Research Article

A Novel Travel Group Recommendation Model Based on User Trust and Social Influence

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The interactions between group members often have a significant impact on the results of group recommendations. The traditional group recommendation algorithm does not consider the trust and social influence among users. It involves a low utilization rate of social relationship information, which leads to a low accuracy and satisfaction of group recommendations. Considering these issues, in this study, we propose a travel group recommendation model based on user trust and social influence. Based on the user trust relationship, this model defines the user direct and indirect trust and calculates the user global trust by combining the two trusts. Subsequently, the PageRank algorithm is used to calculate the social influence of users based on their interaction relationship history. Thereafter, a consensus model integrating the intra- and intergroup prediction scores is designed by integrating users' global trust and social influence to realize group recommendations for tourist attractions. Comparison experiments with several well-known group recommendation models for datasets of different scenic spots in Beijing demonstrate that the proposed model provides a better recommendation performance.

1. Introduction

Online searches have become the main method for tourists to obtain information before traveling. However, with the rise of social networks and travel websites, tourists are often exposed to a large quantity of information and product selections; therefore, a travel recommender system is an effective method for overcoming the issue of information overload [1]. By learning user history, such recommendation systems establish a description of user interest preferences and recommend items or sets of items that the user could be potentially interested in, thereby providing a personalized service. Currently, such recommendation technology has been widely used by major e-commerce sites and has promoted the sales, as well as improved user satisfaction and loyalty [2–4].

Massive data present in social networks are rich in information regarding the users. Mining interaction rules among users can effectively improve the effectiveness of group recommendations. Tourism is an activity with rich and varied contextual information, including food, accommodation, transportation, travel, shopping, and entertainment information, and each aspect has its own attributes. Compared with other items, tourism products comprise increasingly complex information. The choice of a tourist destination is a complex decision-making process, which often requires a collective decision, and the entirety of the decision-making process requires the support of relevant tourism information [5]. However, current research focuses on the tourism project recommendation of a single user, which relies on user and project information and does not sufficiently consider decision-making within a group [6]. Therefore, it is necessary to expand the traditional single-user recommendation method. According to online evaluation information of tourists, the opinions and social relationships of users within a group are utilized to form a common decision-making mechanism and improve the accuracy and satisfaction of a tourism recommendation. This is of great importance to the research of tourism recommendations. Christensen et al. [7] proposed a society-

based approach to travel recommendation systems, which constructs a group strategy model by analyzing users' preferences and the social relationships between group members. Guo et al. [8] attempted to use tag information to determine if users had similar neighbors and extracted tag information from the photos of neighbors to design a group recommendation scheme based on similar neighbors. Currently, the application of matrix factorization method to recommendation has significantly improved the accuracy of recommendation [9–11]. However, this method is not effective for data sparsity, and it cannot solve the problem of new user and new item recommendation. Mining user behavior [12] and extracting item features [13,14] can effectively improve the accuracy of recommendation. These methods are all applied to single-user recommendation, and the current research on group users is still insufficient. The key issue of group recommendations is the preference fusion strategy. At present, the fusion strategy mainly considers the introduction of contextual information, neighbor interactions of user preference, and geographical, spatial, and temporal locations. However, the current group recommendation system is entirely based on the static relationships between users, and the social influence of users within and between groups is not adequately considered. Moreover, the preferences of group users change as social interactions change [15].

It is easier for high-trust group users to reach consensus and achieve accurate item recommendation [16]. How to accurately measure the trust value between users is one of the key steps of using trust to improve the group recommendation efficiency. In addition, due to the complexity of attributes such as context, item, and user in travel recommendation, this paper employs users' social influence to improve the weight of each user in the group user's recommendation to improve the accuracy of recommendation. To overcome this issue, this study proposes a tourist group recommendation model based on a social influence and user trust recommendation model, namely, TSTGR. This model considers the social influence of social networks and trust between the users in the group integration strategy, optimizes the differences within the group consensus, and realizes tourism destination recommendations. Finally, the validity of the proposed group recommendation algorithm is verified using a real dataset from Beijing.

2. Related Works

2.1. Group Recommendations.
The group recommender system expands the recommended service objects from one user to multiple users. Compared with the traditional recommender system for a single user, the group recommender system better considers the interactions between group members and social factors [17,18]. Many differences exist between the group and traditional recommendation systems. First, the recommendation service object is changed from a single user to a group. The group recommender system must consider user interaction behaviors and preference fusion, and the degree of association and interaction between group members will also affect the

