 \leq |P|, 0 \leq |Q_i| \\ \vec{h_i} &= w_{ij} \otimes \vec{h}_i', w_{ij} \in (0,1) \end{aligned} \tag{10}$$

where, $w_{i,j}$ denotes the interaction weight, Q_i represents the influence degree of the user u_i's personality, $\vec{h_i}$ and $\vec{h}_i'$ are both feature vector representations of the node, and $\otimes$ denotes the number multiplication operation of the vector.

The personality-aware interaction bipartite graph is illustrated in Fig. 4c), which is denoted as $G_I = (U, P, \mathcal{E})$, where U and P denote the set of similar users and POIs, respectively, and $\mathcal{E}$ denote the set of connected edges between nodes. After constructing the bipartite graph G_I, we learn the POI interaction preference of similar users from the bipartite graph with our proposed graph neural network PEBGNN. The learning process of PEBGNN is introduced as follows.

(1) Message propagation. Let Set_1 represent the set of nodes containing both similar users and POIs, and Set_2 represent the set of nodes of the same type (e.g., only users or only POIs). For the l_{th} layer of PEBGNN, $W_p^l \rightarrow +u$ and $W_p^l \rightarrow -u$ are used to propagate the messages from p_j to u_i according to the positive edges and negative edges. The process of message propagation is depicted in Eq. (11):

$$\begin{aligned} m^l_{p\rightarrow+u}(p_j, u_i) &= \text{MSG}\left(\vec{\text{h}}^l_{u_i}, \vec{\text{h}}^l_{p_j}\right) = W^l_{p\rightarrow+u} \cdot \vec{\text{h}}^l_{p_j} \\ m^l_{p\rightarrow-u}(p_j, u_i) &= \text{MSG}\left(\vec{\text{h}}^l_{u_i}, \vec{\text{h}}^l_{p_j}\right) = W^l_{p\rightarrow-u} \cdot \vec{\text{h}}^l_{p_j} \end{aligned} \tag{11}$$

where $N_{p\rightarrow+u}(u_i)$ and $N_{p\rightarrow-u}(u_i)$ denote the sets of neighbors of u_i linked by positive and negative edges, respectively. Specifically, p_j is a member of $N_{p\rightarrow+u}(u_i)$ when the connection is positive, and $N_{p\rightarrow-u}(u_i)$ when it is negative. Similarly, we employ $W_u^l \rightarrow +p$ and $W_u^l \rightarrow -p$ to transmit messages from u_j to p_i. This process is outlined in Eq. (12):

$$\begin{aligned} m_{u\to+p}^{l}\left(u_j,p_i\right) &= \mathrm{MSG}\left(\vec{\mathrm{h}}_{p_i}^{l},\vec{\mathrm{h}}_{u_j}^{l}\right) = W_{u\to+p}^{l}\cdot\vec{\mathrm{h}}_{u_j}^{l} \\ m_{u\to-p}^{l}\left(u_j,p_i\right) &= \mathrm{MSG}\left(\vec{\mathrm{h}}_{p_i}^{l},\vec{\mathrm{h}}_{u_j}^{l}\right) = W_{u\to-p}^{l}\cdot\vec{\mathrm{h}}_{u_j}^{l} \end{aligned} \tag{12}$$

where $N_{u\to+p}(p_i)$ and $N_{u\to-p}(p_i)$ denote the sets of neighbors of p_i connected by positive and negative edges, respectively. Specifically, u_j is an element of $N_{u\to+p}(p_i)$ when the edge is positive, and an element of $N_{u\to-p}(p_i)$ when the edge is negative.

Since only the representations of POIs are used here, Set_2 refers to the set of POIs. Therefore, we propagate messages only for the positive and negative edges from p_j to p_i using $W_p^l\to+p$ and $W_p^l\to-p$, respectively. The message propagation formula for Set_2 is defined as Eq. (13):

$$\begin{aligned} m_{p\to+p}^{l}\left(p_j,p_i\right) &= \mathrm{MSG}\left(\vec{\mathrm{h}}_{p_j}^{l},\vec{\mathrm{h}}_{p_i}^{l}\right) = W_{p\to+p}^{l}\cdot\vec{\mathrm{h}}_{p_j}^{l} \\ m_{p\to-p}^{l}\left(p_j,p_i\right) &= \mathrm{MSG}\left(\vec{\mathrm{h}}_{p_j}^{l},\vec{\mathrm{h}}_{p_i}^{l}\right) = W_{p\to-p}^{l}\cdot\vec{\mathrm{h}}_{p_j}^{l}, \end{aligned} \tag{13}$$

where $N_{p\to+p}\left(p_i\right)$ and $N_{p\to-p}\left(p_i\right)$ denotes the positive and negative neighbors for p_i, respectively. $p_j\in N_{p\to+p}\left(p_i\right)$ and $p_j\in N_{p\to-p}\left(p_i\right)$.

(2) Message Aggregation. After obtaining the information of neighboring nodes, the next step performs the message aggregation operation. First, PEBGNN transforms the interaction frequencies on the connected edges considering the influence of user's personality into weights and fuses them with the feature vectors of the nodes, described in Eq. (14):

$$\begin{aligned} & w_{ij} = MinMaxScaler(W_{i,j}*Q_i), 0\le|U|, 0\le|P|, 0\le|Q_i| \\ & \vec{h_i} = w_{ij}\otimes\vec{h_i'}, w_{ij}\in(0,1) \end{aligned} \tag{14}$$

where $W_{i,j}$ denotes the original interaction frequency, and Q_i represents the influence degree of the user's personality. The normalization operation is denoted by $MinMaxScaler(\cdot)$, through which the original interaction number is transformed into the interaction weight in the interval (0, 1). The vectors $\vec{h_i}$ and $\vec{h_i'}$ are feature vector representations of the node, and $\otimes$ denotes the element-wise multiplication operation of the vectors.

