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Leveraging friend and group information to improve social recommender system

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Abstract
In recent years, we have witnessed a flourish of social commerce services. Online users can easily share their experiences on products or services with friends. Social recommender systems are employed to tailor right products for user needs. However, existing recommendation methods try to consider the social information to improve the recommendation performance while they do not differ the impact of different social information and do not have deep analysis on social information. In this paper, we propose a social recommendation framework to leverage the friend and group information to extend the traditional BPR model from different perspectives. Through a detailed experiment on LAST.FM data set, we find that the proposed methods are effective in improving the recommendation accuracy and we also have a good understanding for the impact of friend and group information on recommendation performance.

Keywords Social recommender system · Friend · Group · Positive feedback

1 Introduction

With the development of social networking services, social commerce has attracted lots of attention from both academia and industry [1, 2]. In the context of social commerce, social media and Web 2.0 technologies are employed to facilitate online users' buying and selling products or services. Online users often run into information overload problems due to large volume of online products and services. Recommender systems tailor right products for user-specific preferences and have become crucial for the success

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of many social commerce services. In the existing recommendation systems, the data types used are mainly classified into explicit feedback data and implicit feedback data [3–5]. Explicit feedback data refers to ratings, which can clearly express users' preferences. It is the feedback provided by users on their own initiative and provides a mechanism to express user's interest in items [6]. Implicit feedback data refers to users' clicking, collecting, purchasing or searching information, which cannot directly reflect users' preferences for different items. Recent recommender system technologies focus more on implicit feedback data. However, data sparsity problems are often existing in recommender systems only using implicit feedback data. To address above issues, social recommender systems are gradually becoming hot research topics.

Social recommender systems leverage social information (such as friendship, trust, group et al.) to improve the recommender system performance. Du et al. [7] constrained the traditional BPR (Bayesian Personalized Ranking) model by adding a regularization term of social information to the traditional BPR model to improve the recommendation accuracy. Pan et al. [8] introduced the concept of "group preference" and proposed the GBPR method, which relaxed the assumptions of independence and individuality to reduce the uncertainty of the model and improve recommendation accuracy. Zhao et al. [9] extended the traditional BPR model by building friend feedback set and adding preference set. These approaches have proven their good performance in determining recommendations and they can solve the data sparsity effectively. However, the existing recommendation methods did not explore the impact of different social information on the recommendation performance. The contributions of different social information for recommendation performance were not measured precisely.

In this paper, we propose several social recommendation methods to leverage friends and groups. We list three hypotheses about implicit feedbacks and expand the traditional BPR model to validate the recommendation performance of our model. We also explore the impact of social information behind the results on different evaluation indicators. There are two main contributions in this paper. Firstly, it proves that social information and group information in online social networks can improve recommendation results. Among them, the integration of social information and group information makes recommendation performance the best. Secondly, the recommendation results of different levels of friend links and group links are validated on the last.fm data set. It proves that different levels of friend links and group links have different effects on recommendation results.

The remainder of this paper is organized as follows. Section 2 reviews related work about social commerce and social recommendation system. Section 3 introduces the hypothesis of the model and the construction process of the model. Section 4 shows the experimental design and results and results analysis. We summarize the research of this paper and provide the future research direction in Sect. 5.

2 Related work

2.1 Social commerce

With the development of social networking services, social commerce is emerging and becoming prevalent. Social commerce makes full use of the power of social media to attract users to share, disseminate and comment [10–12]. Social commerce is different from traditional e-commerce and it provides a good opportunity for traditional e-commerce [13]. Marsden et al. [14] found that most respondents were more likely to share shopping information with online friends and listen to online friends' suggestions. Liang et al. [15] found that online friends' social interaction had a significant impact on social commerce. Akar and Hajli et al. [16, 17] found that online reviews in social commerce significantly affected consumers' purchase decisions. Many studies have shown that people are more likely to rely on social technology to obtain goods or services [13, 15–21].