recommendation results. Second, the recommendation results of the group recommendation system are shared by all members of the group and provide a reference for group decision-making, while the recommendation results of the traditional recommendation system are unique to a user. Therefore, the difficulty in researching group recommendation systems stems from the reasonable coordination of the different preferences of group members such that the recommendation results can meet the preferences of the group members to the greatest extent. There are many different preference fusion strategies for group recommendation systems. Previous literature [19] has elaborated on common fusion strategies. Generally, they can be categorized as single-preference [20] and mixed [21] fusion strategies. Tang et al. [15] proposed a preference fusion strategy based on user interaction behaviors, but this strategy did not consider the influence of the consumed items in the group on the recommendation results. Hong et al. [22] implemented group recommendations based on social affinity and credibility according to users' historical records and evaluation content characteristics but did not consider users' ratings. Additionally, their fusion strategy was too simple, leading to a low recommendation accuracy. Wang et al. [23] proposed a bidirectional tensor decomposition model for group recommendations and used the Bayesian personalized ordering technique to learn the parameters in the proposed BTF-GR model. Zhang et al. [24] provided a recommendation list by determining the most similar group to which the target customer belongs by combining a personalized recommendation method for group relevance and customer preference. Xiao et al. [25] used adaptive weighting to aggregate group members' preferences to determine the group's decision for a certain service, which was based on the opinions of familiar members and group influence. Therefore, their method can implement group recommendations. Many useful explorations of group recommendations have been conducted. However, the existing preference fusion strategies for group recommendations are relatively simple while the divergence degree between group members is high, and the accuracy of recommendations must be improved. Moreover, the results of existing research are all based on static relationships, which ignore the influence of changes in the social influence of users on the recommendation performance. Therefore, this study conducts further research on the preference fusion of group recommendation systems.

2.2. Tourism Recommendations.
Online searches have become the main method for tourists to obtain information before traveling. However, with the increasing prevalence of social networks and travel websites, tourists are often exposed to a large amount of information and product options. A travel recommendation system is an effective means of overcoming the issue of information overload. Kofler et al. [26] collected tourism photos shared on the Flickr platform and obtained the metadata and user-generated data of reach photo, among other information. After the user selects the tourist destination, their method

recommends photo sets of tourist attractions related to the destination. Moreno et al. [27] designed a personalized tourism destination recommendation system. They considered the motivation of tourists, as well as user access, evaluation, and personal history records, and then used collaborative filtering technology to recommend scenic spots similar to those visited by the users. Loh et al. [28] established a tourism ontology database and used the text mining method to mine users' preferences for tourism destinations or scenic spots and then query destinations or scenic spots with high similarity to the users' preferences from the tourism ontology knowledge base and recommend these destinations to users. Levi et al. [29] extracted the characteristic values of hotels by analyzing the evaluation records of users on TripAdvisor and Venere using a clustering algorithm. Then, according to the motivation and preferences of the target users, the content-based recommendation technology was adopted to recommend hotels of potential interest to the users, and the satisfaction of the users was verified using a survey. The impact of a single-user travel recommendation is relatively small and the recommendation accuracy is high for this method. Tourism is a complex human activity, and single-user travel recommendations cannot consider all the travel needs of tourists. In the above studies, little attention has been paid to group tourism, the description of tourist user groups has not been adequately precise or detailed, and the granularity of all methods is too coarse. As a result, the recommended tourism items cannot meet the personalized needs of group users. Therefore, with the help of group recommendation technology, this study proposes a group travel recommendation model based on user trust and social influence.

3. Group Recommendation Model Incorporating User Trust and Social Influence

3.1. Recommendation Framework. Group recommendation generally consists of three components: group discovery, preference fusion, and prediction recommendation. According to the social relationships of travel users, this study proposes a group recommendation framework that integrates user trust and social influence, as shown in Figure 1. This framework is mainly composed of three parts: a data acquisition module, preference modeling module, and group recommendation algorithm design module. The data collection module is mainly responsible for the collection and sorting of data for tourist attractions, as well as the collection and processing of social relationships between users. The preference modeling module mainly involves group discovery, trust modeling, and social influence modeling. It is responsible for the division of travel user groups, the quantitative analysis of user influence, and the establishment of trust for users within the group. According to the divided group and preference model, the group recommendation algorithm design module completes the group's rating predictions and recommendations to the tourist.

3.2. User Trust Modeling. Most of the existing group recommendation studies have only considered whether a trust relationship exists between users. Typically, a trusted relationship is denoted as 1 while an untrusted relationship is denoted as 0. This measurement method is relatively simple, and it does not specifically consider the level of trust between users. However, the degree of trust between users will have different effects on the final decision.

This study divides the trust relationship between users into direct and indirect trust. Direct trust is defined when there are common rating items among users and their ratings are consistent. Rating consistency means that the rating is divided into two parts according to the rating level. If a user's rating is greater than the median rating, the user's rating is positive; otherwise, the user's rating is negative. For example, the ratings of user u_i and u_j on item S_k are 4 and 5, and the median rating is 3, indicating that the ratings of user u_i and u_j are both positive, so the ratings of user u_i and u_j are consistent. Indirect trust is obtained by the weighted transfer of direct trust between users. The specific calculation method is shown in Figure 2. Therefore, the trust between u_i and u_j can be obtained by the weighted sum of direct trust and indirect trust, namely, the global trust defined in this paper. Meanwhile, the consensus function among group users can be calculated using the global trust. For users with direct trust relationships, the specific definitions are shown as follows.