Second, PEBGNN aggregates information from neighboring nodes using the graph attention aggregation function. Therefore, the correlation between two nodes needs to be calculated, using Eq. (15):

$$\alpha_{ij} = \frac{\exp\left(\mathrm{LeakyReLU}\left(\vec{a}^T\left[W\overrightarrow{h_i}\|W\overrightarrow{h_j}\right]\right)\right)}{\sum_{k\in N_i}\exp\left(\mathrm{LeakyReLU}\left(\vec{a}^T\left[W\overrightarrow{h_i}\|W\overrightarrow{h_k}\right]\right)\right)} \tag{15}$$

where $\vec{h_i}$ is the feature vector representation of the node *i*, $|\cdot|$ is the splicing operation, W denotes the matrix of trainable attention coefficients, $\vec{a}$ means the trainable parameter vector, N_i indicates the set of neighboring nodes of the node *i*, $\mathrm{LeakyRelu}$ is the activation function, and $\exp(\bullet)$ denotes the $\mathrm{softmax}$ processing, which is used to normalize the weight coefficients so as to ensure that the sum of weight coefficients of the node *i* and all of its neighboring nodes is equal to 1. The aggregation of messages from neighbors is performed using the weight coefficient α_{ij}, as detailed in Eq. (16):

$$\begin{aligned} m^l\left(u_i\right) &= \sum_{j\in N_i}\alpha^{ij}m^l\left(u_j\right) \\ m^l\left(p_i\right) &= \sum_{j\in N_i}\alpha^{ij}m^l\left(p_j\right) \end{aligned} \tag{16}$$

where N_i denotes the set of neighbors of node *i*. We transform attention aggregation into a function that employs a learnable weighted average mechanism.

(3) Updating function. After message propagation and aggregation, each u_i acquires four groups of message sets from neighbors: $m_p^l\to+u$, $m_p^l\to-u$, $m_u^l\to+u$, and $m_u^l\to-u$. Similarly, each p_i receives four sets of messages from neighbors: $m_u^l\to+p$, $m_u^l\to-p$, $m_p^l\to+p$, and $m_p^l\to-p$. PEBGNN then combines the information from these four groups of neighbor nodes into node *i* and exploits MLP to obtain the latest representation of node *i*. This process is detailed in Eq. (17):

$$h_u^{l+1} = \mathrm{MLP}\left(\vec{\mathrm{h}}_u^l \left\| m_{p\to+u}^l \right\| m_{p\to-u}^l \left\| m_{u\to+u}^l \right\| m_{u\to-u}^l\right)$$
$$h_p^{l+1} = \mathrm{MLP}\left(\vec{\mathrm{h}}_p^l \left\| m_{u\to+p}^l \right\| m_{u\to-p}^l \left\| m_{p\to+p}^l \right\| m_{p\to-p}^l\right) \quad (17)$$

where $\vec{\mathrm{h}}_u^l$ represents the representation of similar users, $\vec{\mathrm{h}}_p^l$ represents the representation of points of interest (POIs), and "||" denotes the concatenation operation. MLP consists of two fully connected neural layers, includes a dropout ratio, and utilizes an activation function, as detailed in Eq. (18):

$$\mathrm{MLP}(x) = W_2\left(\sigma\left(\mathrm{dropout}\left(W_1 x + b_1\right)\right)\right) + b_2 \quad (18)$$

where W_1, W_2, b_1 and b_2 are the learnable parameters of MLP, $\sigma(\cdot)$ is an activation function, *dropout* is used to prevent over-fitting. The output sequences of PEBGNN are $Z = [\vec{z}_1^p, \vec{z}_2^p, \ldots, \vec{z}_k^p]$, where $\vec{z}_i^p$ represents the representation of the POI p_i, which indicates users' POI interaction preferences for p_i.

Module III: generating the recommended POI sequence

Once the fitted features of the random group and the POI representations, which include the POI interaction preferences of similar users, are obtained, the next step is to calculate the predicted scores for each POI for the random group. The predicted scores $\widehat{y_i}$ are then sorted in descending order and the top K POIs are selected to create the recommended POI list for the random group. The predicted scores are calculated using Eq. (19):

$$\widehat{y_i} = \mathrm{Sigmoid}(\vec{g}^T \bullet \overrightarrow{h_{\nu_i}}), \widehat{y_i} \in (0,1) \quad (19)$$

where $\vec{g}$ is the fitted feature of the random group, $\overrightarrow{h_\nu}$ means the final feature representation of POIs, $\widehat{y_i}$ is the predictive scores of POIs, and • indicates the inner product operation of vectors. To facilitate the screening of POIs, the predicted score $\widehat{y_i}$ is compressed into the (0,1) interval using the $Sigmoid(\cdot)$ function.

Module IV: accurate POI determination with an improved multi-negotiation model

To address the issue that existing group POI recommendation methods cannot provide accurate POI for groups, we propose a personality-driven multi-negotiation model (PDMNM) based on a multi-agent system to determine the optimal POI for a random group. The main idea of PDMNM is to take the previously generated POI recommendation list as the pre-selection of negotiation, then create an independent agent for each member, which has the member's personality and the approximate expectation of the pre-selection, and each agent selects the accurate POI as the final choice of the group through negotiation. The overall design of PDMNM is shown in Fig. 5.

Step 1: Generate approximate expectations of members in a random group. PDMNM identifies members who join the negotiation process by analyzing their personality profiles. If the extraversion dimension of the member's personality is higher than a threshold (e.g., 0.5), the member is selected and put into the negotiation model. Meanwhile, for each selected member, an independent agent is created, which has the member's personality characteristics and an approximate expectation for preselection. The approximate expectation data of each agent is obtained from the user POI prediction score matrix obtained by PEBGNN, and the approximate expectation $E_i(x_j)$ of each item in the pre-selected POIs is obtained by Eq. (20):

$$E_i(x_j) = \begin{cases} FromPEBGNN_i(x_j), & x \notin R_i \\ r_i(x_j), & x \in R_i \end{cases} \quad (20)$$

where R_i is the evaluation list of POIs in the i^{th} member's pre-selected POIs, $FromPEBGNN_i(x_j)$ is the predicted score of POIs evaluated by the user through the PEBGNN model.

Step 2: Make the initial proposals. At the beginning of the first round of consultations, each agent makes the highest-rated proposal from the current pre-selected proposals as the initial proposal. Then, the initial proposals of all agents are exchanged to determine if the agreement can be reached based on one of the proposals. A negotiation is reached if the proposal made by one agent is at least as good for the other agents as their current proposal. In this case, the proposal that satisfies all agents is returned as the optimal POI for the group.

