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Context-Aware Group Recommendation for Point-of-Interests

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ABSTRACT Group recommendation generates a ranked list of recommendations for a group of users. Point-of-interests (POIs) group recommendation aims to suggest the most agreeable meeting places for a group of users. Although there are a lot of studies on group recommendation for POIs, few studies take into account the rationality of location for the whole group. In this paper, we propose a novel POI group recommendation method which factors into the rationality of the location and the intra-group influence when making group decisions. We take into account the importance of location in POI recommendations and employ distance-based pre-filtering and distance-based ranking adjustment to improve recommendation satisfaction. We have conducted extensive experimental evaluations of the proposed method via a real-world data set, which is prepared from 1 375 024 Beijing POI comment records hosted by a review website. Comprehensive experimental results show that our proposed POI group recommendation method outperforms other representative ones in terms of global satisfaction and distance satisfaction, even in the context of individual recommendation.

INDEX TERMS Group recommendation, point-of-interest, context-aware, global satisfaction, group consensus function.

I. INTRODUCTION

Various recommender systems have been developed in support of preferences-based ranking of news [1], movies [2] and point-of-interests (POIs) [3], etc. with mobile contextual information taken into account when it is desireable to the users [4], [5]. Moreover, many of them are evolving from generating personalized recommendations for individual users into providing group-based recommendation services with usage contexts like music playing at a party, watching a movie with friends in a cinema, celebrating graduation with classmates in a restaurant, and traveling with family. Satisfactory group recommender systems must factor into each group user's preferences when ranking group-based recommendations, and do that in a scalar manner with respect to companion size and preferences complex [6], [7].

Group recommender systems generate ranked lists of recommendations based on per group users' preferences [8]. Major application domains of group recommendation are movie [9], [10], television [11], [12], recipe [13], music [14], [15] and POI [16]–[18]. Existing methods mostly focus on aggregating individual users' relevance when producing recommendations for the target group [7]–[9]. The strategy used is either aggregating preference or aggregating recommendations. This paper employ aggregating recommendations strategy because it offers better flexibility and more opportunities in improving the group recommendation efficiency [9], and the recommended results are more intuitive, easy to be accepted.

POI group recommendation aims to suggest the most agreeable meeting places for a group of users. Although there are a lot of studies on group recommendation for POIs, few studies take into account the rationality of location for the whole group. Fig. 1 illustrates a sample scenario in which Alisa and several friends living in different areas of a city are trying to find a POI as a party venue over the weekend. Alisa cannot eat spicy food, Lily has religious dietary restrictions, and the others may have different food preferences. No one wants to travel far for the party. Although there are many candidate places (shown as red dots in the figure), it is nontrivial to decide on the party venue.

The motivations of this paper are listed below.

- Unlike other recommenders, location must be a key factor in POI recommendation. For example, every user prefers the chosen POI is nearby, and a specific user would be unhappy if the user's travel distance is much greater than the others'. Thus, a specific POI would not

FIGURE 1. The scenario of a group planning for a party.

be accepted by the group if the user-dependent location requirements cannot be satisfied well. We note that the importance of location has not been given sufficient attention in previous studies [16]–[18].

- When making group decisions, we should not only consider the relevance and disagreement among group users, but also quantify and exploit the relative influence of each user. In reality, it is common that some group user is more influential than the others in a specific group recommendation context. For example, Alisa could be more persuasive than the others in the party venue selection because she is most familiar with the area they live. We note most previous work assumes that all group users have equal influence [18], [19]. Although there are literatures also consider user influence [9], [43], however, they use global influence or social influence, which inapplicability in POI recommendation.

In this paper, we propose a novel POI group recommendation method which factors into the rationality of the location and the intra-group influence when making group decisions. The main contributions of this paper are threefold.

1) We take into account the importance of location in POI group recommendations, and employ distance prefiltering and distance ranking adjustment to improve the recommendation satisfaction.
2) We improve the group consensus function by taking into account the intra-group influence in group relevance and the consistency of the ranking criteria in group disagreements.
3) We have conducted extensive experimental evaluations of the proposed method via a real-world dataset, which is prepared from 1,375,024 Beijing POI comment records hosted by a review website. In terms of group recommendation satisfaction metrics, the experimental results shows the proposed method is superior to other four well-known ones in POI group recommendation. Usability of the proposed method for personalized recommendation has also been validated via extensive experimental performance evaluations.

The remainder of this paper is organized as follows. Section 2 presents related work. Section 3 describes the proposed method in detail. Section 4 illustrates experimental evaluation results and analysis. Finally, conclusions and future work are provided in Section 5.

II. RELATED WORK

To alleviate information overload, many recommender systems have been developed in support of content-based similarity analysis [20], [21], collaborative filtering [22]–[24], and hybrid recommendation [25]–[27]. This work is closely related to POI recommendation, group recommendation and group-based POI recommendation.

A number of recommender systems for POI such as touristic attractions, restaurants and hotels have been proposed in the literature. Noguera *et al.* [28] proposed a 3D-GIS mobile location-aware recommender system which combined a location-aware recommendation engine and a mobile 3D GIS architecture together to enable presenting a rich and detailed display of the sight where the users is currently located via mobile devices with a small display. Noulas *et al.* [29] proposed a recommender system for previously not visited venues via behavioral, social, and spatial data (based upon personalized random walks over a user-place graph). Owing to the connection complexity of location based social networks (LBSNs), the decision-making process for a user to choose a POI is complex and can be influenced by various factors. Some recommender systems [30]–[33] provide recommendation based on various types of content information available on LBSNs. Although the above POI recommender systems are designed to generate personalize suggestions for individual users, POI is selected and consumed by group of users rather than by individual in many cases. Group recommendation offers a better solution to problem addressed.

Most group recommendations have been generated either by aggregating individual recommendations into group recommendations (aggregating recommendations) [9], [34] or by aggregating the users' individual preference into a group preference (aggregating preferences) [10], [44]. Jameson and Smyth [34] summarized three strategies for aggregating individual recommendations: average satisfaction, least misery, and maximum satisfaction. Amer-Yahia *et al.* [9] formalized the notion of a consensus function which achieves a balance between an item's aggregate relevance to the group and group users' disagreements over the item. Gartrell *et al.* [10] improved the group consensus function by capturing the social, expertise, and dissimilarity among group users.

Many scholars have already investigated group recommendations for POIs and made important contributions [18], [35], [36]. WhereToGo [35] is a travel recommendation system that provides personalized tourist attractions for individuals and groups. It uses an extended random walk with a restart approach to support group recommendations. In this system, the influence weights of all group users are equal. Park *et al*. [18] proposed a restaurant recommender system that considers the preferences of group users in mobile environment. This recommender system exploited Bayesian network to model the preferences of an individual user and integrated the results for group users using multi-criteria decision making process. In aggregating users' preferences, they take into account the different influence weights of the users. However, it is difficult for this method to determine the influence weight of different users, and results are therefore unconvincing. SocialDining [36] is a system that fuses mobile and social data to power novel context recommendation services, providing recommendation to small groups of users who want to meet together for parties at local restaurants. However, all of the above system does not take into account the rationality of the location for the whole group.

Compared with other recommender systems, competitive POI group recommenders must exploit location related data as much as possible. Although some of studies [18], [37] consider location data as one of the contextual factors, they did not make sufficient use of the data. In this paper, we take into account the influence of multi-dimensional context factors and the rationality of location to improve the performance of POI group recommender systems.

III. OUR PROPOSED METHOD

In this section, we present the proposed POI group recommendation method. First, a pre-filtering strategy is used to filter out the candidate POIs that are considered impossible. Then, using the selected candidate POIs, personalized recommendation for each individual is generated by context-aware matrix factorization method. Finally, all individual recommendation lists are composed into a new candidate set of POIs, and a ranked list of POIs is recommended via a group decision strategy. For the sake of clarity, the notations used in presenting the proposed method are summarized in Table 1.

A. PRE-FILTERING CANDIDATE POIs

Aiming at optimizing the efficiency in making a satisfactory POI group recommendation, the proposed method starts with two pre-filtering steps. Step one is requirements based pre-filtering, which excludes the POIs that do not comply with group users' requirements. In this step, users can choose to describe their requirements and inadmissibilities. Based on the requirements and inadmissibility of the whole group of users, the candidate POIs not qualified will be filtered out. Step two is distance based pre-filtering, which excludes the POIs that are beyond group users' acceptable distance range. In this step, users can choose to enter a maximum tolerance distance. The candidate POIs are filtered based on the maximum tolerable distance of the whole group of users. If the requirements of the whole group users cannot be satisfied, the candidate services will be filtered by a preset distance of the system. The detailed pre-filtering method can be seen in Appendix.

TABLE 1. Summary of notations.