Definition 1 (direct trust). Assuming there are N user reviews in the dataset, the direct trust between users is defined by the following equation:

$$D_{ij} = \frac{\sum_{N_{ij}} f(u_i, u_j)}{N}. \tag{1}$$

Here, N is the total number of evaluations in the user dataset, N_{ij} represents the number of scenic spots jointly evaluated by users u_i and u_j, and $f(u_i, u_j)$ represents the common evaluation function of scenic spots evaluated by users u_i and u_j. If they are consistent, this equation is set to 1; otherwise, it is set to 0. Assume that the rating level is $r = \{1, 2, 3, 4, 5\}$. For example, the rating by user u_i of scenic spot s is 5 and the rating by user u_j of scenic spot s is 4. Both users' ratings are greater than or equal to the median of the rating scale. We then set $f(u_i, u_j) = 1$, which is otherwise set to 0.

Definition 2 (indirect trust). Indirect trust between users is defined using the following equation:

$$I_{ij} = \sum_{k=1,k\neq i}^{N} w_k \times D_{kj}. \tag{2}$$

Here, D_{kj} is the direct trust between users u_k and u_j. The indirect trust between users u_i and u_j is the weighted sum of the direct trust between users u_j and u_k that does not include the direct trust between them, and w_k is the weight.

Based on the direct and indirect trust between users, this study provides a definition of user global trust as follows:
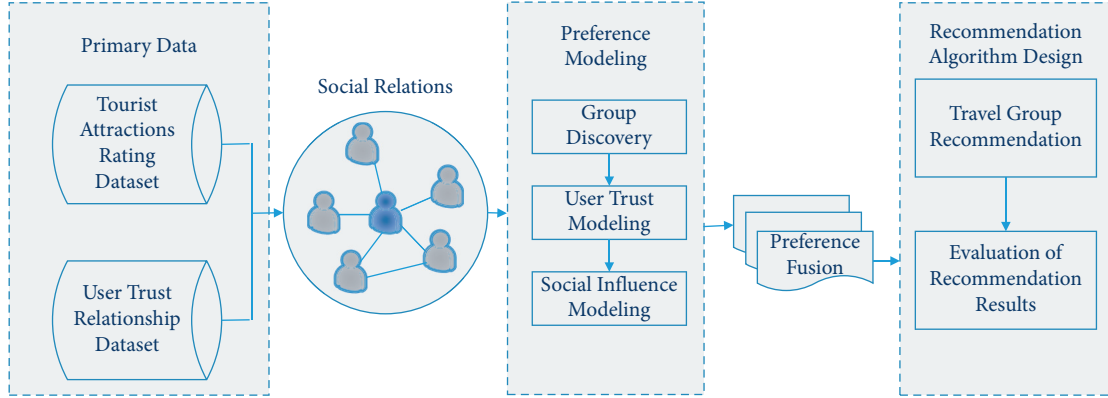
FIGURE 1: Tourism group recommendation framework integrating user trust and social influence.
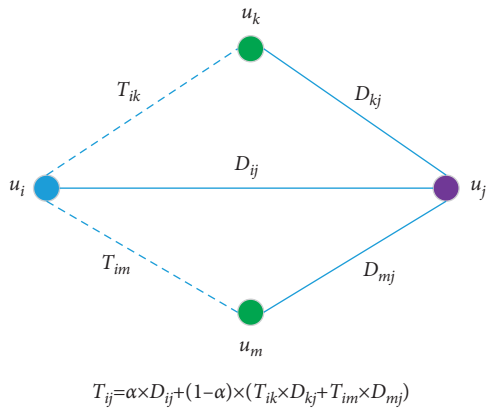

$$T_{ij} = \alpha \times D_{ij} + (1-\alpha) \times (T_{ik} \times D_{kj} + T_{im} \times D_{mj})$$

FIGURE 2: Schematic diagram of the global trust.

$$T_{ij} = \alpha D_{ij} + (1 - \alpha)I_{ij}. \tag{3}$$

Equation (3) can also be written in the following specific form:

$$T_{ij} = \alpha \frac{\sum_{N_{ij}} f(u_i, u_j)}{N} + (1 - \alpha) \sum_{k=1, k \neq i}^{N} w_k \times \frac{\sum_{N_{ik}} f(u_i, u_k)}{N}. \tag{4}$$

The global trust of users u_i and u_j is shown in Figure 2, where α is the regulating coefficient of direct trust and indirect trust in the global trust, and $\alpha \in [0, 1]$. When $\alpha = 1$, the global trust of users u_i and u_j is completely determined by the direct trust. When $\alpha = 0$, the global trust of users u_i and u_j is completely determined by the indirect trust. The weight is set to $w_k = T_{ik}$, which represents the global trust of users u_i and u_j.

The collection of trust data is to use the user's rating dataset, and set the users with common ratings and rating consistency to direct trust. Then, the indirect trust is calculated through the direct trust iteration, and finally the trust relationship and trust value between the whole users are obtained.

3.3. *Social Influence.* Social networks contain a wealth of information, and each user's influence in the network is different. The social network graph of the whole user set can be obtained by abstractions of the connections among users in the social network. After the users submit ratings and text reviews of tourist attractions online, they usually interact with other online users. If there is a common review between user u_i and u_j, then they are called to have social influence, and edge (u_i, u_j) is established. By establishing the connection between users, the user set can be abstract into a graph with users as nodes and their connections as edges, and the improved PageRank algorithm proposed in this paper can be used to calculate the influence of each user in the social network. Therefore, based on the online interaction information of users, we apply the improved PageRank algorithm proposed in this paper to describe the social network influence of users to provide a decision basis for group recommendations.