While recognizing the importance of social commerce, many scholars have conducted research on users' behavior in social commerce environment [22]. Sharma and Crossler's research indicated that the willingness to self-disclose personal information in social commerce was affected by the fairness of information exchange and privacy risks [23]. It is also shown that social shopping willingness is highly correlated with community members' relationship, and social sharing willingness is influenced by members' trust in the community [24]. Furthermore, communities that satisfy users are particularly important for the success of social commerce [25]. Zhang et al. proposed a model to study the factors of customer participation in socialized business behavior. It was found that the intention of social business was depended on social support, social existence and flow [26].

In order to better develop social commerce, important tools have been proposed and designed in recent years. It is shown that the openness and interaction of virtual community attract many network users, which makes it easier for virtual community to carry out targeted marketing activities, thus promoting social commerce [27]. Noor et al. [28] pointed out that e-word-of-mouth (e-word of mouth, rating, comment) was an important factor affecting the trust mechanism of socialized business. The success of e-commerce largely depends on effective product recommendation design, and social recommendation system can accurately generate personalized products [29]. Therefore, social recommendation system is a good tool to promote the development of social commerce. Next, we will give a brief introduction to personalized recommendation and social recommendation.

2.2 Traditional recommender system

Recommendation system has become the primary way to solve the problem of "information overload" in the era of big data. According to the difference of data types used, the recommendation tasks can be divided into two kinds: the rating prediction task based on explicit rating data and the Top N recommendation task based on implicit feedback data [30]. The rating prediction task relies on the user's scoring data for the product. The user's score for the product generally ranges from 1 to 5 points. The larger the score, the greater the user's preference for the product. The Top N recommendation task relies on interactive recording data such as user clicks, purchases, browses and so on. In e-commerce websites and online social networks, the interaction between users and products is often in the form of implicit feedback [31]. Implicit feedback has attracted wide attention of researchers because of its universality, low cost and close to reality. Therefore, Top N recommendation based on implicit feedback data has become a hot research topic in recommendation system.

In the recommendation method based on implicit feedback data, the research can only obtain the positive feedback records of users. Negative feedback cannot be obtained directly from the interactive records of users and products because it is mixed with missing values. The existing methods mainly solve this problem by setting weights and constructing partial order relations. Hu et al. [32] proposed a weighted matrix decomposition WR-MF model based on implicit feedback, which regarded negative feedback products and some missing values as negative products, and reduced the impact of negative feedback by setting weights. Pan et al. [33] proposed three different negative sample weight strategies according to user activity and commodity popularity, and further proposed the method of optimizing weighted matrix decomposition [34]. According to the distribution probability of positive and negative feedback, Sindhwani et al. [35] replaced the missing feedback with the probability that the item may be positive feedback, which further improved the accuracy of the weight matrix. Paquet et al. [36] used random graph to represent the user-item relationship and constructed the weight value of users to items. These methods are typical methods of setting weights. Rendle et al. [7] proposed Bayesian Personalized Ranking Criterion BPR-opt. They assumed that the preference order of the products browsed was larger than that of the products not browsed, and there is no partial ordering relationship within all products browsed or all products not browsed. Based on this assumption, the posterior probability of item ranking is obtained, and it is completed through parameter learning. To maximize the posterior probability. BPR method is a typical method to construct sorting relationship.

In addition to using the known relationship between users and objects to construct the weights of positive and negative feedback, the introduction of auxiliary information has gradually become a hot topic for scholars. From the user's point of view, user's auxiliary information includes a series of information such as social network [33, 37–42], search record [43], comment content [44, 45], time series [46–49], geographical location [31, 50], which are applied to recommendation algorithm.

2.3 Social recommender system

Previous studies have shown that with the spread of information in social networks, users are affected by the social connections of social impact theory, resulting in similar preferences among social neighbors [51–54]. At the same time, homogeneity theory shows that similar users have similar preferences

[55–57]. With the development of online social platforms, social information is gradually used to deal with sparsity, which improves the recommendation performance of recommendation algorithms [58]. According to the different types of data used, the recommendation methods of social recommender system can be divided into social rating prediction based on explicit feedback data and social item recommendation based on implicit feedback data.