Symbol	Description
u_i	A user in a group
G	A group
N	The length of recommendation list
n	The group size
n_u	The rating number of user u in context constrains
P	The set of all POIs in the database
p_j	A POI
P^r	The result of requirements pre-filtering
p_i^r	The set of POIs meeting the requirement of user i
P^ε	The POIs set that strictly excluded by user
P^d	The result of distance pre-filtering
p^m	The midpoint of the two users based on their maximum specified distance
$\hat{r}_{up}$	The calculated rating of POI p given by user u under contextual factors c
r_{up}^c	The real rating of POI p given by user u under contextual factors c
μ	The overall average rating
b_u	The observed deviations of user μ
b_p	The observed deviations of POI p
b_p^c	The evaluation bias caused by the contextual factors
D_i^{mt}	The maximum tolerance distance of user i
D^{mu}	The maximum distance between any two users in a group
D^{pre}	The preset distance
f_k	The distance factor of POI k, represents the distance rationality
Df_k	The distance decay function for POI k
RL_i	The recommendation list for user i
RL	The recommendation list for the group
GI_u	The intra-group influence of user u in group G
I_u	The normalized intra-group influence of user u in group G
$dis(a,b)$	The distance between a and b
$mean(u)$	The mean of all scores from user u
$F(G,p)$	The value of group consensus, which represents the rating of POI p obtained by group consensus
$rele(G,p)$	The relevance of group G for POI p
$disa(G,p)$	The disagreement of group G for POI p

B. INDIVIDUAL RECOMMENDATION

In this subsection, we make personalized recommendations for each individual. First, the context relevance is analyzed in Section A. Then the influence of multi-dimensional context is modeled by back propagation (BP) neural network in Section B. Finally, an improved context-aware matrix factorization method is employed to make personalized recommendations in Section C.

1) ANALYSIS OF CONTEXT RELEVANCE

There are some contextual factors that may have an impact on user decisions. A sample list of such contextual factors are

TABLE 2. Selected contextual factors.

Contextual factors	Attribute value
Season	Spring, Summer, Autumn, Winter
Time	Moring, Noon, Afternoon, Evening
Transport	Walk, Bicycle, Bus, Car
Companion	Couples, Friends, Family, Children
Weather	Good, Bad
Distance	Far away, Near by
Number of people	Two, More than three
Price	Expensive, Inexpensive

listed in Table 2. In order to analyze the deviation between the objective rating and the rating in a given scenario, we developed a web questionnaire for acquiring the relevance of the selected contextual factors for the POI categories. In the web questionnaire, we classified all POIs into 7 categories and assumed that the influence of a contextual factor is uniform for all the POIs in the same category.

We attempted to obtain the user's evaluation bias in a specific context through questionnaires. A number of contextual factors were combined into a questionnaire and volunteers were asked to imagine the evaluation deviation for the POIs in a given situation. The deviation was divided into five levels: -1 (negative effect), -0.5 (slightly negative effect), 0 (no effect), 0.5 (slightly positive effect), 1 (positive effect). 158 volunteers participated in our online survey, most of them are college students, university teachers, or IT engineers. 1358 responses were received for the investigation.

2) MULTI-DIMENSIONAL CONTEXT MODELING

In order to obtain the evaluation for any contextual factor, we adopt BP neural network to model the influence of multi-dimensional contextual factors.

The BP neural network algorithm is a multi-layer feed-forward network trained with an error-BP algorithm, which is among the most widely used neural network models [38]. They can be used to learn and store a large number of input-output model mapping relations, and there is no requirement to disclose in advance the mathematical equations that describe these mapping relations. Its learning rule employs the steepest-descent method, in which BP is used to achieve the minimum error sum of the square by regulating the weight value and a threshold value for the network. The application of the standard BP network model is converted to a mathematical optimization problem. More specifically, the input-output problem of training samples is transformed into a non-linear mathematical optimization problem. Thus, nonlinear mapping ability of BP neural network is very strong. This is the reason that we choose BP neural network to model the context factors.

As described in Fig. 2, the BP neural network consists of three layers: input layer, hidden layer, and output layer.

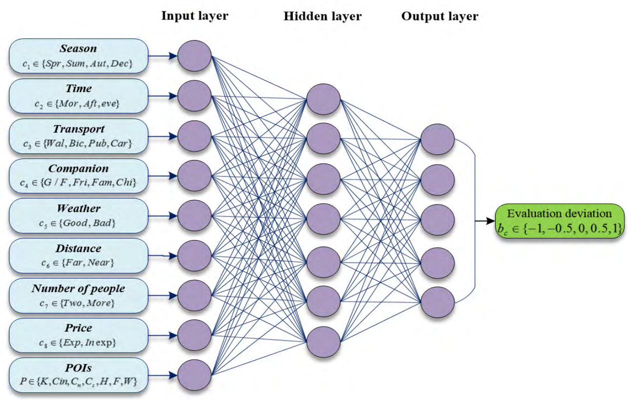


FIGURE 2. BP neural network model for evaluation deviation.

The input layer contains nine nodes: the first eight nodes represent eight contextual factors described in Table 2, and the last node is the type of POI. The output layer contains five nodes, representing five kinds of deviation levels (−1, −0.5, 0, 0.5, 1). To get training data, we extract contextual factors, POIs categories, and the evaluation deviation given by the volunteers from the investigation results as well as remove the noises. The BP network model can be trained by the training data off-line, and the evaluation deviation of a certain POI category under any contextual factors can be obtained through the model. Therefore, during the personalized recommendation, we can introduce the influence bias of contextual factors to improve recommendation quality.

3) PERSONALIZED RECOMMENDATION

In this subsection, we describe how the proposed POI group recommendation method makes personalized recommendations for every individual. In order to take into account multi-dimension contextual factors when making POI recommendations, we enhanced the context-aware matrix factorization method proposed by Baltrunas *et al.* [6], who extended a matrix factorization method that uses "baseline" parameters for each user and item. They represent the general deviation of the rating of a user or an item from the global average. For example, if a user tends to rate higher than the average of the user population's ratings, the user's baseline will be a positive number. Based upon this approach, they incorporated more contextual dimensions into matrix factorization model under the assumption that the contextual factors are independent.

In reality, various factors may be dependent and may have some influence on each other. For example, if a user is far away from a restaurant, evaluation deviations may be negative; however, there would be no significant impact if the user drives there. If road congestion is a factor, the result may change again. Therefore, we propose an estimation model to compute a personalized rating as follows:

$$\hat{r}_{up}^{c} = \mu + b_u + b_p + v_u q_p^T + b_p^c, \tag{1}$$

where $\hat{r}_{up}^{c}$ denotes calculated rating of POI p given by user u under contextual factors c and μ is the overall average rating.

b_u and b_i indicate the observed deviations of user u and POI p, respectively. v_u and q_p are d dimensional real-valued vectors representing the user u and the POI p. b_p^c is the evaluation bias caused by the contextual factors, which can be obtained by the aforementioned BP network model.

Each row in user matrix v_u represents a user vector, and each element in a row indicates the degree of user's preference to features of a POI. Each column of a POI matrix represents a POI vector, and each element in a column indicates the weight degree of the features in the POI. The calculated rating is no longer a single user-item interactive value, but takes into account a user deviation b_u, POI deviation b_p, contextual factors deviation b_p^c and the overall average rating μ. In order to obtain the rating predictions, the model learns by minimizing the squared error function:

$$\min_{v_*,q_*,b_*} \sum_{(u,p,c)\in K} [(r_{up}^c - v_u q_p^T - \mu - b_u - b_p - b_p^c)^2 + \lambda(b_u^2 + ||v_u||^2 + ||q_p||^2 + b_p^2)], \quad (2)$$

where r_{up}^c is the real rating of POI p given by user u under the contextual factor c, and K is the set of the (u, p, c) pairs for which r_{up}^c is known, i.e., the training set. $\sum_{(u,p,c)\in K} (r_{up}^c - v_u q_p^T - \mu - b_u - b_p - b_p^c)^2$ strives to find v_u, q_p, b_u and b_p that fit the given ratings. The regularizing term $\lambda \sum_{(u,p,c)\in K} (b_u^2 + ||v_u||^2 + ||q_p||^2 + b_p^2)$ avoids overfitting by penalizing the magnitudes of the parameters. λ is a constant which controls the extent of regularization and is usually determined by cross-validation. The meaning of other parameters (v_u, q_p, b_u, b_p, μ and b_p^c) is described in Eq. 1.

In order to obtain the minimum, the stochastic gradient algorithm is used. After the completion of matrix factorization, the rating prediction of a specified user can be obtained by Eq. 1. Thus, the Top-N recommendation list of each group user is generated, which is denoted as:

$$RL_i = \{(p_m, r_m), m = 1 \ldots N\}, \quad i \in [1, n], \quad (3)$$

where RL_i is the recommendation list of user i, (p_m, r_m) is the recommended POI m, and the prediction rating of this POI, N is the length of recommendation list, and n is the group size.

C. GROUP RECOMMENDATION

In this subsection, we describe how the proposed method generates a POI recommendation list for the whole group. By the POI selection process described in the previous section, each of the selected POI candidates satisfies at least one user's preference. In order to find a number of POIs that satisfy the whole group, the proposed method's group recommendation scheme comprises of two parts: group decision strategies and ranking adjustment. Group decision strategies aim to reach a consensus on the qualified POIs among the group users per everyone's preferences, and to propose a POI recommendation list for the group. The ranking order of the POI recommendation list will then be adjusted according to the distance rationality of the POIs.

1) GROUP DECISION STRATEGIES

In order to achieve a consensus among group users on the qualified POIs, we employ group consensus functions [9] to aggregate the recommendation results. As shown in Eq. 4, the group consensus function has two key components: *group relevance* and *group disagreement*.

$$F(G, p) = (1 - \omega) \times rele(G, p) + \omega \times (1 - disa(G, p)), \quad (4)$$

where $\omega > 0$, $F(G, p)$ is the value of group consensus, which represents the rating of POI p obtained by group consensus. $rele(G, p)$ is the relevance of group G for POI p, and $disa(G, p)$ is the disagreement of group G for POI p. Compared with [9], we have enhanced both components for the proposed POI group recommendation method.