In this study, the social rating information of users is described as a social network G and users are set as nodes, represented by V. If there is a common rating among users, it is considered that there is a connection between users, which is denoted as an edge set E. If G has n nodes, then the node set is $V = \{v_1, v_2, \ldots, v_n\}$. If there is a connection between users u_i and u_j, denoted by v_{ij}, then the edge set is $E = \{v_{ij} | i, j \in n\}$. According to the above definition, all users and their relationships are represented as $G = \{V, E\}$ in this study. To obtain the social influence of each user node, we improved the traditional PageRank algorithm and weighted the trust function with the damping coefficient to obtain a new damping coefficient, $\beta = a \cdot T_{ij} + b$, where a and b are linear weights used to adjust the damping coefficient. We set the default values for a and b to 0.5. The setting of this damping coefficient can dynamically adjust the transmission of influence between users. Therefore, the greater the trust between users, the greater the transmission of influence between them, and vice versa. Through the above settings, the PageRank algorithm is used to obtain the social influence of each user. The specific steps are as follows:

Step 1: traverse each node v_i in the node set V and randomly initialize the PageRank value of node v_i to obtain $PR(v_i)$

Step 2: calculate the degree N_i of v_i

Step 3: double traverse the user node and calculate $PR(v_i) = (1 - \beta)PR(v_i) + \beta \times (PR(v_i)/N_j)$

Step 4: repeat Step 3 until the entire PageRank influence converges

3.4. Implementation of the Tourism Group Recommendation Algorithm. To improve the accuracy of group recommendations and reduce the degree of disagreement among group members, this study first proposes a new group consensus model that integrates group social influence and trust among users. In this study, $F(G_i, S_j)$ is used to represent the predicted rating of group G_i for a tourist attraction S_j, which is defined as follows:

$$F(G_i, S_j) = \gamma \left(\sum_{u_i \in G_i} PR(u_i) \cdot R_i + \sum_{u_i \in G_i} R_{CF}(u_i, S_j) + \sum_{u_i \in G_i} R_{TF}(u_i, S_j) \right) + (1 - \gamma) \left(\sum_{G_t \in \text{Neighor}(G_i)} \text{Sim}(G_t, G_i) \cdot R_{G_t} \right). \quad (5)$$

Here, γ is the weighting parameter, $PR(u_i)$ represents the social influence of user u_i, and R_i represents the average rating of the scenic spots reviewed by user u_i. $R_{CF}(u_i, S_j)$ represents the predicted rating of a single user in the group for tourist attraction S_j based on collaborative filtering technology, wherein $R_{CF}(u_i, S_j) = (\sum_{u_t \in \text{Neighor}(u_i)} \text{Sim}(u_i, u_t) \cdot r_{tj}) / (\sum_{u_t \in \text{Neighor}(u_i)} \text{Sim}(u_i, u_t))$, and Neighor$(u_i)$ represents similar neighbors of user u_i. $R_{TF}(u_i, S_j)$ represents the predicted rating of tourist attraction S_j by a single user in the group based on the global trust among users; i.e., $R_{TF}(u_i, S_j) = (\sum_{u_t \in \text{Neighor}(u_i)} T_{it} \cdot r_{tj}) / (\sum_{u_t \in \text{Neighor}(u_i)} T_{it})$. $\text{Sim}(G_t, G_i)$ represents the similarity between groups G_i and G_t, and R_{G_t} represents the average rating given by users in group G_t to tourist attraction S_j. The consensus model is composed of two parts, namely, intra- and intergroup prediction ratings, and the weights of these two parts are adjusted using parameter γ. The first part is composed of the social influence score, collaborative filtering score, and trust user score. The second part is composed of the cooperative prediction scores between groups. The specific implementation steps are shown in Algorithm 1.

This algorithm is mainly composed of three parts: the PageRank algorithm used to calculate social influence, traversing user sets for calculating the global trust among users, and the Top-K group rating prediction for scenic spots. The complexity of the PageRank algorithm in the first part is $O(kn^2)$, where k is the number of iterations and n is the number of users. The second part involves the time complexity of calculating the degree of global trust, which is mainly composed of the degrees of direct and indirect trust. Its complexity is $O(C_1(n^2 + n))$, where C_1 is a constant. The third part involves the calculation of the consensus function to achieve the Top-K group recommendation, and its complexity is $O(Kmn + n^2 + C_2 n)$, where m is the number of scenic spots in the dataset, K is the number of scenic spots recommended by the Top-K group, and C_2 is a constant. Therefore, the time complexity of the entire algorithm is $O(Kmn + C(n^2 + n))$, where C is a constant.