There are many studies on social recommendation methods using explicit feedback data. Ma et al. [40], utilize user's social network proposing the SocRec model to solve the data sparsity and improving the performance of recommendation. In the recent years, more new social recommender algorithms are created. Li and Yeung [59] present the relation regularized matrix factorization called RRMF for relational data analysis, merging the social relation and content information into a fundamental framework. Ma et al. [60] improve the original method and apply user's social information in very large data set, and take better performance. Mohsen et al. [61] add the principle of trust propagation into the matrix factorization method, on the basis of trust propagation. Ma et al. [62] analyze the differences between social-based recommender systems and trust-aware recommender systems, improving the matrix factorization framework with social network information. Tang et al. [63] study a new method to acquire local and global social network, and present an improved algorithm LOCABAL making use of local and global social context to recommend items. Fang et al. [64] decompose the primitive single-aspect trust information into multiple trust dimensions, integrating the information into the probabilistic matrix factorization model to improve rating by using the technique of regression support vector. Guo et al. [65] propose TrustSVD by improving a trust-based matrix factorization method. Li et al. [66] for the purpose of solving the problem that there are few social connections for targeted users, add the overlapping community regularization into the matrix factorization algorithm, proposing two alternative models. Tang et al. [67] study weak dependency connections and the heterogeneity of friend relations, proposing the method to build the model to create social dimensions, creating a novel recommendation framework named SoDimRec. Yang et al. [68] raise new matrix factorization to get better user preference model for high quality recommendation, in order to more accurately calculate the interaction between users and their opinions. Sedhain et al. [69] aim to reduce the high dimensionality phenomenon in social network data, using linear regression technology to train an appropriate weighting of social aspects for preferences, and using the weight of low-rank parameterization. Wu et al. [70] propose a novel framework by integrating social network information and user-item interaction relation into matrix factorization, creating a neural framework considering the intrinsic relationship. Zhao et al. [71] utilize user's review and friendship relation to calculate the popularity and reliability of users, using word2vector to get users' sentiment, fusing these parameters to matrix factorization framework to improve the performance of rating. Xu et al. [72] consider user preferences and the social network relationships among users, clustering users and making use of diversified factors to alleviate the problems of sparsity and cold-start in recommender systems.

However, there are few social recommendation methods using implicit feedback data. Existing research is as follows: Zhao et al. [9] proposed SBPR model, which integrates user friend relations into traditional Bayesian personalized ranking algorithm for personalized recommendation, and explores how friends influence user preferences; Jiang et al. [73] used social label information to subdivide users' preferences, and thus constructed a finer-grained preference relationship, which achieved good recommendation results.

In summary, most of the existing social recommendation methods focus on rating prediction based on explicit feedback data, and lack of research on top N recommendation based on implicit feedback data. Therefore, this paper considers using additional social information (group information, social information) to integrate it into a more mature and scalable Bayesian personalized recommendation framework, in order to expand the research on implicit feedback in social recommendation system.

3 The proposed social recommendation model

In this section, we propose the social recommendation framework which leverages the friend information and group information. Figure 1 illustrates the flow chart of the proposed social recommendation framework. As shown in Fig. 1, our