Owing to the differences in users' familiarity with specific areas or regions, different individuals in the group have different degrees of influence. Although there are literatures also consider user influence [9], [43], [45], however, they use global influence or social influence, which can not reflect the real influence in a particular environment. Different from the above works, intra-group influence is exploited in our group relevance calculation. The intra-group influence of a user is defined as:

$$GI_u = \frac{1}{n} + \frac{n_u}{\sum_{u=1}^{n} n_u}, \quad (5)$$

where GI_u represents the intra-group influence of user u in group G. The first part represents basic influence (where n is the group size) and the second part the experience influence (where n_u is the rating number of user u in context constrains).

Eq. 6 is used to normalize the intra-group influence into the range from 0 to 1:

$$I_u = \frac{GI_u}{\sum_{u=1}^{n} GI_u}, \quad (6)$$

where I_u is the normalized intra-group influence of user u in group G. The meaning of the other parameters (GI_u and n) are the same as in Eq. 5.

Taking into account the intra-group influence, we define the group relevance by Eq. 7:

$$rele(G, p) = \sum_{u\in G} (I_u * rele(u, p)), \quad (7)$$

where $relevance(u, p)$ is the prediction rating of user u to POI p. I_u represents the intra-group influence of user u, which is related to empirical value in context constrains.

Amer-Yahia *et al.* [9] proposed two group disagreement calculation methods: average pair-wise disagreement and disagreement variance. Both methods reflect the evaluation differences for a specific POI among the group users. The average pair-wise disagreement is defined by Eq. 8:

$$disa\,(G, p) = \frac{2}{n(n-1)} \sum |rele(u, p) - rele(v, p)|, \quad (8)$$

where $disa\,(G, p)$ is the value of average pair-wise disagreement. G represents a group. u and v ($u \neq v$) are two different

TABLE 3. An example of rating deviation.

Score	service1	service2	service3	service4
user1	5	3	4	4.5
user2	4.5	2.5	3.5	4
user3	4	2	3	3.5

TABLE 4. The group disagreement value.

service	service1	service2	service3	service4
$dis\,(G,p)$	0.167	0.167	0.167	0.167

users in group G. p is a POI. $rele\,(u,p)$ and $rele\,(v,p)$ are the prediction rating of user u and v to POI p, respectively.

In practice, some users may be very accommodating (giving high scores to many POIs) whereas some users may be very inflexible (giving low scores to many POIs). Thus, when all of the users give higher or lower scores to all POIs at the same time, we presume that they have no disagreement or little disagreement.

Table 3 exemplifies a case that needs attention when determining group relevance functions. In the example, user1's rating for each POI is always more than user2's by 0.5, and user2's rating is always more than user3's by 0.5. Although the three users have no disagreement in ranking the POIs, the group disagreement values calculated by Eq. 8 (see Table 4) suggest that they are in total disagreement because the difference of baseline scores is not considered.

In order to avoid the influence of this bias, we use the mean to adjust the average pair-wise disagreement method. The improved calculation method is shown in Eq. 9:

$$disa\,(G,p) = 2 \times \frac{\sum |rele_m(u,p) - rele_m(v,p)|}{n(n-1)}, \quad (9)$$

where $disa(G,p)$ and G have been defined in Eq. 8. $rele_m(u,p)$ is adjusted as follows:

$$rele_m(u,p) = rele(u,p) - mean(u), \quad (10)$$

where $mean(u)$ is the mean of all scores from user u, $rele\,(u,p)$ is defined the Eq. 8. With the adjustment of the mean, the group disagreement factor can avoid the influence of the bias of baseline scores.

For each POI p generated from individual recommendation, $F(G,p)$ can be calculated by the improved $rele(G,p)$ and $disa\,(G,p)$, and the Top-N POIs with the highest $F(G,p)$ scores would meet the common preferences of the group users. A recommendation list of N POIs is denoted as:

$$RL = \{(p_i, r_i), i = 1 \ldots N\}, \quad (11)$$

where p_i is a POI in recommendation list and r_i is an estimation rating of the POI p_i for the group.

The recommendation list reflects the preferences of the whole group. Group users may have a higher satisfaction degree with all POIs in the recommendation list. However,

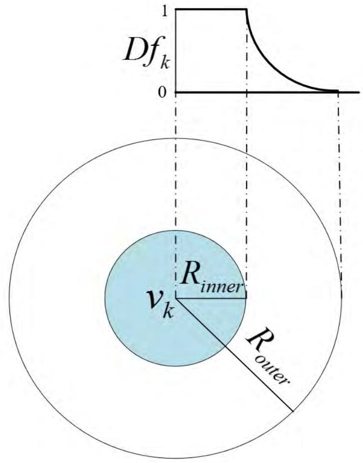


FIGURE 3. Distance decay function.

these POIs may need be ranked differently in terms of distance rationality.

2) RANKING ADJUSTMENT

Recognizing the key role of the location factor in POI group recommendation, we re-rank the recommendation list generated by the previous step using a distance factor. For example, for two POIs having comparable group recommendation scores calculated by the aforementioned steps, if one of them is more appealing in terms of distance of travel, it would be better to rank that higher than the other one. Generally speaking, under the premise of meeting the common preferences, a good POI with an appropriate location should be within the tolerance distance of all users, the sum of distance to all users should be minimal, and the distance difference among all users should be minimal. Taken together, Eq. 12 shows the distance factor the proposed method uses:

$$f_k = \frac{C_k}{2n}\left(\frac{D_k}{D_{mk}} + \frac{\Delta_k}{\Delta_{mk}}\right), \quad (12)$$

where f_k is the distance factor of POI k, representing distance rationality. $C_k = count(dis(u_i,p_k) > D_i^{mt})$ represents the number of users such that the distance from POI k is greater than their respective maximum tolerance distance. $dis(u_i,p_k)$ is the distance between the user i and POI k. D_i^{mt} is the maximum tolerance distance of user i. n is the group size. $D_k = \sum_{i=1}^{n} dis(u_i,p_k)$ is the sum of the distance between each user and POI k. $D_{mk} = \max_{k=1:K} D_k$ is the maximum value of D_k. $\Delta_k = \sum_{i=1}^{n}\sum_{j=1}^{n} |\alpha_i dis(u_i,p_k) - \alpha_j dis(u_j,p_k)|$ is the weighted distance difference of all user to POI k. α_i is the weight of $user_i$'s transportation. Δ_{mk} is the maximum value of Δ_k. Obviously, $f_k \in [0, 1]$.

In order to re-rank the list of top-N recommended POIs employing the distance factor, the distance decay function described in [28] is used. As shown in Fig. 3, the method utilizes two parameters to define two concentric areas. In contrast to the definition in [28], the inner and outer radii are not actual distance, but the synthesis of three kinds of distance factors, i.e., the distance factor f_k. The outer radius (R_{outer}) defines an acceptable area for the group. Outside this area, the distance is considered to be inappropriate. Therefore, all POIs located out of this area will be ignored and will not be recommended to the group. The inner radius (R_{inner}) is a smaller value. Within the inner circle, the distance is considered good, and have no influence on the rating of a POI. Eq. 13 defines the distance decay function used by the proposed method.

$$Df_k = \begin{cases} 1 & f_k < R_{inner} \\ e^{-\alpha(f_k - R_{inner})} & R_{inner} \le f_k < R_{outer} \\ 0 & f_k \ge R_{outer}, \end{cases} \tag{13}$$

where $\alpha = \frac{-\ln \varepsilon}{R_{outer} - R_{inner}}$. ε being a sufficiently small positive real number (close to 0), we set $\varepsilon = 0.001$, $R_{inner} = \frac{1}{2n}$, $R_{outer} = \frac{1}{n}$.

After distance re-ranking, the new prediction rating p_i is computed as: $v_i = r_i \cdot Df_i$. The final group recommendation list is $RL' = \{(p_i, v_i), i = 1...N\}$, where p_i is a POI in the recommendation list. v_i is the final prediction rating of p_i. The recommendation list is sorted by v_i in descending order.

D. COMPUTATIONAL COMPLEXITY ANALYSIS

We now discuss the computational computational complexity of our group recommendation method. Suppose the dataset is an $c \times d$ matrix containing c users and d POIs, and each entry in this matrix is a user rating for a POI.

In the pre-filtering process, the computational complexity is $O(d)$, because each kind of pre-filtering n times cycle. After pre-filtering process, the dataset becomes an $e \times f$ matrix containing e users and f POIS. For BP neural network, suppose we have m training samples, then the computational complexity of training a neural network should be $O(m * h)$, if it is to predict a sample, the computational complexity should be $O(h)$, where h is the number of nodes in the hidden layer. As the training process can be carried out off-line, so, the computational complexity can not be calculated. In the individual recommendation, the computational complexity of matrix factorization is $O(fe^2)$, where e and f represent the number of filtered users and POIs, which are far less than c and d. In group recommendation, the computational complexity is $O(n^2)$, where n is the group size. In summary, the computational complexity of the proposed group recommendation algorithm is $O(fe^2)$.

E. LIMITATIONS OF OUR PROPOSED APPROACH

- Due to lack of user historical context information, the dataset for the influence of contextual factors on service evaluations was obtained from questionnaires. The assumption that all users have similar evaluation bias in a particular context may not be true on all situations in practice.
- The context information data set is not sufficient, using BP neural network to obtain the user evaluation deviation is not obviously better than other algorithms (such as SVM). It is more applicable when the data set is relatively large. In the future, we will further enrich the context information, and try to obtain accurate user preference information employing deep learning algorithm.
- In this algorithm, we focus on the importance of key factor (distance), and pay more attention to the effect of key factor(distance) in the evaluation process, In future work, we will take into account more context factors such as (consumption level, traffic etc.) group recommendation.