Step 3: Handle the negotiation conflict. If an agreement cannot be reached, one (or more) agents must concede. Here "concede" means that an agent will look for a proposal based on his or her lesser satisfaction with a POI and aims to reach an agreement. If none of the agents can concede, the negotiation fails and PDMNM generates the final choice for the random group based on the members' current expectations of the pre-selected POI. The method for selecting the members that must concede is proposed with the *Zeuthen Strategy*[40] based on the concept of *Willingness to Risk Conflict* (WRC), which can be calculated according to Eq. (21):

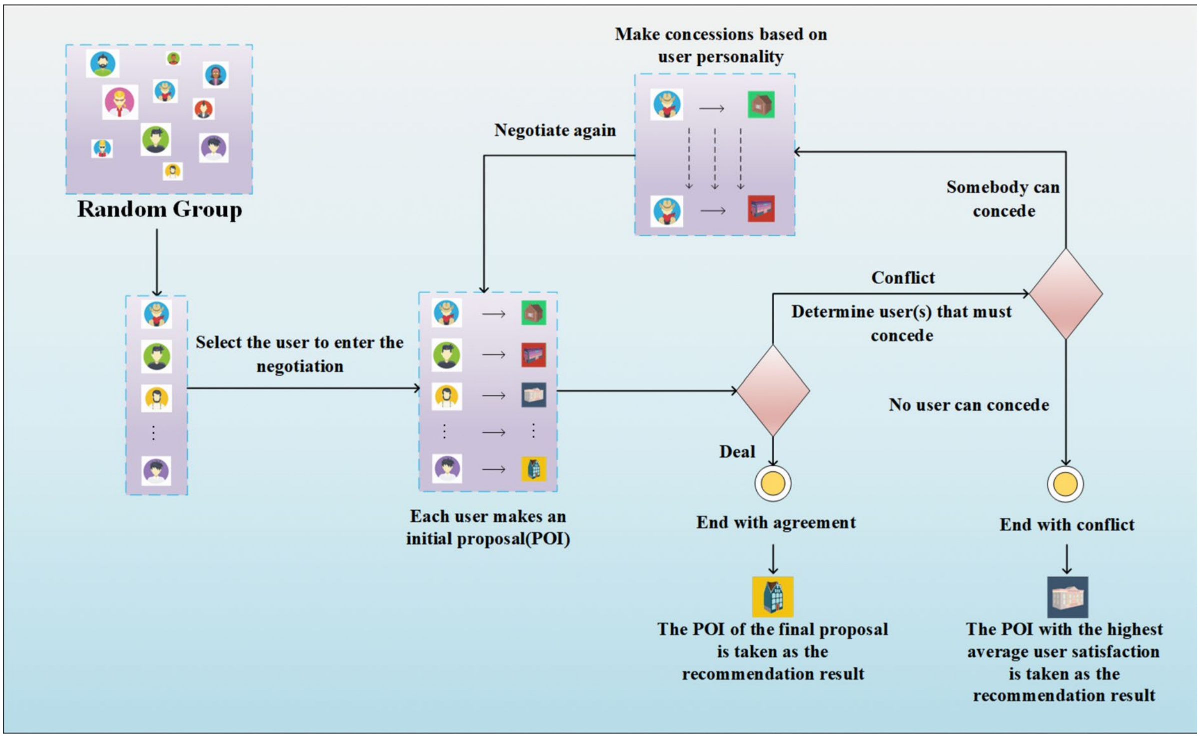

Figure 5. The flowchart of the personality-driven multi-negotiation model.

$$WRC_i = \begin{cases} 1 & , E_i\left(x_j\right) = 0 \\ \frac{E_i\left(x_j\right) - \min\{E_i\left(x_k\right) | k \in U\}}{E_i\left(x_j\right)} & , \text{ otherwise} \end{cases} \tag{21}$$

During each round of negotiation, one (or more) user(s) to be conceded is identified by calculating each user's WRC_i.

Step 4: Choosing a concession strategy. User concession strategies are explicitly proposed in Endriss et al.'s work[40] in which seven concession strategies are proposed (*Strong concession, Weak concession, Pareto concession, Utilitarian concession, Egalitarian concession, Nash concession*, and *Egocentric concession*). In fact, random group members do not only use one concession strategy in the negotiation process and users with different personalities adopt different concession strategies. Inspired by[40], the PDMNM model proposed in our work adopts different concession strategies according to the degree of influence of users with different personalities in group decision making, and makes the following assumptions: (1) Users with the degree of user personality influence in the interval of [0,0.5] will make collectivist concessions in the negotiation process, so the *Strong Concession* strategy is adopted. (2) Users with the degree of user personality influence in the [0.5,1] interval are prone to emotional stubbornness and will make egoistic concessions in the negotiation process, so the *Egoistic Concession* strategy is adopted.

In this case, the *Strong Concession* strategy means that the user who is asked to make a concession proposes a proposal that is strictly more favorable to others, i.e., other users rate the new POI proposal made by the user who needs to make a concession higher than the previous proposal; the *Egoistic Concession* means that the user who is asked to make a concession proposes a POI proposal that has a slightly lower rating than the current proposal, i.e., each time the user makes a concession, it selects the POI from the sequence of its POI ratings from the highest to the lowest the following proposal. Through multiple rounds of negotiation and concessions, PDMNM can get the final POI recommendation for the random group.

An example of PDMNM (including three agents) is illustrated in Fig. 6, In the first round, $AGENT_1$, $AGENT_2$ and $AGENT_3$ present their own proposals POI_3, POI_2 and POI_1, respectively. Assume that no current proposals can satisfy all the agents at the same time, one of the agents must make a concession. Then, according to the concession rule, assume that the value of WRC_1 of $AGENT_1$ is the lowest, $AGENT_1$ must make a concession. At the beginning of the second round, $AGENT_1$ proposes a POI named POI_{15}, which completes the concession process and continues the negotiation process as shown in Fig. 6. After that, the cycle repeats until the k^{th} round of negotiation as shown in Fig. 6. In this round, the model finds that POI_4 can satisfy $AGENT_1$, $AGENT_2$ and $AGENT_3$ at the same time, and each agent expects that POI_4 is higher than the other current proposals. The final POI choice is POI_4.