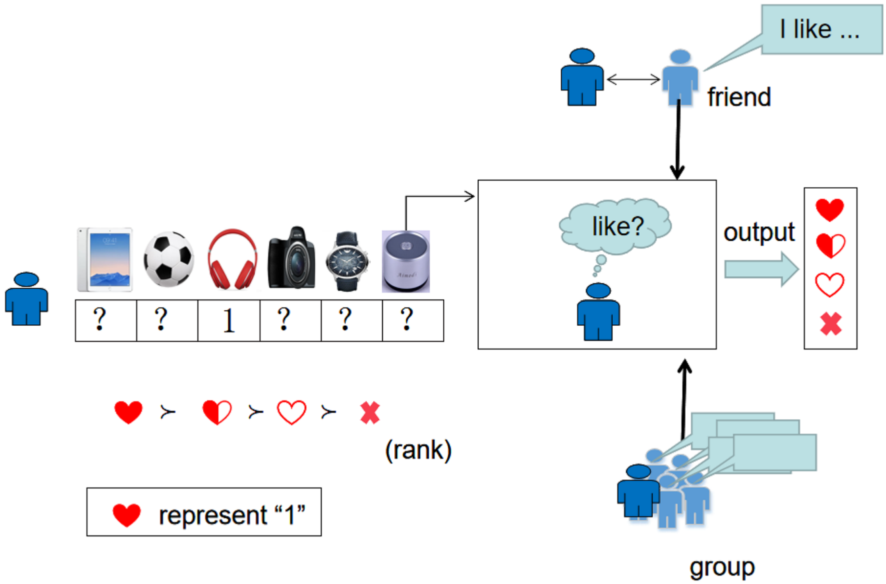

Fig. 1 The overview of social recommendation framework

recommendation model focus on implicit feedback data. "1" indicates that the user u shows the positive feedback (such as like, purchase et al.) to the item p, and the symbol "?" indicates that there is no feedback for the user u on the item p and the preference of user for this item is unknown. In our framework, we introduce friend information and group information to infer users' unknown preferences.

3.1 Preliminaries

To make a clear description of our recommendation model, we firstly formalize the problem and introduce the notations used in the paper. The notations are shown in Table 1.

Our approach aims to recommend items of interest to users in online social networks, taking into account group information and friend information. Social information refers to information existing in online social networks, such as friends, groups, social labels, etc. In this paper, we mainly use the information of friends and groups. As the name implies, friend information refers to the actual friendship in online social networks. Group information is the group information that users join spontaneously in the online social network environment.

We have a user set U, and an item set P. The binary group $< u, p_i > \in D$ represents that user u has positive feedback with the item p_i, where u $\in U$ and $p_i \in P$. The binary group $< u_i, u_j > \in$ F represents that users u_i and users u_j are friends. The binary group $< u_i, u_j > \in G$ indicates that the user u_i and the user u_j are joining the same group.

The task of our recommendation system is to predict user preferences for unknown items. Firstly, we incorporate friend information and group information into social recommendation model and divide preference relationships into finer grains. Based on the three hypotheses proposed by us, partial ordered sets are constructed respectively. Next, we construct the objective function of Bayesian personalized ranking using partial ordering set and use matrix to express preference degree. We use BPR-MF model to solve the objective function to explore the influence of group information on social recommendation.

Table 1 Notation

Notations	Description
U	A set of users
P	A set of items
M	the number of users
N	the number of items
D	The set of user-item relationships(only include positive feedback)
G	The set of group relation
F	The set of friend relation
θ	The parameters in the objective function
ψ	The objective function

3.2 Model construction

Firstly, we introduce three hypotheses and construct preference sets based on them. Next, we construct the objective function of Bayesian personalized ranking based on these hypotheses.

3.2.1 Model assumption

In this part, we analyze the positive feedback information, friend information and group information in detail, and propose assumptions.

Previous studies [9] have shown that the integration of social information can help to distinguish non-interactive items (i.e. the user has no interaction with the item, such as browsing, collecting, purchasing), build preference relationships more finely, and improve the recommendation effect. We have noticed that in the real online social network environment, there are not only friend relationships, but also group relationships (In this article, friends and groups are real online social networks, not artificially defined). So what's the difference between friend and group relationships?

In the social network environment, friend relations are direct links between users. Group relationship is that users join the same group because of common interests. Friend relations are two-way links between users and they are often very sparse. Group relationship is a kind of one-way link from users to products. Because users can join more than one group, it is relatively dense.

Here, for each user, we divide all items into four parts: positive feedback set, friend feedback set, group feedback set and negative feedback set.

Positive feedback Positive feedback is a binary group extracted directly from user-item relationship set D. We define the user u's positive feedback set as $PF_u = \{< u, p_i >\}$, where $< u, p_i > \in D$.

Friend feedback Friend feedback refers to the fact that the user u himself has no feedback with item p_f, but one of his friends v has interaction with the item p_f.We define the user u's friend feedback set as $FF_u = \{< u, p_f >\}$, where $< u, p_f > \notin D$ and $\exists < u, v > \in F$, $< v, p_f > \in D$.