TABLE 5. Data fields of the BJRC data-set.

No.	Attribute	Description
1	ID	service's ID
2	name	service's name
3	address	service's address
4	coordinates	service's coordinate, latitude and longitude
5	star	The average of evaluation scores of each service
6	type	service's type, such as Western, Sichuan and so on
7	price	Per capita consumption of a service
8	uid	user's ID
9	user	user's name
10	level	user's evaluation scores
11	comment	user's comment content

IV. EXPERIMENTAL EVALUATIONS

In this section, a series of experiments were conducted to compare the performance of the proposed method with existing methods. In Section 4.1, we describe our experimental environment and datasets. The group recommendation performance is shown in Section 4.2. Finally, considering the special case of only one user in the group, we verify the performance of the personalized recommendation algorithm in Section 4.3.

A. EXPERIMENTAL EVALUATION SETUP

Our experimental evaluation setup employs matlab 8.3 on an IBM server with an Inter Xeon E5-2670 eight-core 2.60 GHz CPU and 32G of RAM.

The dataset we used was sourced from Beijing POI comment data on a review website, called BJPC. The dataset contains 302,498 users, 3,760 POIs, and a total of 1,375,024 comment records. As illustrated in Table 5, every record in the dataset includes eleven data fields conveying a specific user's evaluation and comment on a specific POI. Value of the POI 'type' field is usually restaurant, KTV, and cinema. The 'star' field indicates the average of evaluation score of the referenced POI, and the 'level' field is evaluation score rated by the referenced user. Both fields are ratings on a five-point scale. Value of the 'coordinates' field indicates the precisely location of the referenced POI, which is key to our use of the BJPC dataset for our research on POI group recommendation. The dataset for the influence of contextual factors on POI evaluation was obtained from the questionnaires described in Section III. Each questionnaire record contains 10 fields. The first eight fields convey the contextual factors described in Table 1. The ninth field is the type of the referenced POI. The last field is the rating bias in the current context for the referenced user.

In our comparative experimental evaluations, the two aforementioned datasets were combined in support of our validating the proposed POI group recommendation method. Since both datasets do not include group information, we formed user groups randomly, and generated a random set of parameters for contextual information and user location.

The comment dataset is split into a training set (80 percent of the records) and a test set (20 percent of the records). In the remainder of this section, we present our evaluation results in terms of service recommendation for group and personalized recommendation for individual.

B. EXPERIMENTS OF SERVICE RECOMMENDATION FOR GROUP

1) ACCURACY METRICS

Since user groups could be formed dynamically with different users, group information was not stored in a database in our experimental evaluation setup. Therefore the conventional performance metrics, such as MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error), could not be utilized for comparative evaluation of group recommendation methods. The accuracy metrics we used are described below.

Definition 4 (Global Satisfaction): Global satisfaction [39] is a metric for measuring the satisfaction level of a whole group. The formula of global satisfaction runs as follows:

$$gs(G) = \bar{S} - \sigma_S, \tag{14}$$

where G represents a group and $0 \leq gs(G) \leq 1$ is the global satisfaction for the whole group. σ_s is the standard deviation of individual satisfaction, which measures the uniformity of the satisfaction levels. $\bar{S}$ is the mean of all group users' satisfaction. S is a user's satisfaction value to the group recommendation list, which is defined as follows:

$$S(u_i, G) = \begin{cases} 1.0, & esl(GR, list_{ui}) \leq 3 \\ 0.9, & 3 < esl(GR, list_{ui}) \leq 4 \\ 0.8, & 4 < esl(GR, list_{ui}) \leq 6 \\ 0.6, & 6 < esl(GR, list_{ui}) \leq 8 \\ 0.4, & 8 < esl(GR, list_{ui}) \leq 10 \\ 0.2, & 10 < esl(GR, list_{ui}) \leq 12 \\ 0.0, & esl(GR, list_{ui}) > 12, \end{cases} \tag{15}$$

where GR represents the recommendation list generated for the whole group, and $list_{ui}$ is the individual recommendation list. The Expected Search Length (esl) function returns the position of the last element of GR that appears in $list_{ui}$, which maps the satisfaction level of an individual to a recommendation generated for the whole group.

The global satisfaction metric only reflects the overall satisfaction of the whole group in terms of distance-independent user preferences. In the context of POI group recommendation, a POI candidate could be unsuitable for a group if its location is inappropriate in terms of the distances between it and all of the group users. Thus, we defined a distance satisfaction metric to support our need of measuring the performance of POI group recommendation methods.

Definition 5 (Distance Satisfaction): Distance satisfaction is a metric used to measure the satisfaction level of a whole group in terms of distance.

Eq. 16 shows distance satisfaction is determined mainly by the distances between the group users and the POI under evaluation as well as the differences in those distances.

$$ds(G) = \frac{1}{n}\sum\nolimits_{p \in P}(M(G) - \frac{\sum_{i,j \in G}|dis(u_i, p) - dis(u_j, p)|}{\frac{n(n-1)}{2}\sum_{b \in G} d(u_b, p)}), \tag{16}$$

where G represents a group and $0 \leq ds(G) \leq 1$ is the distance satisfaction for the whole group. n is the group size. $dis(u_i, p)$ represents the distance between user i and POI p. M is the group users' overall satisfaction in terms of maximum tolerance distance, and is defined as follows:

$$M(G) = \begin{cases} 1, & count(dis(u_i, P) < D_{mti}) = n \\ 0.9, & \frac{3n}{4} \leq count(dis(u_i, P) < D_{mti}) < n \\ 0.8, & \frac{n}{2} \leq count(dis(u_i, P) < D_{mti}) < \frac{3n}{4} \\ 0.5, & \frac{n}{4} \leq count(dis(u_i, P) < D_{mti}) < \frac{n}{2} \\ 0.3, & count(dis(u_i, P) < D_{mti}) < \frac{n}{4}, \end{cases} \tag{17}$$

where $count(dis(u_i, P) > D_{mti})$ represents the number of users for whom the distance from POI P is greater than their maximum tolerance distance.

2) COMPARISON METHODS

We compare our proposed group recommendation method with other four well-known prediction methods:

- Analytic Hierarchy Process (**AHP**) [18]. This approach uses Bayesian network to model the preference of each user and AHP of multi-criteria decision making to integrate the preference of individual users.
- Least-Misery Relevance (**LMR**) [40]. This approach uses a user-based collaborative filtering algorithm to obtain individual recommendations, and computes a POI's score as its minimum relevance among all group users. The disagreement weight is set to zero.
- Consensus with Pair-wise Disagreement (**CPD**) [9]. This approach uses a consensus function with pair-wise disagreement to computes a POI's score, and the individual recommendations is based on collaborative filtering algorithm.

- SocialDining (**SD**) [36]. This approach uses mobile and social data to power novel contextaware recommendation services that provide recommendations to small groups of users.

Our proposed POI group recommendation method (called **CMFC**) is based upon context-aware matrix factorization and an improved group consensus function, and uses pre-filtering and ranking adjustment to ensure the quality of the recommendation.

3) COMPARISON RESULTS OF DIFFERENT GROUP SIZE

In this subsection, we present the results of group recommendations generated by the aforementioned methods, and analyze the POI group recommendation of varying group size. In the experiment, we randomly form user groups, and randomly assign contextual information (e.g., season, weather, etc.), location information (from a 30km×30km location dataset) and personal information to the user. Each user's maximum tolerance distance is set to a random positive integer number from 5 to 15. For each method, the length of recommendation list is set to 10. For CPD and CMFC, we set group consensus function parameters $\omega_1 = 0.2$, $\omega_2 = 0.8$. In the matrix factorization process of CPD and CMFC, the number of iterations is set to 500, and the matrix dimensions is set to 20. In order to investigate the influence of group size on the quality of group recommendation, the group size was varying from 2 to 10. Global satisfaction and distance satisfaction for each group size are calculated 20 times and the average is taken as an estimation of group recommendation quality.

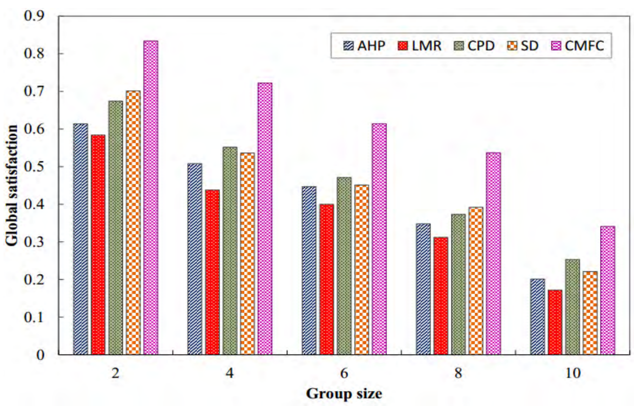


FIGURE 4. **The global satisfaction of different group size. CMFC outperforms all the other methods regardless of group size, and the global satisfaction decreases with the increase of group size.**

Fig. 4 shows the global satisfaction of different group sizes. Clearly, our proposed CMFC outperforms all the other methods regardless of group size, and the global satisfaction decreases with the increase of group size. With the increase of group users, users' preferences tend to diversify, so it is difficult to satisfy all users. When aggregating recommendation results, the LMR consider the relevance among the users and do not consider the disagreement among them. Thus, they could not achieve good results in the trade-off. Although AHP uses multi-criteria decision making method to obtain the recommended results, however, the results are not directly related to the individual recommendation results, so it does not get good results. The CPD and SD use group consensus functions to make a trade-off among group users and considers the relevance and disagreement together among the group users, thereby obtaining better results. However, without consider the user's influence or inappropriate user influence will have a bad impact on the recommendation results. Our method takes intra-group influence into account in group relevance and considers the consistency of ranking criteria in group disagreement. These innovations make the consensus more effective and increase the possibility of improving global satisfaction.