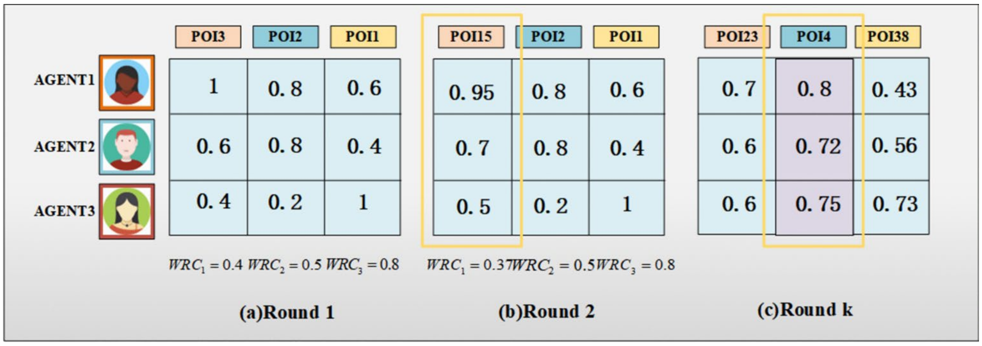

Figure 6. An example of MCP negotiation.

Dataset	Number of users	Number of POIs	Number of check-ins
Foursquare	2551	13,474	124,933
Gowalla	5628	31,803	620,683
Yelp	30,887	18,995	860,888

Table 1. Statistics for Foursquare, Gowalla, and Yelp.

Experiments and analysis

In this section, we first verify the performance of the sub-model PRRG, and then verify the effectiveness of the sub-model APDMN.

Datasets and experimental platform

In our experiment, we adopt three benchmark datasets (the Yelp dataset (https://www.kaggle.com/datasets/yelp-dataset/yelp-dataset), the Gowalla dataset (https://snap.stanford.edu/data/loc-gowalla.html) and the Foursquare dataset (https://sites.google.com/site/yangdingqi/home/foursquare-dataset)) to evaluate the performance of our proposed model PRRG. The three datasets consist of extensive check-in records at POIs, with each entry including a distinct user ID and a POI ID. Within our research, we first perform data preprocessing on all three datasets to filter out inactive users and unwanted POIs. Then, we randomly generate the Big Five personality information of each user during the preprocessing process. Finally, 60% of the dataset was selected as the training set, 20% as the validation dataset, and the remaining 20% are used as the test dataset. Table 1 gives the details of the three datasets after preprocessing.

The random groups are formed by randomly selecting users from each of the benchmark datasets. It is important to note that the POI interaction preferences learning module is trained using the POI interaction data of similar users, whereas the fitted feature generation module utilize the POI interaction data of the group members. The experimental equipment and platform are as follows: Operating System is Windows 10 Professional 64-bit; CPU is 3.19 GHz 12th Generation Intel Core i9-12900K and GPU is NVIDIA GeForce RTX 3090; RAM is Crucial 32GB (16GBx2) DDR5-6000; Model Platform is PyCharm Community Edition (https://www.jetbrains.com/pycharm/); Programming Language is Python 3.8 (https://www.python.org/); and finally Deep Learning Framework is PyTorch (https://pytorch.org/).

The training strategy for PRRG

The PRRG model consists of two modules, which are PaFFG and PEBGNN. Since each module of PRRG is responsible for learning different types of information, we use a training strategy that trains the two modules separately and individually. After the two modules are trained, we apply them together to perform POI recommendations for random groups. Due to the different computational mechanisms of the three modules, to optimize the overall recommendation performance of the PRRG model, we conduct a large number of experiments based on empirically fixed values and make targeted settings for the relevant parameters used by each module as well as the loss function. The detailed information is described in Table 2.

Specifically, the PRRG model first adopts the random method to produce the initial representations of members as well as the initial representations of POIs. Then, the PaFFG and PEBGNN modules are trained and optimized to generate the fitted feature of random groups and the representations of POIs. Next, the predictive scores of POIs for the random group are computed based on the fitted feature of the random group as well as the representations of POIs. For PaFFG, traditional regression prediction is used as the driven task, and the mean square error (MSE) is used as the loss function for the optimization PaFFG module. Moreover, PEBGNN applies the prediction of the connected edge of the nodes as the driven task, and adopts the binary cross entropy loss function (BCELoss) to optimize the module.

Parameters	PaFFG	PEBGNN
Num layers	4	2
Epochs	32	10
Batch size	1,024	512
Hidden dim	9	9
Dropout	0.3	0.5
Learning rate	0.01	0.005
Optimizer	RMSprop	Adam
Weight decay	-	1×10^{-5}
Loss function	MSE	BCELoss

Table 2. Sub-model parameter table.

Performance evaluation of POI recommendation model PRRG

Performance evaluation metrics

To verify the recommendation performance of PRRG, we adopt two evaluation metrics that are widely used in POI recommendation research field to verify the recommendation performance of PRRG, which are *Presicion@K* and *NDCG@K*. The formulas for the three metrics are defined as follows:

$$Precision@K = \frac{|R(g) \cap T(g)|}{|R(g)|} \tag{22}$$

$$\begin{aligned} DCG@K &= \sum_{k=1}^{K} \frac{rel_i}{\log_2(i+1)} \\ NDCG@K &= \frac{DCG@K}{IDCG@K} \end{aligned} \tag{23}$$

where *R*(*g*) denotes the POI recommendation list and *T*(*g*) denotes the real POI check-in list of the random group *RG*. rel_i is a binary value (i.e., $\mathrm{rel}_i \in \{0,1\}$), which is used to indicate whether the *i*-th POI in the recommendation list is in the real list, and *IDCG@K* denotes the maximized *DCG@K* value. In general, a larger value of *NDCG@K* indicates the better performance of the recommendation model. In our work, we use *N* to denote the length of the POI recommendation list and the value of *N* is set at $N = [2, 5, 10, 15, 20]$.