Group feedback Group feedback refers to the fact that user u himself does not interact with item p_g, and all his friends do not interact with the item p_g, but one of users who join the same group as user u interact with the item p_g.We define the user u's group feedback set as $GF_u = \{< u, p_g >\}$, where $< u, p_g > \notin D$, $\forall < u, u_f > \in F$, $< u_f, p_g > \notin D$ and $\exists < u, v > \in G$, $< v, p_g > \in D$.

Negative feedback Negative feedback means that user u does not interact with item p_j, all his friends do not interact with the item p_j, and all users who belong to the same group do not interact with the item p_j.We define the user u's negative feedback set as $NF_u = \{< u, p_j >\}$, where $< u, p_g > \notin D$, $\forall < u, u_f > \in F$, $< u_f, p_j > \notin D$ and $\forall < u, v > \in G$, $< v, p_g > \notin D$. Here negative only means no explicit feedback can be observed from the user and does not represent users' dislike of the items. In fact, negative feedback consists of two parts: real negative feedback (the user is not interested in buying the item) and missing values (the user might want to buy the item in the future). Therefore, the addition of negative feedback also adds a user preference.

From the above definition, it is easy to find that $PF_u \cap FF_u \cap GF_u \cap NF_u = \emptyset$ and $PF_u \cup FF_u \cup GF_u \cup NF_u = P$ contains the total item sets.

In order to verify the influence of friend information and group information, we propose three assumptions.

Assumption 1 Considering that social links are two-way links, they can be considered strong links. Group links are one-way links and can be considered weak links. We propose hypothesis 1 as follows:

$$\text{positive feedback} \succ \text{friend feedback} \succ \text{group feedback} \succ \text{negative feedback}$$

Thus, positive feedback set, friend feedback set, group feedback set and negative feedback set are defined as above.

Hypothesis 2 On the one hand, we consider that group relationship is based on user's interest and users join the group independently, while friend relationship requires clear links between the two, so group feedback is much denser than friend feedback. On the other hand, this paper mainly solves the sparse problem of personalized recommendation, so it introduces additional information. Based on these two considerations, we can also think that dense group feedback is more effective than sparse friend feedback.

Thus, we put forward assumption 2 as follows:

$$\text{positive feedback} \succ \text{group feedback} \succ \text{friend feedback} \succ \text{negative feedback}$$

Hypothesis 3 Because group relationships and friend relationships are built in online social networks, there may be no difference. Therefore, we can consider the difference between group feedback and friend feedback as feedback with the same preference level. Assumption 3 is as follows:

$$\text{positive feedback} \succ \text{group feedback/friend feedback} \succ \text{negative feedback}$$

We construct the preference set of Hypotheses 2 and 3 in a similar way as Hypothesis 1. We do not expand in detail here.

3.2.2 Model formulation

Bayesian personalized ranking algorithm (BPR) [7] is one of the popular technologies in Top N recommendation task. It only considers user-item interaction records. In addition to explicit positive feedback (i.e. user-item interaction), negative feedback is randomly extracted from all user-item non-interaction records. This paper chooses Bayesian personalized recommendation as the basic model of the framework and extends it.

BPR decomposes the ranking matrix X of user U and item P into user matrix W_{M*K} and item matrix H_{N*K}, satisfying that

$$\hat{X} = WH^{\mathrm{T}} + b \tag{1}$$

where K is rank of matrix, W_{M*K} represents the feature matrix of user set U, H_{N*K} represents the feature matrix of item set P, b represents the deviation term of item set P.