4. Evaluation

4.1. Experimental Dataset and Environment. To verify the effectiveness of the group tourism recommendation scheme proposed in this study, we collected the evaluation data [30] of 200 scenic spots from 37000 tourists extending from July 1, 2014, to June 30, 2017, including the user ID, scenic spot, ticket prices, scores, text evaluation, evaluation time, travel types, etc. A total of 472,710 comment data were collected. The distribution of the scenic spots is shown in Figure 3. In addition, we added a Yelp Restaurant dataset to further verify the effectiveness of the method proposed in this paper. In this dataset, we extracted data from the US state of Arizona, including 622,446 reviews of 9,427 restaurants (https://www.yelp.com/dataset/).

The experimental environment in this study is a 64-bit operating system on the Windows 10 platform, the CPU is an Intel(R) Core(TM) i7-8750H, the main frequency of the processor is 2.20 GHz, and the physical memory is 16.0 GB. The algorithm proposed in this study is implemented by Microsoft Visual C++. To evaluate the recommendation results and algorithms effectively, 80% of the dataset is randomly selected as the training set for training the algorithm and the remaining 20% is used as the test set. The recommendation results are then verified using the test data, and the experimental results are compared and analyzed.

4.2. Evaluating Indicator. In this study, the accuracy rate, recall rate, and normalized loss cumulative gain are used as performance indicators to measure the performance of the group recommendation model such that the performance of several comparison models may be measured more accurately.

(1) Accuracy is defined as follows:

$$\text{precision} = \frac{N_{RL}}{N_R}, \quad (6)$$

where N_R denotes the total number of items recommended by the recommendation system to users, N_{RL} denotes the number of favorite items in the recommended item set, and N_L denotes the number of items that users like in the whole dataset.

(2) Normalized discounted cumulative gain (nDCG) is an evaluation method based on ranking, which is an

Input: tourism user evaluation dataset **R**, tourism user dataset U, scenic spot dataset S, and parameters $\{\alpha, \gamma\}$
Output: **Top-K** prediction rating of the group for the tourist attraction
(1) divide Groups
(2) **for each** u **in U**
(3) calculate $PR(u)$ and $\text{Sim}(G_t, G_i)$
(4) **end for**
(5) **for each** u_i **in U**
(6) **for each** u_j **in U**
(7) calculate T_{ij}
(8) **end for**
(9) **end for**
(10) **for** $k \longleftarrow 1$ **to** K
(11) **for each G in** Group
(12) $F_{\text{IntraGroup}} \longleftarrow \sum_{u_i \in G_i} PR(u_i) \cdot R_i + \sum_{u_i \in G_i} R_{\text{CF}}(u_i, S_j) + \sum_{u_i \in G_i} R_{\text{TF}}(u_i, S_j)$
(13) $F_{\text{InterGroup}} \longleftarrow \sum_{G_i \in \text{Neighor}(G_i)} \text{Sim}(G_t, G_i) \cdot R_{G_i}$
(14) $F \longleftarrow \gamma F_{\text{IntraGroup}} + (1 - \gamma) F_{\text{InterGroup}}$
(15) **end for**
(16) Update recommendation scenic spot list
(17) **end for**
(18) **return** Top K scenic spot

ALGORITHM 1: Group recommendation algorithm based on social influence and user trust recommendation.
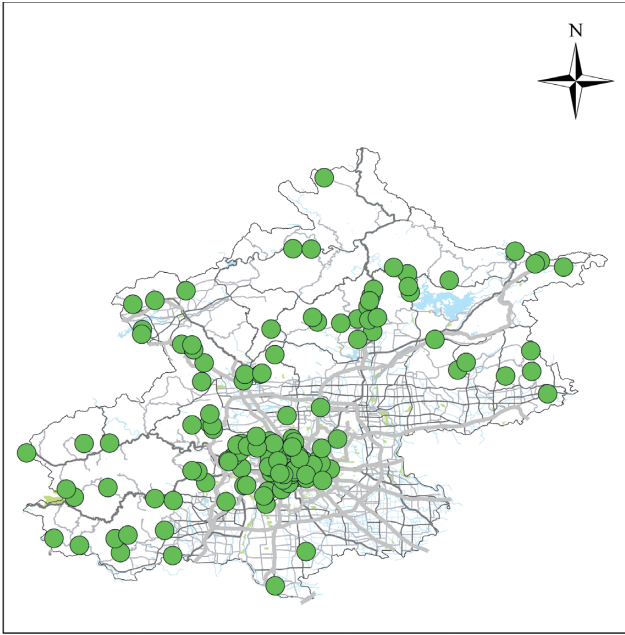

FIGURE 3: Distribution map of Beijing attractions.

important indicator of the recommendation accuracy of the evaluation group. It is defined as follows:

$$\text{nDCG@}k = \frac{\sum_{g \in G} \text{DCG}_g @ k}{\text{IDCG}_g},\quad (7)$$

where $\text{DCG}_g @ k$ denotes the cumulative discount revenue of the recommendation algorithm to the group g recommendation list and IDCG_g denotes a list of the best recommended results for the group g.

4.3. Contrast Model.
Herein, four classical group recommendation models are selected and compared with the TSTGR model proposed in this study. The details are as follows:

(1) GRSAT model [22]: this model realizes group recommendations based on social affinity and credibility according to user history and evaluation content characteristics, without considering the user's score.