Baseline models

Existing works for POI group recommendation is primarily focused on fixed groups and little attention has been paied to POI recommendations for random groups. Therefore, there are few baseline models that can be used for comparison with the model PRRG. Moreover, PRRG first acquires the fitted features of the random group and then takes the random group as a virtual user and performs POI recommendations for the virtual. The idea of PRRG is quite similar to the process of POI recommendation for individuals. In our experiment, we select nine personalized POI recommendation models and four group POI recommendation models as the baseline models, which are introduced as follows:

- **TransMKR**[52]: TransMKR, a multi-task learning model, uses knowledge graph translation for point-of-interest (POI) recommendations. It constructs the knowledge graph based on POI attributes (e.g., visit numbers, geographic location), enabling detailed and accurate characterization through various attribute values.
- **NPGR**[53]: NPGR builds a heterogeneous LBSN graph comprising users, POI categories, and check-in time windows, extracting node feature representations via Node2Vec. It also considers user check-in frequency, POI geographic location, and POI hotness for recommendations.
- **GSTN**[54]: GSTN leverages graph neural network techniques to create a spatio-temporal network model, effectively capturing correlations between time and space in POIs.
- **STORE**[55]: STORE examines the impact of spatio-temporal factors on user check-in behavior for POI recommendations. Unlike traditional methods that separate time and space analysis, STORE integrates them.
- **MBR**[56]: MBR, a multivariate bipartite graph neural network model, reduces the computational overhead of traditional bipartite graph models through clustering operations. It enhances recommendation performance by deeply analyzing the effects of users' social networks, POI geographic locations, and check-in times.
- **STGN**[57]: STGN incorporates the gating mechanism to study spatio-temporal factors, improving recommendation accuracy by modeling user check-in behavior patterns, which are serialized, using this efficient tool for handling serialized data.
- **FG-CF**[58]: FG-CF combines collaborative filtering with graph convolutional networks to mitigate sparse user check-in data issues in POI recommendations. It integrates user social information into the user-POI bipartite graph for better characterization of user features.

- **DSMR**[59]: DSMR enhances trajectory embedding quality by learning deep semantic information from discrete trajectory data. It performs continuous semantic modeling on the data and uses pre-trained language models to extract implicit deep semantic information, thereby improving recommendation performance.
- **TGSTAN**[60]: TGSTAN incorporates cooperative signals and dynamic user preferences in graph learning by proposing a GCN model with self-attention. This model enhances recommendation performance by emphasizing the relative proximity of spatio-temporal intervals.
- **CubeRec**[61]: CubeRec represents group preferences using hypercubes in the vector space to better capture the multifaceted user preferences within a group. It learns individual user and item embeddings through interactions and then aggregates these into group-level hypercubes via geometric bounding or attentive fusion methods.
- **ConsRec**[62]: ConsRec aims to capture the consensus behind group interactions for group recommendations by designing three distinct views for multi-view learning, including member-level aggregation, item-level tastes, and group-level inherent preferences.
- **DHMAE**[63]: DHMAE is a method for group recommendation that integrates a disentangled hypergraph neural network with a masked autoencoder. It emphasizes learning the unique characteristics of members and items separately during convolution to prevent over-entanglement of information. This approach aims to improve the effectiveness of group recommendations by focusing on low-degree entities within the hypergraph structure.
- **CGNN-PRRG**[21]: CGNN-PRRG is a POI recommendation model for random groups proposed in our previous work, which considers the influence between group members to generate group fitting features and uses similar users to learn the comprehensive POI interaction preferences of users for generating feature representations of POIs.

Impact of group size on performance of PRRG

In POI recommendation for groups, group size is an important factor affecting the recommendation performance of the model[28]. To obtain the optimal value of group size and to enable sub-model PRRG to achieve better performance, we carry out an experiment to discover the influence of different group sizes on the performance of PRRG. In the experiment, we set the value of the random group size as 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100. We execute sub-model PRRG and get the average accuracy of POI recommendation on the three datasets (Foursquare, Gowalla, and Yelp). The experimental results are presented in Fig. 7.

From Fig. 7 we can find that, for the Foursquare dataset, when the group size is in the interval of [10, 50], the average accuracy of PRRG increases when the group sizes are in the interval of [10, 20], and slightly decreases when the group sizes are in the interval of [20,30], and then gradually increases when the group sizes are in the interval of [30,50]. When the group size is in the interval of [50,70], the average accuracy of the PRRG model gradually decreases, but it is still higher than the lowest average accuracy; after that, when the group size is in the interval of [70,100], the average accuracy of PRRG model shows an increase. The average accuracy of PRRG model achieves the maximum value when the group size is set as 50.

For the Gowalla dataset, when the group size is in the interval of [10, 30], the average accuracy of the PRRG model gradually increases, and then, when the group sizes are in the interval of [30,40], the average accuracy of PRRG slightly decreases. When the group sizes are in the interval of [30,90], the average accuracy of PRRG shows a gradual increase. When the group size is set as 100, it slightly decreases compared to situation that when the group size is set as 90, and its average accuracy is approximately equal to the average accuracy at the group size of 90. For the Gowalla dataset, PRRG has the highest average accuracy when the group size is set as 90.

In the Yelp dataset, the average accuracy of PRRG shows fluctuations throughout the interval of group size [10,100] and reaches the highest when the group size is 100. Based on the experimental outcomes, we can draw

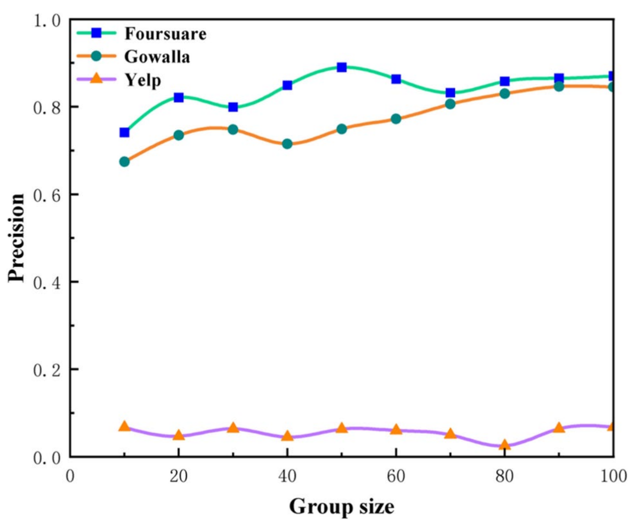

Figure 7. Performance of PRRG with different group sizes on the three datasets.