Based on above three hypotheses, we construct the objective function. This paper only takes Hypothesis 1 as an example. Our goal is to maximize the following objective function:

$$\Psi = \sum_{u}^{M} \left[\begin{array}{c} \sum\limits_{i \in PF_u} \sum\limits_{f \in FF_u} \ln\left(\sigma\left(\frac{\hat{x}_{ui} - \hat{x}_{uf}}{1+C_f}\right)\right) + \sum\limits_{f \in FF_u} \sum\limits_{g \in GF_u} \ln\left(\sigma\left(\frac{\hat{x}_{uf} - \hat{x}_{ug}}{1+C_g}\right)\right) \\ + \sum\limits_{g \in GF_u} \sum\limits_{j \in NF_u} \ln\left(\sigma\left(\hat{x}_{ug} - \hat{x}_{uj}\right)\right) \end{array} \right] - \lambda_{\Theta} \| \Theta \|^2 \tag{2}$$

where $\hat{x}_{ui}$ denotes user u's preference for item p_i in positive feedback set PF_u; $\hat{x}_{uf}$ denotes user u's preference for item p_f in friend feedback set FF_u; $\hat{x}_{ug}$ denotes user u's preference for item p_g in group feedback set GF_u; $\hat{x}_{uj}$ denotes user u's preference for item p_j in negative feedback set NF_u; $\sigma(\cdot)$ represents logistic function; $\Theta = \{W, H, b\}$ represents the set of parameters in the objective function; λ_{Θ} represents regularization coefficient. From formula (1), we can know that $\hat{x}_{ui} = W_{uk}^{\mathrm{T}} H_{ik} + b_i$, $\hat{x}_{uf} = W_{uk}^{\mathrm{T}} H_{fk} + b_f$, $\hat{x}_{ug} = W_{uk}^{\mathrm{T}} H_{gk} + b_g$, $\hat{x}_{uj} = W_{uk}^{\mathrm{T}} H_{jk} + b_j$.

Friend coefficient For a given user u and item p_f, C_f is the number of friends who have interacted with item p_f among users u's friends. The larger value of $(1+C_f)$, the closer the user u's preference for positive feedback item p_i and friend feedback item p_f are.

Group coefficient For a given user u and item p_g, in the same group of users as user u, the number of users who have interaction with item p_g is C_g. The larger value of $(1+C_g)$, the closer the user u's preference for friend feedback item p_f and group feedback item p_g.

3.3 Parameter learning

We use the stochastic gradient descent (SGD) algorithm to solve the objective function of formula (2). The main process of SGD is divided into two steps. Firstly, For a user u, randomly extract positive feedback item p_i, friend feedback item p_f, group feedback item p_g and negative feedback item p_j. Thus, we constitute a user preference item combination $C(u, p_i, p_f, p_g, p_j)$.Second, we update the parameters alternately. For each training example, we calculate the derivative and update the corresponding parameters by walking along the ascending gradient direction.

For any user u, the gradient of $b_i, b_f, b_g, b_j, w_{uf}, h_{if}, h_{ff}, h_{gf}, h_{jf} w_{uf}$ is as follows:

$$\nabla b_i = \frac{\partial \Psi}{\partial b_i} = \frac{1}{1 + e^{\frac{x_{ui} - x_{uf}}{1 + C_f}}} \cdot \frac{1}{1 + C_f} \tag{3}$$

$$\nabla b_f = \frac{\partial \Psi}{\partial b_f} = -\frac{1}{1 + e^{\frac{x_{ui} - x_{uf}}{1 + C_f}}} \cdot \frac{1}{1 + C_f} + \frac{1}{1 + e^{\frac{x_{uf} - x_{ug}}{1 + C_g}}} \cdot \frac{1}{1 + C_g} \tag{4}$$

$$\nabla b_g = \frac{\partial \Psi}{\partial b_g} = -\frac{1}{1 + e^{\frac{x_{uf} - x_{ug}}{1 + C_g}}} \cdot \frac{1}{1 + C_g} + \frac{1}{1 + e^{x_{ug} - x_{uj}}} \tag{5}$$

$$\nabla b_j = \frac{\partial \Psi}{\partial b_j} = -\frac{1}{1 + e^{x_{ug} - x_{uj}}} \tag{6}$$