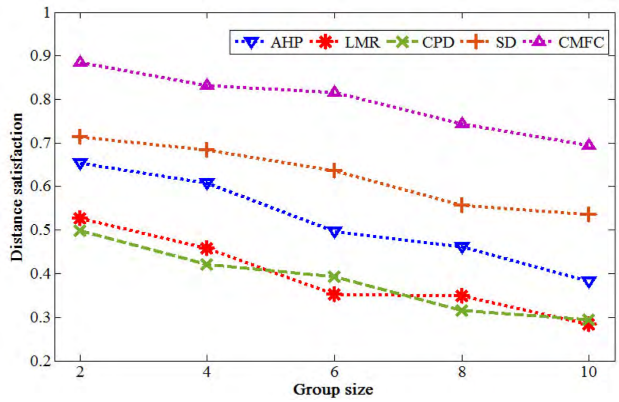


FIGURE 5. **The distance satisfaction of different group size. The distance satisfaction of all methods significantly weakened when the group size increased from 2 to 10, and CMFC significantly higher than the others.**

Fig. 5 illustrates the effect of group size on users' distance satisfaction levels. The distance satisfaction of CMFC significantly weakened when the group size increased from 2 to 10. Other methods show similar trends, but at a significantly smaller scale than that for CMFC. The reason is that CMFC performs pre-filtering according to the location information in the candidate database during preprocessing, and gives a distance based re-ranking in the group recommendation phase. Double insurance guarantees that the rationality of the location is considered. However, with the increase of group size, users may be more dispersed, and meeting the requirements of more people at the same time becomes more difficult. Therefore, the distance satisfaction decreases with the increase of group size. For SD and AHP, distance as a context factor plays a positive role in the personalized recommendations. However, this effect is relatively weak, and can only improve the distance satisfaction to a certain extent. The other two methods consider the users' ratings only and do not consider the location factor, and delivered the worst results.

Fig. 6 shows intuitively the superiority of our proposed method for distance satisfaction. Four users were randomly selected at four different locations (Peking University, Birds

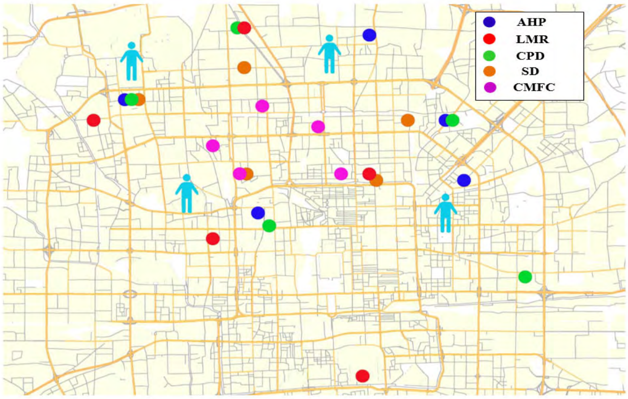


FIGURE 6. The comparison results of different group recommendation methods. CMFC is more reasonable than other three methods in terms of location.

Nest, Beijing Zoo, and Workers Stadium). For each method, the length of recommendation list is set to 5, and other information and parameters are the same as in the previous experiments. As shown in Fig. 6, our proposed CMFC method is more reasonable than the other four methods in terms of location. The recommendation results of other methods are not reasonable, and some of them are very far away geographically from the users, making it impossible for users to take their recommendations. Thereby, even if some of the recommendations may meet everyone's preferences, it is meaningless in terms of distance satisfaction.

4) COMPARISON RESULTS OF DIFFERENT INTRA-GROUP SIMILARITY

The second experiment investigated the influence of the similarity of group users on the performance of group recommendations. In this experiment, the groups were formed with users more or less similar to each other. The user-user similarities in a group are calculated by Pearson correlation metric using the users' ratings in the dataset, and a minimum intra-group similarity is calculated as the minimum threshold for the similarity of each pair of users in the group. Groups were created by selecting users that met the required minimum intra-group similarity. In order to study the influence of intra-group similarity, the group size was fixed to 4, and the minimum intra-group similarity was varied from -0.8 to 0.8 in intervals of 0.4. Other parameters are the same as above. Results for each group size were calculated 20 times and the average was taken as an estimate.

As illustrated in Fig. 7, with the increase of minimum intra-group similarity, the global satisfaction of all methods increased. The reason is that the greater the intra-group similarity, the closer the preferences of group users; and they can easily find common interests. For each minimum intra-group similarity, CMFC performed significantly better than the other four methods, especially for low minimum intra-group similarity. For low intra-group similarity, group disagreements are relatively large, and it is difficult to reach agreement. CMFC, SD and CPD consider the impact of

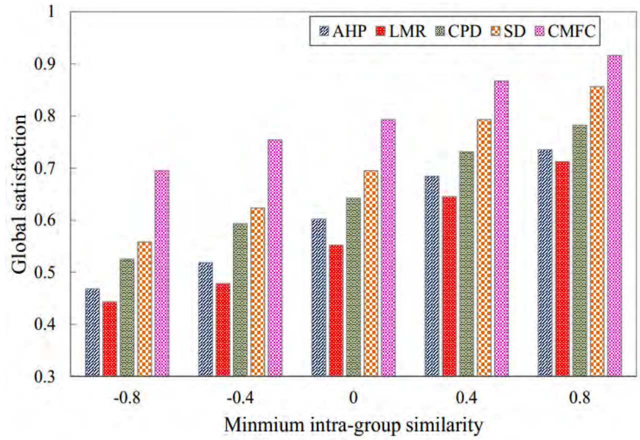


FIGURE 7. The global satisfaction with different minimum intra-group similarity. With the increase of minimum intra-group similarity, the global satisfaction of all methods increased, and CMFC performed significantly better than the other three methods.

group disagreements, which is beneficial for balancing the preference of the group users. Hence, they are obviously better than the other two methods. However, with the increase of the intra-group similarity, the group disagreements are reduced, and the superiority of the group consensus function decreased. All methods can achieve a higher global satisfaction levels. Therefore, we can conclude that the lower the intra-group similarity, the more superior of our proposed method becomes to the other methods.

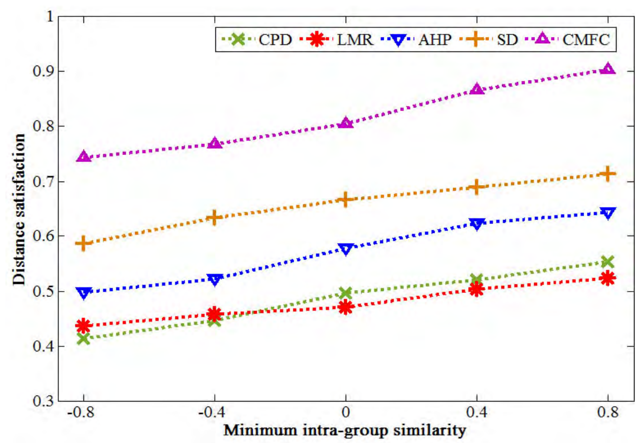


FIGURE 8. The distance satisfaction with different minimum intra-group similarity. CMFC obviously outperform other three methods at each intra-group similarity level, but the distance satisfaction does not change significantly with different minimum intra-group similarity.

Fig. 8 shows distance satisfaction for different intra-group similarity levels. Our proposed method CMFC obviously outperformed other three methods at each level of intra-group similarity. However, this seems to have little relation to the intra-group similarity because distance satisfaction did not change significantly with different minimum intra-group similarity levels. For all of the methods, the influence of the intra-group similarity is not obvious. With the increase of intra-group similarity, the users' preferences are more similar,

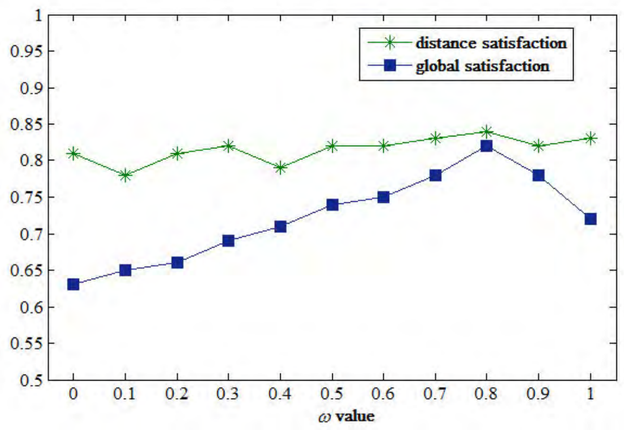


FIGURE 9. The impact of parameter ω. With the increase of ω, the global satisfaction rose significantly until ω=0.8, and distance satisfaction is not obvious with the change of ω.

making it easier to reach consensus within a group. However, this is not a significant contribution to distance satisfaction. This result is mainly due to using different recommendation methods in the specific group size. So we conclude that the influence of intra-group similarity on distance satisfaction is slight.

5) STUDIES ON PARAMETER ω

ω is a parameter of the group consensus function which indicate the weight of group relevance and group disagreement, respectively. To study the impact of these two parameters on group recommendation performance, we vary the value of ω from 0 to 1.0 in steps of 0.1. We set group size=4, minimum group similarity=0, length of the recommendation list $N = 10$, and other parameters the same as in the previous experiments. For each setting, results were calculated 20 times and the average was taken as an estimate.