Models	Precision@K					NDCG@K				
	2	5	10	15	20	2	5	10	15	20
FG-CF	–	–	–	–	–	–	0.13	0.16	–	–
GSTN	–	–	–	–	–	0.16	0.2	0.22	-	–
NPGR	–	0.05	0.04	0.04	0.04	–	–	–	–	–
TransMKR	–	–	0.4	0.35	–	–	–	–	–	–
DSMR	–	0.51	0.59	–	–	–	–	–	–	–
TGSTAN	–	0.47	0.57	–	–	–	0.34	0.41	–	–
ConsRec	–	–	–	–	–	–	–	0.52	–	–
DHAME	–	–	–	–	–	–	0.58	0.58	–	0.58
CGNN-PRRG	**0.98**	0.89	0.75	0.58	0.45	**0.98**	0.91	0.81	0.68	0.58
PRRG	0.97	**0.91**	**0.87**	**0.86**	**0.85**	0.96	**0.92**	**0.89**	**0.88**	**0.87**

Table 3. Evaluation of PRRG model's performance compared to baseline models on the Foursquare dataset. Significant values are given in bold.

Models	Precision@K					NDCG@K				
	2	5	10	15	20	2	5	10	15	20
FG-CF	–	0.09	0.07	0.06	0.06	–	–	–	–	–
GSTN	–	–	–	–	–	0.12	0.15	0.17	–	–
MBR	-	0.03	0.02	0.02	0.02	–	–	–	–	–
TransMKR	–	0.43	0.42	–	–	–	–	–	–	–
TGSTAN	–	0.30	0.40	–	–	–	0.23	0.26	–	–
ConsRec	–	–	–	–	–	–	–	0.56	–	–
DHAME	–	–	–	–	–	–	0.62	0.62	–	0.62
CGNN-PRRG	0.87	**0.88**	0.76	0.58	0.45	**0.88**	0.81	0.81	0.67	0.57
PRRG	**0.88**	0.80	**0.84**	**0.86**	**0.85**	0.87	**0.82**	**0.84**	**0.85**	**0.85**

Table 4. Evaluation of PRRG model's performance compared to baseline models on the Gowalla dataset. Significant values are given in bold.

the following conclusions: when the group size is small, the quantity of training data available for PRRG is insufficient, leading to a degradation in its performance. Conversely, when the group size is large, the substantial differences in preferences among group members negatively impact the performance of the recommendation model PRRG. Therefore, to optimize the recommendation effectiveness of PRRG, guided by the experimental results depicted in Fig. 7, we set the optimal group sizes for the three datasets (Foursquare, Gowalla, and Yelp) to 50, 90, and 100 respectively.

Performance verification of POI recommendation model PRRG

To verify the performance of our proposed POI reocommendations for random groups (PRRG), evaluation metrics *Precision@K* and *NDCG@K* are used as performance evaluation indicators. Three public benchmark datasets (Foursquare, Gowalla, and Yelp) are adopted. Specifically, since not all the baseline models are tested on the three benchmark datasets, the @K values of some baseline models are inconsistent. In this experiment, performance comparisons between PRRG and baseline models are carried out on the same data set with the same @K value. Our experimental results are presented from Table 3 to Table 5, where the optimal results of each column are highlighted in bold, and "-" indicates results of the model lacks corresponding indicators.

For the Foursquare dataset, we select FG-CF, GSTN, NPGR, TransMKR, DSMR, TGSTAN, ConsRec, DHAME and CGNN-PRRG as baseline models to compare their performance against our proposed PRRG model. As shown in Table 3, for the Precision@K metric, the highest value of 0.97 is achieved when $K = 2$. At $K = 20$, the Precision@K value drops to 0.85. Regarding the NDCG@K metric, its peak value of 0.96 is achieved when $K = 2$, after which it gradually declines as K increases, reaching a minimum of 0.87 at $K = 20$. According to the results in Table 3, compared to the baseline models (excluding CGNN-PRRG), our PRRG model shows an improvement of approximately 50% in Precision@K and 43.5% in NDCG@K. Furthermore, when comparing PRRG to CGNN-PRRG, our model shows significantly higher values for both Precision@K and NDCG@K as K increases.

For the Gowalla dataset, we choose FG-CF, GSTN, MBR, TransMKR, TGSTAN, ConsRec, DHAME and CGNN-PRRG as baseline models to compare their performance against our PRRG model. As shown in Table 4, the Precision@K metric exhibits a fluctuating pattern as K increases from 2 to 20. Specifically, as K increases from 2 to 5, Precision@K increases from 0.88 to 0.80; subsequently, as K increases from 5 to 15, the Precision value gradually declines from 0.80 to 0.86. Finally, as K progresses from 15 to 20, the Precision value gradually

Models	Precision@K					NDCG@K				
	2	5	10	15	20	2	5	10	15	20
FG-CF	–	**0.28**	0.02	0.02	0.02	–	–	–	–	–
CubeRec	–	–	–	–	–	–	–	0.024	–	0.03
PRRG	**0.08**	0.07	**0.06**	**0.06**	**0.06**	**0.09**	**0.07**	**0.06**	**0.07**	**0.07**

Table 5. Evaluation of PRRG model's performance compared to baseline models on the Yelp dataset. Significant values are given in bold.