(2) PLTSGR model [24]: this model adopts a personalized recommendation method combining group relevance and customer preference. An unsupervised method and PLTS are used to determine group association between a customer group and a restaurant group, and a recommendation list is provided by finding the most similar group to which target customers belong.

(3) PFGR model [25]: based on the opinions of familiar members and group influence, this scheme uses adaptive weighting to aggregate the preferences of group members to determine the group's decision for a certain service. A strategy based on the alliance game is used to realize the group recommendation.

(4) SIGR model [18]: this group recommendation model uses the attention mechanism to learn the social impact of each user and adapt their social impacts to different groups. Group information fusion is realized by using and integrating the global and local social network structure information of users.

(5) TSTGR model: in this study, considering the difficulty of merging the preferences of group members for group recommendations, a global trust model is
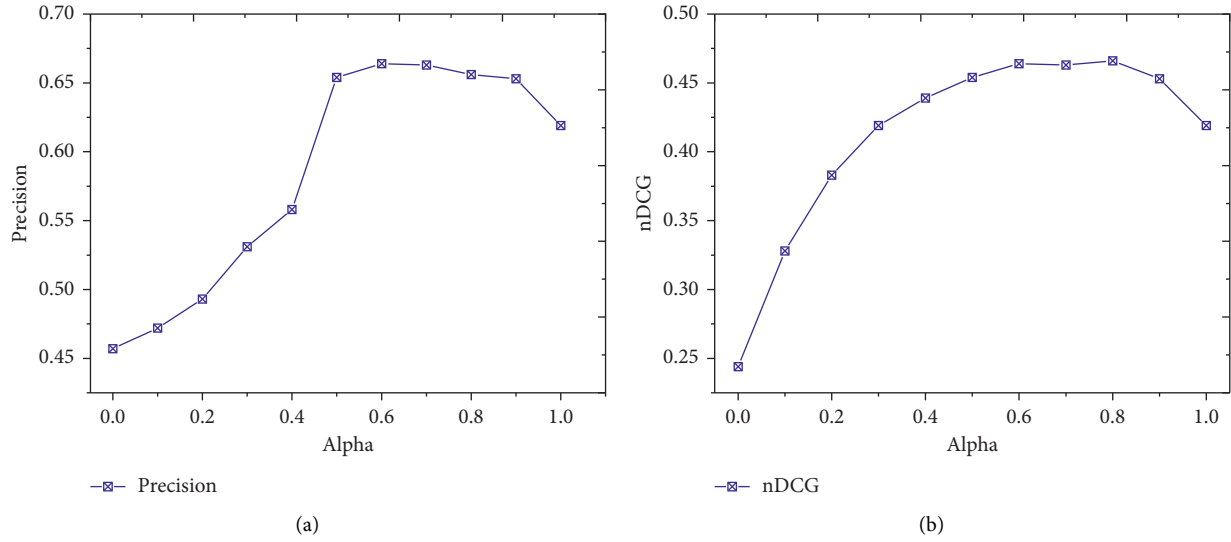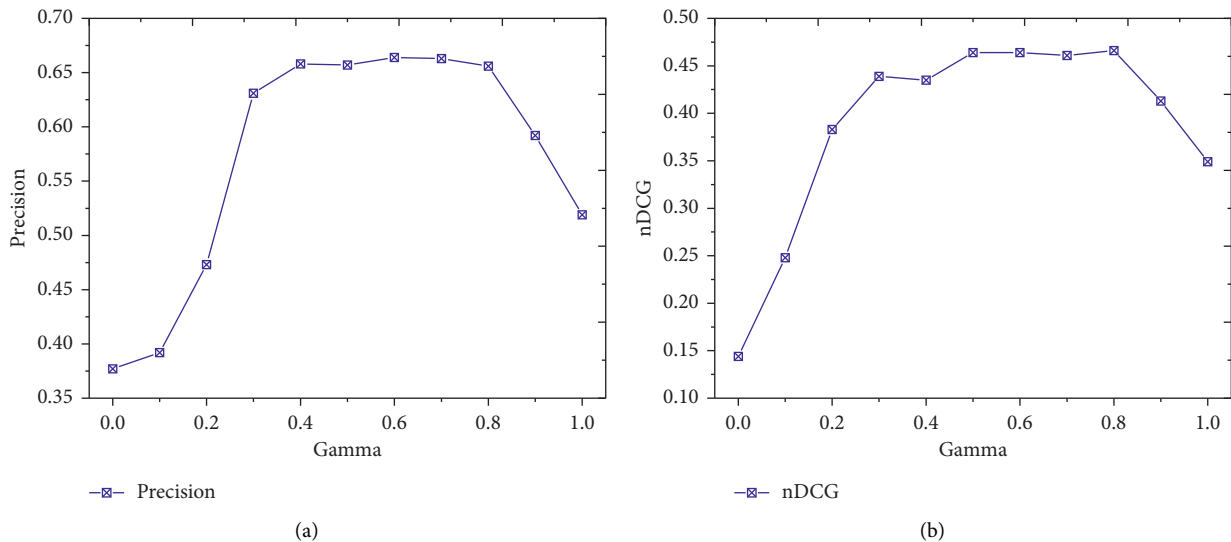
FIGURE 4: Influence of parameter α on the performance of the TSTGR model. (a) Influence of parameter α on the precision index. (b) Influence of parameter α on the nDCG index.