$$\nabla w_{uf} = \frac{\partial \Psi}{\partial w_{uf}} = \frac{1}{1 + e^{\frac{x_{ui} - x_{uf}}{1 + C_f}}} \cdot \frac{h_{if} - h_{ff}}{1 + C_f} + \frac{1}{1 + e^{\frac{x_{uf} - x_{ug}}{1 + G}}} \cdot \frac{h_{ff} - h_{gf}}{1 + C_g} + \frac{h_{gf} - h_{jf}}{1 + e^{x_{ug} - x_{uj}}} \tag{7}$$

$$\nabla h_{if} = \frac{\partial \Psi}{\partial h_{if}} = \frac{1}{1 + e^{\frac{x_{ui} - x_{uf}}{1 + C_f}}} \cdot \frac{w_{uf}}{1 + C_f} \tag{8}$$

$$\nabla h_{ff} = \frac{\partial \Psi}{\partial h_{ff}} = -\frac{1}{1 + e^{\frac{x_{ui} - x_{uf}}{1 + C_f}}} \cdot \frac{w_{uf}}{1 + C_f} + \frac{1}{1 + e^{\frac{x_{uf} - x_{ug}}{1 + C_g}}} \cdot \frac{w_{uf}}{1 + C_g} \tag{9}$$

$$\nabla h_{gf} = \frac{\partial \Psi}{\partial h_{gf}} = -\frac{1}{1 + e^{\frac{x_{uf} - x_{ug}}{1 + C_g}}} \cdot \frac{w_{uf}}{1 + C_g} + \frac{w_{uf}}{1 + e^{x_{ug} - x_{uj}}} \tag{10}$$

$$\nabla h_{jf} = \frac{\partial \Psi}{\partial h_{jf}} = -\frac{w_{uf}}{1 + e^{x_{ug} - x_{uj}}} \tag{11}$$

The specific algorithm process is shown in Algorithm 1.

In order to ensure the increase of the objective function in the process of model training, we set the iteration times $iter = 500$ and iteration steps $\alpha = 0.1$, set the coefficients $\lambda = 0.01$ to prevent over-fitting in the experiment.

Algorithm 1

Input: The set of user-item relationships D, the set of social relation S, the set of social relation G.

Output: parameters $\Theta = \{W,H,b\}$

Constructing four feedback sets for each user: PN,FF,GF,NF
Initialize W,H,b randomly
for iter=1; iter<=MaxIter; do
    for η=1; η<=|D| do
        Randomly extract a user u
        Randomly extract a item p_i from PF_u
        Randomly extract a item p_f from FF_u
        Randomly extract a item p_g from GF_u
        Randomly extract a item p_j from NF_u
        we can get a user u's preference item combination $C(u, p_i, p_f, p_g, p_j)$;
        Updating parameters $\Theta = \{W,H,b\}$ using formula (3)-(11);
    end
end
return W,H,b

4 Experimental evaluation

We conducted a series of experiments to evaluate the effectiveness of the proposed social recommendation methods. We describe the detailed settings of the experiment and analyze the results.

4.1 Data description

In order to validate the proposed model in this paper, we use the real social network data set Last.FM (http://www.last.fm) to do experimental verification. Last.FM, a personalized music sharing service, is the largest social music platform in the world. The site provides personalized recommendations, contacts users with similar tastes, customized radio broadcasting and more other services through each user's music listening. In Last.fm, music enthusiasts can also create groups to share music. For the robustness of the experiment, 3000 users are randomly selected and all item records, friends and group information of 3000 users are retained. Table 2 shows the experimental data set information.

Table 2 The description of the Last.FM dataset

	Experimental dataset
Number of users	3000
Number of items	183,628
Observed feedback	277,006
Friend relations	1113
Group relations	432,260
Average number per user	92.34
The sparsity(%)	99.95

We use three subsets of Last.fm data set, namely friend relations data set, group relations data set and user-item interaction data set. The interactive data set of users and items refers to the positive feedback of users, and the negative feedback set of users-item pairs which are not included in the positive feedback set belongs to users.

In our experiment, we employ two-fold cross validation method to verify the effectiveness of proposed recommendation methods. We divide the dataset into two parts. First, we determine whether the user's interactive items are greater than or equal to 2. For users with no less than 2 interactive items, we divided each user's items into 50% training set and 50% testing set. For users with less than 2 interactive items, we allocate them into the training set. Finally, we get the training set and testing set for the experiment. In addition, according to the training set, we can get friend feedback set and group feedback set. Details are shown in Table 3.