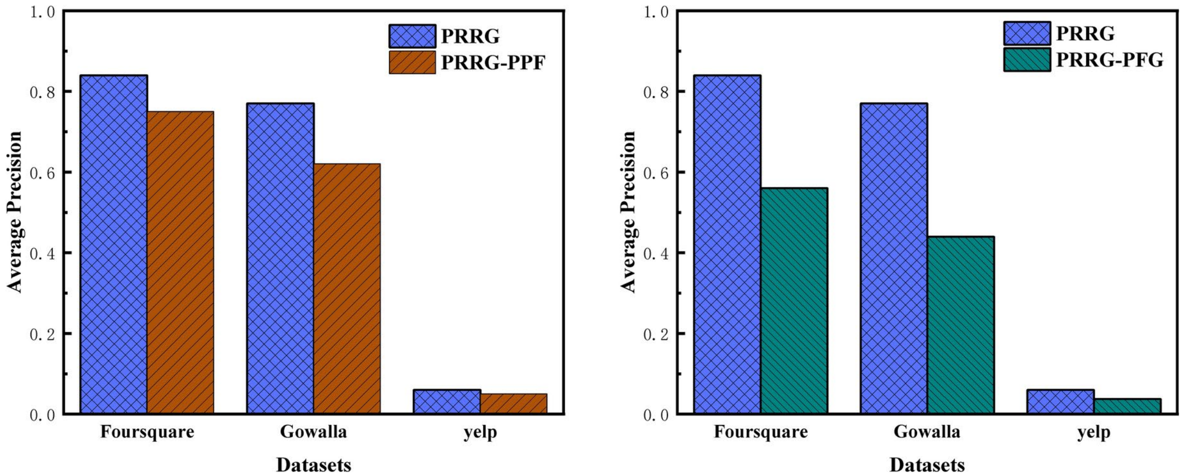

Figure 8. Comparison of average accuracy across the three datasets.

increases from 0.86 to 0.85. For the NDCG@K metric, the value initially decreases and then increases as K increases from 2 to 20. Specifically, as K grows from 2 to 5, NDCG@K decreases from 0.87 to 0.82; thereafter, as K increases from 5 to 20, NDCG@K increases from 0.82 to 0.85. Based on the results in Table 4, the PRRG model achieves an average improvement of 61.5% in Precision@K and 35% in NDCG@K compared to the baseline models, excluding CGNN-PRRG. When compared to CGNN-PRRG, there is little difference in Precision@K and NDCG@K for K in the range of [2,10]. However, for K greater than 10, the PRRG model shows clear advantages.

In POI recommendation, the Yelp dataset is less frequently used than the Foursquare and the Gowalla dataset. Among the baseline models selected in our work, FG-CF and CubeRec model have carried out performance tests on the Yelp dataset. Therefore, for the Yelp dataset, we select FG-CF and CubeRec as the baseline model and perform a comparative analysis with our proposed PRRG model. The experimental outcomes are detailed in Table 5. From this table, we observe that for the Precision@K metric, as K increases from 2 to 20, the Precision@K value decreases from 0.08 to 0.06. Notably, PRRG outperforms the baseline model when K is set to 10, 15, and 20. Overall, based on the results presented in Tables 3 to 5, we can conclude that our proposed PRRG model produces superior recommendation results compared to the eight baseline models.

Ablation experiments for PRRG

Our proposed PRRG model uniquely utilizes personality traits within its fitted feature generation and POI preference learning modules. Therefore, we conduct the ablation experiment to verify the effectiveness of considering personality in POI recommendations for random groups. We generate two models PRRG-PPF and PRRG-PFG from PRRG in this experiment. More specifically, PRRG-PFG is generated by removing the personality-aware fitted feature-generating module from PRRG and applying a fitted feature-generating module that does not consider members' personalities. The other modules of PEBGNN-RM keep the same with PRRG. PRRG-PPF is generated by removing the consideration of members' personalities from the POI interaction preference learning module in PRRG. Moreover, other modules of PRRG-PPF are the same with that of PRRG.

In this experiment, the "Average Precision" is used as the performance evaluation index to compare the performance of PRRG and the other two ablation models (PRRG-PFG and PRRG-PPF) on the three data sets. Since we have 10 group sizes ranging from 10 to 100, "Average Precision" is the average of the model's Precision@K of the ten groups. The experimental results are presented in Fig. 8. The figure shows that the recommendation effectiveness of the PRRG model consistently outperforms that of PRRG-PFG and PRRG-PPF across the three datasets, which proves that when conducting POI recommendation for random groups, integrating members personalities in POI interaction preferences learning and fitted feature generating can significantly enhance the model's performance.

Conversely, the PRRG-PPF model consistently demonstrates the poorest performance across the three datasets, which indicates that solely relying on group characteristics derived from personality-aware fitted feature generation has a weaker impact on recommendation effectiveness compared to incorporating random group POI interaction preferences. Focusing solely on personality-based group feature fitting does not enhance the model's recommendation performance.

Furthermore, the recommendation performance of the PRRG-PPF model surpasses that of the PRRG-PFG model across the three datasets. Since the PRRG-PPF model exclusively learns the POI interaction preferences through random group personality learning and lacks the integration of random group feature fitting based on personality, it struggles to accurately predict the POIs that random groups may interact with. Consequently, its recommendation performance is inferior to that of the PRRG model.

Evaluation of the improved multi-negotiation model

Evaluation metrics

The multi-negotiation model aims to determine the accurate POI from the POI recommendation list generated by PRRG.

To verify the effectiveness of our proposed multi-negotiation model, we conduct experiments to verify members' satisfaction in the multi-negotiation model. Two evaluation indicators are adopted: Group Satisfaction (GS) and Member Satisfaction Dispersion (MSD). GS aims to measure the group's overall satisfaction with the determined POIs, while MSD aims to evaluate the satisfaction of group members with a single proposal POI. GS and MSD are calculated using:

$$GS\left(p_j\right) = E_{\mathrm{g}}\left(p_j\right) = \frac{\sum_{i=1}^{n} E_i\left(p_j\right)}{n} \tag{24}$$

$$\mathrm{MSD}\left(p_j\right) = \sqrt{\frac{\sum_{i=1}^{n}\left(E_i\left(p_j\right) - E_g\left(p_j\right)\right)^2}{n}} \tag{25}$$

where $E_i\left(p_j\right)$ represents member $u_i^{'}$s approximate estimated preference for POI p_j and *n* represents the group size.

Influence of group size on the multi-negotiation model

This experiment aims to test the influence of group size on the performance of the multi-negotiation model. Here, the Foursquare dataset is selected and the group size is set as 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100. With different group sizes, our proposed improved multi-negotiation model negotiates on the TOP-5 POI sequence recommended by PRRG and verify the effectiveness of the multi-negotiation model with the group satisfaction degree of group members to the negotiated POI and the dispersion degree of member satisfaction. The experimental results are shown in Fig. 9.