As can be seen in Fig. 9, with the increase of ω, the global satisfaction rose significantly until ω=0.8, attain-ing an optimal value of 0.82 when $\omega = 0.8$. After that, the global satisfaction decreased. This result indicates that it is necessary to consider group disagreement, but not to an arbitrary extent. Unlike global satisfaction, distance satisfaction is not obvious with the change of ω. In other words, the impact of ω on distance satisfaction is not obvious. The reason for this is that the group consensus function has little impact on distance, and distance-based ranking adjustment can guarantee distance satisfaction.

C. PERSONALIZED RECOMMENDATION EXPERIMENTS

In order to validate the usability of our method in the case of one user, we also evaluated the method's performance for personalized recommendation.

1) ACCURACY METRICS

The mean absolute error (MAE) and root mean squared error (RMSE) are frequently used to measure the difference between values predicted by a model (or estimator) and observed values [42]. We adopted MAE and RMSE to measure the prediction accuracy of our algorithm through comparisons with other methods. However, for the POI recommendation, the distance is also a key factor to measure the recommendation performance. If a highly valued POI is too far from the user, it still cannot be accepted by the user. Therefore the mean of distance (MD) between the user and a recommended POI is used as a measure of personalized recommendation performance. MAE is defined as:

$$MAE = \frac{\sum \left| R_{up} - \hat{R}_{up} \right|}{N}, \tag{18}$$

where R_{up} denotes the actual value of POI p rated by user u, $\hat{R}_{up}$ is the predicted value, and N is the number of predicted values. RMSE is defined as:

$$RMSE = \sqrt{\frac{\sum \left(R_{up} - \hat{R}_{up} \right)^2}{N}}, \tag{19}$$

where the meaning of the parameters is the same as in Eq. 18. This is a good measure of accuracy when comparing prediction errors from different models for a particular variable [41]. MD is defined as:

$$MD = \frac{\sum_{p \in P} dis(u, p)}{N}, \tag{20}$$

where MD is the mean distance from user u and recommendation POI p, $dis(u, p)$ denotes the distance between user u and POI p, P is the set of POIs in recommendation list, N is the length of the recommendation list.

2) COMPARISON METHODS

Our personalized recommendation method is a kind of biases matrix factorization based upon context, called **BMFC**. We compare the performance of our BMFC with other four well-known recommendation methods. These compared methods are introduced follows:

- User Mean Method (**UMEAN**). UMEAN employs the average rating value of a user to predict the unknown values. The rating R_{ij} for a POI j from $user_i$ is computed as:

$$R_{ij} = \frac{\sum_{k \in V} R_{ik}}{N}, \tag{21}$$

where V is the set of POIs $user_i$ has rated. N is the number of POIs rated by $user_i$.

- Item Mean Method (**IMEAN**). IMEAN uses the average rating value of the POI from other users to predict the unknown values. The rating R_{ij} for a POI j from $user_i$ is computed as:

$$R_{ij} = \frac{\sum_{k \in U} R_{kj}}{N}, \tag{22}$$

where U is the set of users that POI j has been rated. N is the number of users that POI j has been rated.

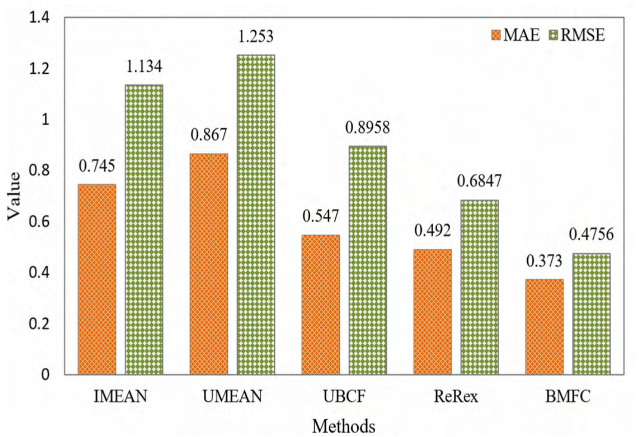


FIGURE 10. Comparison results on the MAE and RMSE. BMFC is the best both on MAE and RMSE. Since the first three algorithms do not consider contextual factors, there is a greater deviation in the calculation of the recommendation results.

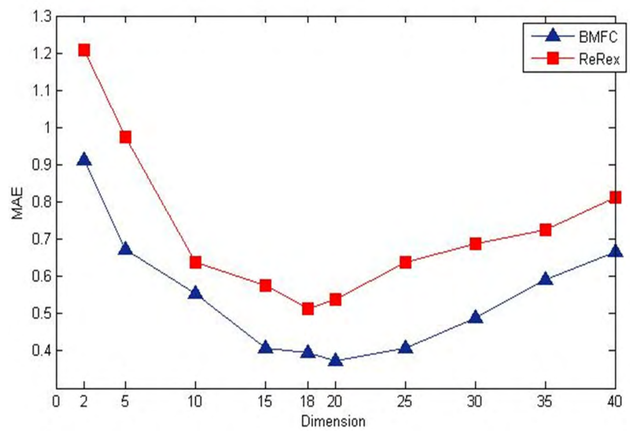


FIGURE 11. MAE of different dimension. BMFC and ReRex methods achieve the optimal result in 18 and 20, respectively, so the dimension is not the bigger the better.

- User-based Collaborative Filtering Method (**UBCF**) [42]. Using the k-Nearest Neighbor (k-NN) approach, UBCF measures the similarity within the users' profiles to find the extent to which users visit the same POIs. Based on the similarities, k-NN set of a given user is computed. The nearest neighbor set is used to generate the rating for a POI via the following equation:

$$R_{ij} = \bar{R}_i + \frac{\sum_{k \in U} sim(i,k)(R_{kj} - \bar{R}_k)}{\sum_{k \in U} sim(i,k)}, \tag{23}$$

  where $\bar{R}_i$ and $\bar{R}_k$ represent the average rating given by $user_i$ and $user_k$. U denotes the set of users that are most similar to $user_i$, $sim(i, k)$ denotes the similarity between $user_i$ and $user_k$.
- **ReRex** [6]. It is similar to our algorithm, which incorporates context into matrix factorization model. However, it assumes that contextual factors are independent of each other.

3) COMPARISON RESULTS

In this subsection, we observe the performance of our proposed personalized recommendation algorithm. The first three algorithms did not consider the influence of contextual factors. For UBCF, the number k is set as 10. For ReRex, the influence of the individual contextual factor is obtained by the BP neural network model trained by the training dataset. In the matrix factorization process of ReRex and BMFC, the iteration number is set to 500, and other parameters are the same as the previous setting.

Fig. 10 shows the MAE and RMSE of the different methods. Obviously, BMFC is the best in both MAE and RMSE, 0.373 and 0.4756, respectively. Since the first three algorithms do not consider contextual factors, their results are worse than the other two. Although ReRex considers the influence of contextual factors, it does not achieve the best results. That is because it assumes that contextual factors are independent of each other and calculates the impact of contextual factors by superimposing. In fact, the impact of contextual factors is an overall feeling, not a simple superposition. For example, a restaurant, more than 50 kilometers away from the user, the distance factor is a negative impact to the restaurant. Even if other factors such as season, weather, prices, etc. are all positive effects, the user will not choose this restaurant. Because it is too far away, beyond the user's tolerance. So the superposition method is not a good solution to the problem of contextual factors. Our proposed BMFC, using BP neural network to train a large amount of rating biases data, so as to get a contextual factor influence model, thus it is very good to solve the problem of the influence of many kinds of contextual factors on user's evaluation.

In the above results, the matrix dimensions d in the matrix factorization process of ReRex and BMFC is set to 20. However, the dimension is not the bigger the better. As shown in Fig. 11, MAE changes with the change of dimension. At the beginning, the MAE is reduced with the increase of the dimension. However, two methods reached the lowest point at 18 and 20, respectively. After that, the value of MAE increased with the increase of dimension. In other words, two methods achieve the optimal result in 18 and 20, respectively. So dimension is not the higher the better, we have validated it by a lot of experiments.

In order to observe the location rationality of the recommendation results, we selected several users to carry out experiments, and observed the MD of each method. For each method, the length of recommendation list is set to 10. For ReRex, we assume that more than 10 kilometers is far. For our BMFC, each user's maximum tolerance distance is set to 10. Table 6 lists the mean distance of each method between the user and recommended POIs. We can see that BMFC is superior to other methods. For each user, the mean distance between the user and recommended POIs is much lower than the other methods. The reason is that our proposed method use the maximum tolerance distance to pre-filter the

TABLE 6. Comparison results on the MD.

User ID	UMEAN	IMEAN	UBCF	ReRex	BMFC
4693117	16.7	21.5	14.6	12.7	7.3
6159443	22.6	10.4	15.8	9.6	4.9
1864576	9.7	15.6	17.4	11.4	6.5
4746909	13.2	17.3	12.5	10.6	5.1
5398258	18.3	22.3	17.8	8.8	3.6

candidate POIs. Therefore it will not recommend far away POIs to the user. However, the first three methods only consider the user's preferences, and do not consider the distance factor and any other contextual factors, so the distance of recommended POIs is dissatisfactory. ReRex takes into account the location as a contextual factor, so the effect is better than the first three methods. Since location is considered just as one of the contextual factors, its impact is relatively weak. Thus, ReRex cannot obtain the best effect. It is easily to understand that distance is a very important factor when choosing a POI. If a POI is not reasonable, even if it can meet the user's preferences, it will not be chosen by the user. Thus, it should not be recommended to the user.

V. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a POI recommendation method for a group of users. The main idea is to generate personalized recommendation for each individual based upon contextual information, and then use group consensus function to generate a ranked recommendation list for the whole group. In order to improve the accuracy of recommendation, we considered the impact of contextual factors on user's ranking deviation, and modeled them using a neural network. During the recommendation making process, we exploited distance rationality with the goal of reducing the distance between the qualified POIs and the group users. Owing to the important role of distance for POI group recommendation, we first proposed the concept of distance satisfaction to measure the user satisfaction, and adopt distance based pre-filtering and ranking adjustment to improve recommendation satisfaction and distance rationality. Comprehensive experiments showed the effectiveness of our proposed POI group recommendation method.

Due to lack of group historical evaluation information and historical context information, we verify the performance of the approach only by simulation on a real data set. In the future work, we will extend the experiment to more data sets, such as meetup, plancast and whrrl, and try to test it in practical application.

APPENDIX

PRE-FILTERING METHOD

In order to reduce the search space of candidate POIs for group recommendation, the proposed method pre filters the candidate POIs by two pre-filtering steps. Step one is requirements based pre-filtering, which excludes the POIs that do not meet group users' requirements. Step two is a distance based pre-filtering, which excludes the POIs that are beyond group users' acceptable distance range.

Step One (Pre-Filtering by Requirements): This step excludes unqualified POIs from the candidate POI database per user requirements. For example, some people want to go to KTV while others want to eat Western food. All these POIs need to appear in the candidate database. On the other hand, restaurants that do not conform to some user's religious dietary restrictions need be excluded from the candidate database. We use Eq. 24 to filter the service database,

$$P^r = \bigcup_{i}^{n} (p_i^r \in (P - P^\varepsilon)), \tag{24}$$

where P^r denotes the results of requirement-based pre-filtering and P is the set of all POIs. p_i^r represents the set of POIs meeting the requirements of user i. P^ε is the strictly excluded POIs set, and n is the group size. In this step, the POIs that do not meet any user's requirements will be filtered out.

When a user logs into the recommender system, it can choose the POI type and taboo type. Howeve, if the user does not make a choice, we think that all POIs can be used as candidate sets.

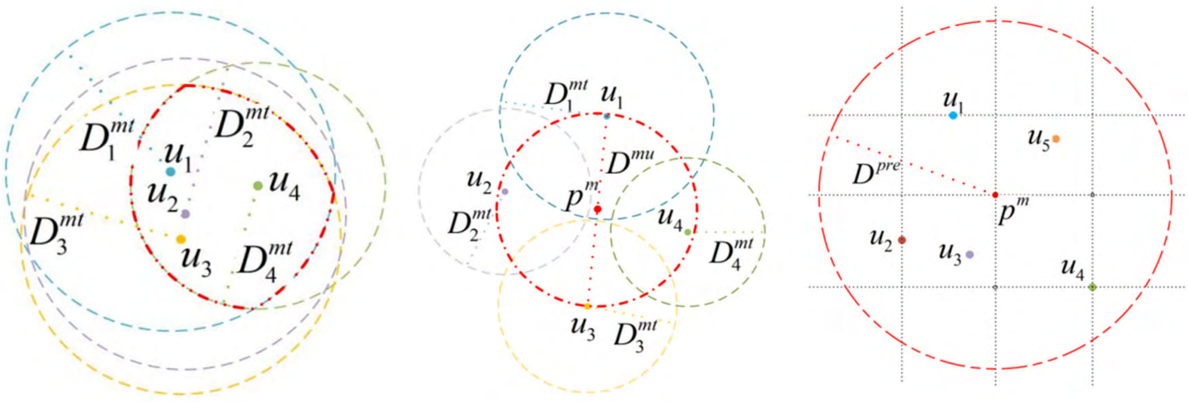
Step Two (Pre-Filtering by Factor): In light of the importance of location in POI group recommendation, distance is used as a pre-filtering factor. In order to facilitate presenting this pre-filtering strategy, we first define three terms with the illustrations shown in Fig. 12.

Definition 1 (Maximum Tolerance Distance): This term refers to a specific distance range D^{mt}, such that if the distance ($dis(u, p)$) between the user's current location and the destination is within the range:$dis(u, p) \leq D^{mt}$, the user is satisfied; otherwise, the user is dissatisfied. For example, Peter's maximum tolerance distance is 10 km if he will join the party only when the distance to the chosen restaurant is less than 10 km.

Definition 2 (Users' Maximum Distance): This term refers to the maximum distance between any two users in a group:$D^{mu} = \max_{u_i, u_j \in G} (dis(u_i, u_j))$. For example, in a group of three users A, B, and C, if the distances between A and B, B and C, and A and C are 4, 3, and 5, respectively, the users' maximum distance of the group is 5.

Definition 3 (Preset Distance): When users do not specify a maximum tolerance distance or when the search space is too small to provide a sufficient number of candidate POIs, the system could use a pre-configured distance, a.k.a., preset distance, to filter the candidate POIs.

When a user logs into the recommender system, it can choose wether to enter its maximum tolerance distance. If it gives up the input of maximum tolerance distance, the preset distance will be its maximum tolerance distance. The system will make distance-based POI filtering decisions based upon the intersection of the maximum tolerance distance input



(a) User's maximum tolerance (b) Users' maximum distance (c) Preset distance

FIGURE 12. **Distance pre-filtering strategy. (a) User's maximum tolerance. (b) User's maximum distance. (c) Preset distance.**

of all of the users within the group. If there are enough candidate POIs in this intersection, the system will use the intersection of the maximum tolerance distance pre-filter. Otherwise, if some users' maximum tolerance are not large enough, it may cause their intersection may be empty or very small. In this case, the candidate POIs set can not meet the requirements. For example, if the number of candidate POI after pre-filtering is no more than 100, we think the candidate POI is not enough. In this case, the maximum distance between any two users in a group is used as the diameter of the pre-filtering. We note that these two schemes may not result in enough candidate POIs when all users in the group are located closely and/or the maximum tolerance distance is not large enough. When that happens, a sufficiently large preset distance is used as the pre-filtering radius. Below is a detailed description of the three use cases.

Case 1: In fact, so as to obtain ideal recommendation results, we encourage users to input a larger tolerance distance. As depicted in Fig. 12 (a), for every user u_i, if $D_i^{mt} > D^{mu}$, we use Eq. 25 to filter the POI database:

$$P^d = \{\bigcap_i^n (dis(u_i, p_j) < D_i^{mt}) \,|p_j \in P^r\}, \tag{25}$$

where P^d is the result of distance pre-filtering and p^r is the result of requirements pre-filtering. u_i(e.g., u_1, u_2, u_3 and u_4) is a user in the group and p_j is a POI. $dis(u_i, p_j)$ represents the distance between u_i and p_j, and $dis(u_i, p_j) < D_i^{mt}$ indicates the POI p_j is within the maximum tolerance distance of user u_i. D_i^{mt} is the maximum tolerance distance of u_i, and D^{mu} is the maximum distance between any two users in the group. n is the group size.

Case 2: If some people's maximum tolerance distance inputs are too small such that $\bigcap_i^n (dis(u_i, p_j) < D_i^{mt}) = \phi$, or the resulting set of candidate POIs is not large enough, we have to sacrifice someone's requirements. As depicted in Fig. 12 (b), we use Eq. 26 to filter POI database:

$$P^d = \{dis(p^m, p_j) < D^{mu} \,|p_j \in P^r\}, \tag{26}$$

where p^m is the midpoint of the two users based on their maximum specified distances. $dis(p^m, p_j)$ is the distance between p^m and p_j. The meaning of the other parameters (P^d, p^r, p_j, D_i^{mt}, D^{mu}) are the same as in Eq. 25.

Case 3: If the users' maximum tolerance distance inputs are small, and/or if all of the users are located closely to each other, their intersection may be empty or very small. In this case, the above two schemes may not produce enough candidate POIs. As depicted in Fig. 12 (c), we propose a preset distance D^{pre} to filter the POI database,the specific operations are as follows:

$$P^d = \{dis(p^m, p_j) < D^{pre} |p_j \in P^r\}, \tag{27}$$

where D^{pre} is the preset distance. If this does not obtain enough candidate POIs, D^{pre} is automatically doubled until satisfactory results are obtained. The meaning of the other parameters (P^d, p^r, and $dis(p^m, p_j)$) are the same as in Eq. 26.

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REFERENCES

[1] L. Li, L. Zheng, F. Yang, and T. Li, "Modeling and broadening temporal user interest in personalized news recommendation," *Expert Syst. Appl.*, vol. 41, no. 7, pp. 3168–3177, 2014.

[2] Q. Diao, M. Qiu, C.-Y. Wu, A. J. Smola, J. Jiang, and C. Wang, "Jointly modeling aspects, ratings and sentiments for movie recommendation (JMARS)," in *Proc. 20th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, 2014, pp. 193–202.

[3] D. Lian, C. Zhao, X. Xie, G. Sun, E. Chen, and Y. Rui, "GeoMF: Joint geographical modeling and matrix factorization for point-of-interest recommendation," in *Proc. 20th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, 2014, pp. 831–840.

[4] R. Pálovics, A. A. Benczúr, L. Kocsis, T. Kiss, and E. Frigó, "Exploiting temporal influence in online recommendation," in *Proc. 8th ACM Conf. Rec. Syst.*, 2014, pp. 273–280.

[5] H.-P. Hsieh, S.-D. Lin, and Y. Zheng, "Inferring air quality for station location recommendation based on urban big data," in *Proc. 21th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, 2015, pp. 437–446.