FIGURE 5: Influence of parameter γ on the performance of the TSTGR model. (a) Influence of parameter γ on the precision index. (b) Influence of parameter γ on the nDCG index.

constructed using direct and indirect trust between users, and the PageRank algorithm is used to measure user influence. The global trust and social influence of users are integrated into the group consensus model to realize the Top-K recommendation for tourist attractions.

4.4. Sensitivity Analysis.

(1) The parameter α: this parameter is the weighting coefficient between direct and indirect trust, and its value range is [0, 1]. If the value of α is 0, the global trust is composed solely of indirect trust. If the value of α is 1, the global trust is only composed of direct trust. In this experiment, the value of α is selected

between 0 and 1 to test the influence of this parameter on the performance of the group recommendation method proposed in this study. It can be seen from Figure 4 that when the parameter α is set within [0.5, 0.9], we can achieve a relatively good recommendation performance. Therefore, in the subsequent experiments in this study, the default value of α is set to 0.7.

(2) The parameter γ: the parameter γ is the weighting coefficient of the intra- and intergroup prediction scores in the parameter group consensus model, with a value range of [0, 1]. If the value of γ is 1, the prediction scores of the consensus model are determined by the scores in the group. If the value of γ is 0, the prediction score of the consensus model is
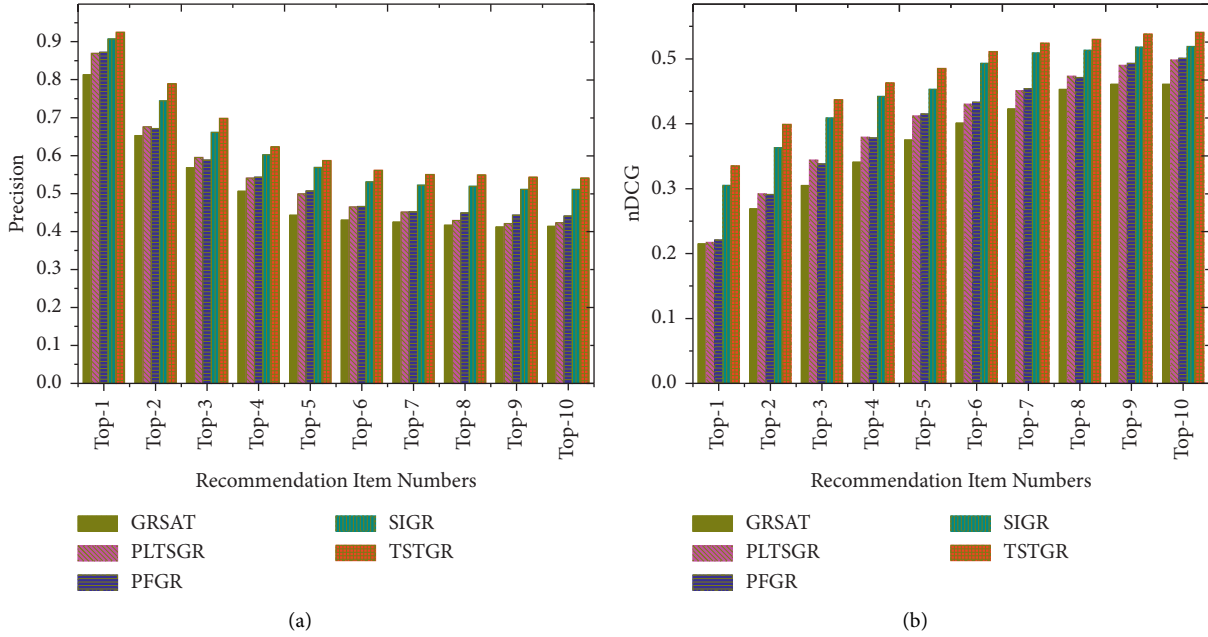
FIGURE 6: Performance comparison of the five models on Beijing attractions. (a) Comparative experimental results for the precision index. (b) Comparative experimental results for the nDCG index.
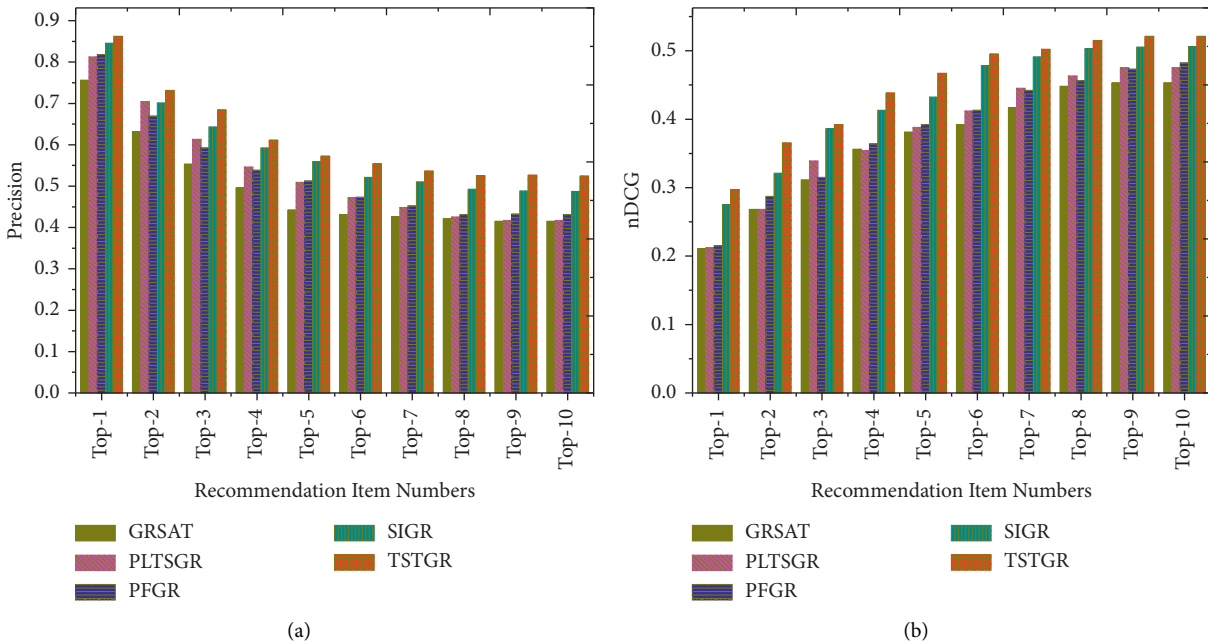