From Fig. 9, we can observe that, for the Foursquare dataset, when the group size is in the range of [10,100], group satisfaction and member satisfaction dispersion fluctuate, although the overall fluctuation amplitude is small. Since the Foursquare dataset does not record the specific rating of user u_i to POI p_i

and only records the check-in times of user u_i to POI p_i, we take the check-in frequency as the estimated score of the user when obtaining the user's score.

The estimated rating of POI p_i by user u_i is lower. However, we notice that the value of member satisfaction dispersion is in the range of [0.005, 0.03], which indicates that our proposed model APDMN performs well in

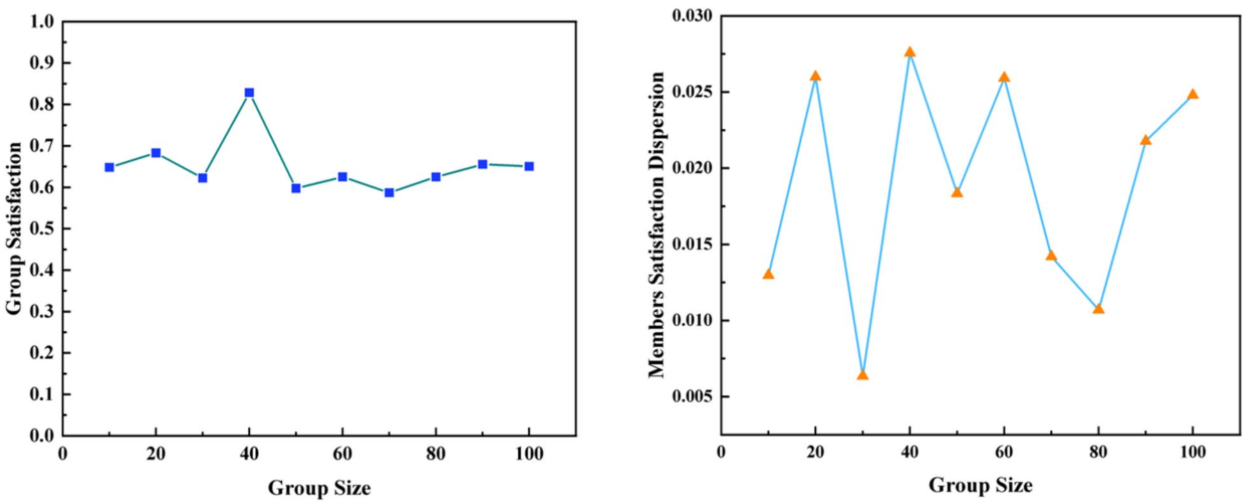

Figure 9. Negotiation effect of the APDMN model under different group sizes on the Foursquare dataset.

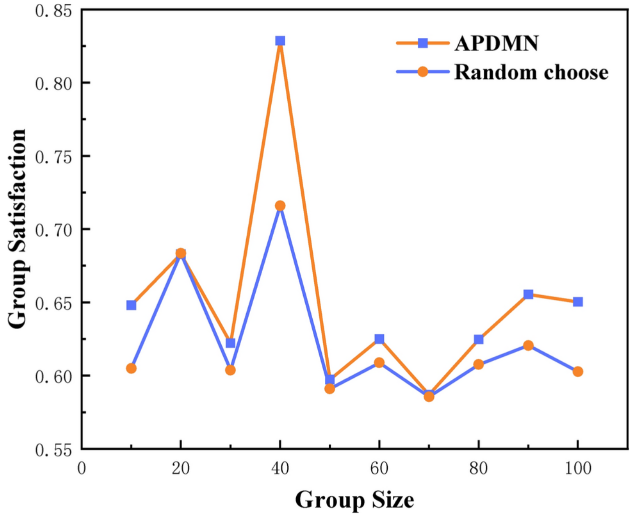

Figure 10. Effectiveness verification of the APDMN model.

the negotiation deduction process. This also proves that even if the actual ratings of users are low, APDMN can still

achieve a good member satisfaction dispersion in group negotiation and demonstrate the superiority of our proposed model in the negotiation process.

Verify the effectiveness of multi-negotiation models

In this work, to obtain the accurate POI for random groups, our proposed method first generates the recommended POI list through the POI recommendation model for random groups and then determines the optimal POI through the improved multi-negotiation model. Moreover, in our proposed multi-negotiation model, members' personalities are taken into consideration, which is useful for enhancing the overall performance of the negotiation model. Moreover, the accurate POI recommendation method proposed in our work is quite new to the best of our knowledge and it is difficult to find a baseline model to verify the synergistic effect of APDMN. To verify the effectiveness of APDMN, we take the random method as the baseline and apply group satisfaction of the randomly selected POIs and POIs determined through APDMN as the evaluation metric. The experimental results are depicted in Fig. 10.

As shown in Fig. 10, the POIs obtained by APDMN are better than or equal to those obtained by a random method in terms of group satisfaction. The experimental results prove that the APDMN model can accurately select POIs from the recommended POI sequence, thereby improving the user experience for random group members.

Conclusion and future work

To tackle the problem of accurate POI recommendation for random groups, we propose an accurate POI recommendation method based on graph neural networks and multi-negotiation model (named APRRGM). Specifically, APRRGM first generates the fitted feature of the random group based on members' personalities and their POI interaction data. Then, APRRGM learns POIs' features from the bipartite graph of users and POIs using an improved GNN with consideration of members' personalities. Next, APRRGM recommends a POI list based on the fitted feature of the random group and the features of POIs. Finally, based on the recommended POI list and members' personalities, APRRGM determines the optimal POI for the random group with an improved multi-negotiation model, which conducts the negotiation process for the random group. Since group-related knowledge can help improve the accuracy of recommendations, in our future research work, we will study POI recommendations driven by data and knowledge fusion, and introduce geographic data to further enhance the accuracy and contextual relevance of the recommender systems. This will allow our system to not only take into account member personality and POI interaction data, but also provide more accurate services based on geographical location information.

Data availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on request.

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Author contributions
X.S. conceived the experiment(s), X.S. and J.Y. conducted the experiment(s), Z.L. and J.Y. analyzed the results, Z.L. provided resources, L.M. and Q.Z.S. edited the manuscript, D.C. reviewed the manuscript. All authors reviewed the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
Correspondence and requests for materials should be addressed to Z.L.

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