[6] L. Baltrunas, B. Ludwig, S. Peer, and F. Ricci, "Context relevance assessment and exploitation in mobile recommender systems," *Pers. Ubiquitous Comput.*, vol. 16, no. 5, pp. 507–526, 2012.

[7] T. De Pessemier, S. Dooms, and L. Martens, "Comparison of group recommendation algorithms," *Multimedia Tools Appl.*, vol. 72, no. 3, pp. 2497–2541, 2014.

[8] S. Zhou, "Research on recommendation for group users," Pennsylvania State Univ., State College, PA, USA, Tech. Rep., 2013.

[9] S. Amer-Yahia, S. B. Roy, A. Chawlat, G. Das, and C. Yu, "Group recommendation: Semantics and efficiency," *Proc. VLDB Endowment*, vol. 2, no. 1, pp. 754–765, 2009.

[10] M. Gartrell *et al.*, "Enhancing group recommendation by incorporating social relationship interactions," in *Proc. 16th ACM Int. Conf. Supporting Group Work*, 2010, pp. 97–106.

[11] R. Sotelo, Y. Blanco-Fernández, M. López-Nores, A. Gil-Solla, and J. J. Pazos-Arias, "TV program recommendation for groups based on muldimensional TV-anytime classifications," *IEEE Trans. Consum. Electron.*, vol. 55, no. 1, pp. 248–256, Feb. 2009.

[12] N.-R. Kim and J.-H. Lee, "Group recommendation system: Focusing on home group user in TV domain," in *Proc. 7th Int. Conf. Adv. Intell. Syst.*, Dec. 2014, pp. 985–988.

[13] S. Berkovsky and J. Freyne, "Group-based recipe recommendations: Analysis of data aggregation strategies," in *Proc. 4th ACM Conf. Rec. Syst.*, 2010, pp. 111–118.

[14] H.-C. Chen and A. L. P. Chen, "A music recommendation system based on music data grouping and user interests," in *Proc. 10th Int. Conf. Inf. Knowl. Manage.*, 2001, pp. 231–238.

[15] A. Theodoridis, C. Kotropoulos, and Y. Panagakis, "Music recommendation using hypergraphs and group sparsity," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, May 2013, pp. 56–60.

[16] T. Liu, F. Xu, Y. Yao, and J. Lu, "A group recommendation approach for service selection," in *Proc. 4th Asia–Pacific Symp. Internetware*, 2012, p. 10.

[17] O. Khalid, M. U. S. Khan, S. U. Khan, and A. Y. Zomaya, "OmniSuggest: A ubiquitous cloud-based context-aware recommendation system for mobile social networks," *IEEE Trans. Serv. Comput.*, vol. 7, no. 3, pp. 401–414, Jul./Sep. 2014.

[18] M.-H. Park, H.-S. Park, and S.-B. Cho, "Restaurant recommendation for group of people in mobile environments using probabilistic multi-criteria decision making," in *Computer-Human Interaction*. Berlin, Germany: Springer, 2008, pp. 114–122.

[19] I. Garcia, L. Sebastia, and E. Onaindia, "On the design of individual and group recommender systems for tourism," *Expert Syst. Appl.*, vol. 38, no. 6, pp. 7683–7692, 2011.

[20] L. Liu, F. Lecue, and N. Mehandjiev, "Semantic content-based recommendation of software services using context," *ACM Trans. Web*, vol. 7, no. 3, 2013, Art. no. 17.

[21] M. Tkalcic, A. Odic, A. Kosir, and J. Tasic, "Affective labeling in a content-based recommender system for images," *IEEE Trans. Multimedia*, vol. 15, no. 2, pp. 391–400, Feb. 2013.

[22] M. D. Ekstrand, J. T. Riedl, and J. A. Konstan, "Collaborative filtering recommender systems," *Found. Trends Human-Comput. Interact.*, vol. 4, no. 2, pp. 81–173, Feb. 2010.

[23] M. Tang, Y. Jiang, J. Liu, and X. Liu, "Location-aware collaborative filtering for QoS-based service recommendation," in *Proc. 19th IEEE Int. Conf. Web Services (ICWS)*, Jun. 2012, pp. 202–209.

[24] S. Wang, Z. Zheng, Z. Wu, M. R. Lyu, and F. Yang, "Reputation measurement and malicious feedback rating prevention in Web service recommendation systems," *IEEE Trans. Serv. Comput.*, vol. 8, no. 5, pp. 755–767, Sep./Oct. 2014.

[25] A. Klašnja-Milićević, B. Vesin, M. Ivanović, and Z. Budimac, "E-Learning personalization based on hybrid recommendation strategy and learning style identification," *Comput. Edu.*, vol. 56, no. 3, pp. 885–899, 2011.

[26] J. P. Lucas, N. Luz, M. N. Moreno, R. Anacleto, A. A. Figueiredo, and C. Martins, "A hybrid recommendation approach for a tourism system," *Expert Syst. Appl.*, vol. 40, no. 9, pp. 3532–3550, 2013.

[27] Y. Ma, S. Wang, F. Yang, and R. N. Chang, "Predicting QoS values via multi-dimensional QoS data for Web service recommendations," in *Proc. 22th IEEE Int. Conf. Web Services (ICWS)*, Jun./Jul. 2015, pp. 249–256.

[28] J. M. Noguera, M. J. Barranco, R. J. Segura, and L. Martínez, "A mobile 3D-GIS hybrid recommender system for tourism," *Inf. Sci.*, vol. 215, pp. 37–52, Dec. 2012.

[29] A. Noulas, S. Scellato, N. Lathia, and C. Mascolo, "A random walk around the city: New venue recommendation in location-based social networks," in *Proc. 22th IEEE Int. Conf. Social Comput. (SocialCom)*, Sep. 2012, pp. 144–153.

[30] B. Liu, Y. Fu, Z. Yao, and H. Xiong, "Learning geographical preferences for point-of-interest recommendation," in *Proc. 19th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, 2013, pp. 1043–1051.

[31] M. Ye, P. Yin, W.-C. Lee, and D.-L. Lee, "Exploiting geographical influence for collaborative point-of-interest recommendation," in *Proc. 34th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, 2011, pp. 325–334.

[32] Q. Yuan, G. Cong, Z. Ma, A. Sun, and N. M. Thalmann, "Time-aware point-of-interest recommendation," in *Proc. 34th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, 2011, pp. 363–372.

[33] H. Gao, J. Tang, X. Hu, and H. Liu, "Content-aware point of interest recommendation on location-based social networks," in *Proc. 29th AAAI Conf. Artif. Intell.*, 2015, pp. 1721–1727.

[34] A. Jameson and B. Smyth, "Recommendation to groups," in *Adaptive Web*. Berlin, Germany: Springer, 2007, pp. 596–627.

[35] L. Guo, J. Shao, K. L. Tan, and Y. Yang, "WhereToGo: Personalized travel recommendation for individuals and groups," in *Proc. 15th Int. Conf. Mobile Data Manage. (MDM)*, Jul. 2014, pp. 49–58.

[36] M. Gartrell, K. Alanezi, L. Tian, R. Han, Q. Lv, and S. Mishra, "Social-Dining: Design and analysis of a group recommendation application in a mobile context," Tech. Rep., 2014.

[37] J. F. McCarthy, "Pocket restaurantfinder: A situated recommender system for groups," in *Proc. ACM Conf. Hum. Factors Comput. Syst. Workshop Mobile Ad-Hoc Commun.*, 2002, pp. 1–10.

[38] H.-X. Huang, J.-C. Li, and C.-L. Xiao, "A proposed iteration optimization approach integrating backpropagation neural network with genetic algorithm," *Expert Syst. Appl.*, vol. 42, no. 1, pp. 146–155, 2015.

[39] L. Quijano-Sanchez, J. A. Recio-Garcia, B. Diaz-Agudo, and G. Jimenez-Diaz, "Social factors in group recommender systems," *ACM Trans. Intell. Syst. Technol.*, vol. 4, no. 1, 2013, Art. no. 8.

[40] J. Masthoff, "Group recommender systems: Combining individual models," in *Recommender Systems Handbook*. Boston, MA, USA: Springer, 2011, pp. 677–702.

[41] R. J. Hyndman and A. B. Koehler, "Another look at measures of forecast accuracy," *Int. J. Forecasting*, vol. 22, no. 4, pp. 679–688, 2006.

[42] L. Shao, J. Zhang, Y. Wei, J. Zhao, B. Xie, and H. Mei, "Personalized QoS prediction forWeb services via collaborative filtering," in *Proc. 14th Int. Conf. Web Services (ICWS)*, 2007, pp. 439–446.

[43] E. Ntoutsi, K. Stefanidis, K. Nørvåg, and H.-P. Kriegel, "Fast group recommendations by applying user clustering," in *Conceptual Modeling*. Berlin, Germany: Springer, 2012, pp. 126–140.

[44] H. Zhao, Q. Liu, Y. Ge, R. Kong, and E. Chen, "Group preference aggregation: A nash equilibrium approach," in *Proc. IEEE Int. Conf. Data Mining*, Dec. 2016, pp. 679–688.

[45] X. Liu, Y. Tian, M. Ye, and W.-C. Lee, "Exploring personal impact for group recommendation," in *Proc. ACM Int. Conf. Inf. Knowl. Manage.*, 2012, pp. 674–683.

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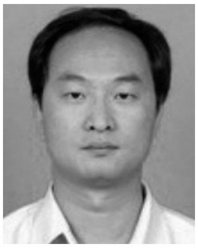

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