FIGURE 7: Performance comparison of the five models on Yelp restaurant. (a) Comparative experimental results for the precision index. (b) Comparative experimental results for the nDCG index.

determined by the scores between groups. In this experiment, the value of γ is selected between 0 and 1, and the influence of this parameter on the performance of the TSGGR model proposed in this study is evaluated. It can be concluded from Figure 5 that the TSTGR model proposed in this study can achieve the best recommendation accuracy and performance when the value of γ is selected within

[0.3, 0.8]. In the subsequent comparative experiment in this study, we set $\gamma = 0.5$.

4.5. Contrast Experiment.

To further verify the feasibility of the proposed method and evaluate the performance of the TSTGR method, the number of items recommended by a group was varied from 1 to 10 in this experiment to compare

the performances of various comparison models considering the recommendation of Top-K. Figure 6 shows the comparison experiment on the dataset of Beijing attractions. Figure 6(a) demonstrates the recommendation precision of the five comparison models when the number of recommended items changes from 1 to 10, and Figure 6(b) shows the nDCG results of the five comparison models when the number of recommended items changes from 1 to 10. Figure 7 shows the comparative experiment results on the Yelp Restaurant dataset. It can be concluded from Figures 6 and 7 that the TSTGR model provides great advantages in terms of precision and nDCG. In addition, as the amount of recommended items is increased, the recommendation accuracy decreases and the nDCG index gradually increases. The GRSAT model only considers the trust and rating of uses, and its decision-making factors for group recommendations are inadequate. The PLTSGR and PFGR models consider the preference and group influence of users within a group and construct a consensus model to achieve group recommendations. They demonstrated performance improvements compared with the GRSAT model. The SIGR model uses an attention mechanism to learn the social impacts of each user, and it then integrates the global and local social network structure information of users to achieve group information fusion, resulting in a relatively high recommendation accuracy. The TSTGR model proposed in this study not only considers social influence, but also increases global user trust by combining direct and indirect trust. In addition, this model also integrates intragroup decision-making and intergroup collaborative recommendations, which further improves the performance of the resulting group recommendation. Therefore, compared with the four previously developed models, the model proposed in this study is more competitive.

5. Conclusion

With the rapid development of smart tourism, tourism group recommendations have become an important topic of research in the field of recommendation systems. In this study, a tourist attraction group recommendation model based on user trust and social influence was proposed. First, according to the dataset of a trust relationship between users, the model integrated the direct and indirect trust between users and calculated the degree of global trust between users. Second, according to the historical evaluation interaction records between users, the PageRank algorithm was used to determine the social influence of the users. Finally, a new consensus function was designed by combining the intra- and intergroup prediction scores to complete the evaluation score for tourist attractions and realize Top-K recommendations. Compared with many well-known group recommendation models, the proposed method demonstrated a good performance. The experimental results demonstrated that the integration of global trust and social influence can effectively improve the accuracy of the resulting group recommendation. In a future work, we will further explore the application of group recommendations in other tourism recommendation fields.

Data Availability

The evaluation data of 200 scenic spots from 37000 tourists extending from July 1, 2014, to June 30, 2017, including the user ID, scenic spot, ticket prices, scores, text evaluation, evaluation time, and travel types, were collected. This dataset is now available from this URL (doi:https://doi.org/10.21227/cnfs-6p81).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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