As can be seen from Table 3, nearly one-sixth of users have less than two interactive items. However, the total number of interactive items observed in the training set and the testing set is not much different. We partition and validate the original data set of last.fm. The results show that the segmentation effect of the original data set is the same as that of the experimental sample. Then, we can think that the distribution of the data set used in the experiment is the same as that of the original sample, and the results of the small sample experiment can represent the results of the original data set.

Table 3 The description of the training set and the testing set

	Training set	Testing set
Number of users	3000	2452
Number of items	102,995	101,944
Observed feedback	139,348	137,658
The sparsity (%)	99.95	99.94
Average positive feedback	46.45	–
Average friend feedback	97.92	–
Average group feedback	8934.40	–

4.2 Compared methods

In order to test our proposed methods, we use two benchmark methods as comparison algorithms. At the same time, on the basis of three hypotheses, three methods are compared. In order to verify the validity of group information separately, we introduce group information instead of social information and run a benchmark method.

BPR The traditional Bayesian personalized ranking recommendation algorithm uses user-item interaction information to randomly construct a binary < positive feedback, negative feedback > to obtain the ranking preferences of items [7].

SBPR This method integrates friend information into the traditional Bayesian personalized ranking algorithm. By using the positive feedback information and the friend information among users, the preference of item ranking can be obtained by randomly constructing a triple < positive feedback, friend feedback, negative feedback > [9].

G-BPR We replace friend information with group information, and run G-BPR recommendation algorithm to get preference of item ranking by randomly constructing a triple < positive feedback, group feedback, negative feedback > .

SGBPR (Assumption 1) This method is based on Hypothesis 1 and its learning algorithm is shown in Algorithm 1.

GSBPR (Assumption2) This method is based on Hypothesis 2 and its learning algorithm is similar to that of Algorithm 1.

G_SBPR (Assumption 3) This method is based on Hypothesis 3 and its learning algorithm is similar to that of Algorithm 1.

4.3 Evaluation metrics

To evaluate the effectiveness of our proposed methods, we adopt the following four evaluation criteria:

(1) *Rec@K* The recall of user u is defined as

$$\mathrm{Re}c_{\mathrm{u}}@K = \frac{hit}{\left|u_u^{te}\right|} \tag{12}$$

where hit indicates how many of the user u's recommended lists are actually purchased by the user u. $\left|u_u^{te}\right|$ represents the number of items actually purchased by user u. Generally speaking, recall is to calculate how many items users like in the testing set appear in the recommendation list. Then we have

$$\mathrm{Re}c@K = \sum_{u \in u^{te}} \mathrm{Re}c_u@K / \left|u^{te}\right| \tag{13}$$

where $|u^{te}|$ is the number of users in the testing set. That is to say, the recall rate of the total sample is the average of the individual recall rate.

(2) *Pre@K* The Pre@K ranking metric is described as the fraction of relevant results among the top K results, and the precision of user u is defined as

$$Pre_u@K = \frac{hit}{K} \tag{14}$$

where hit indicates how many of the user u's recommended lists are actually purchased by the user u. K is defined as the number of recommended items. Generally speaking, precision is the proportion of the items that users like in the recommendation list. So we can describe Pre@K as

$$Pre@K = \sum_{u \in u^{te}} Pre_u@K/\left|u^{te}\right| \tag{15}$$

That is to say, the precision of the total sample is the average of the individual precision.

3) *MRR@K* MRR@K ranking metric examines the pros and cons of the list set of recommended items, depending on the location of the first correct item. The more advanced the first correct item is, the better the result will be. Then there is definition as follows:

$$MRR@K = \sum_{u \in u^{te}} \frac{1}{rank_u}/\left|u^{te}\right| \tag{16}$$

where $rank_u$ represents the location of the first predicted product in user u's recommendation list.

4) *MAP@K* MAP@K is used to evaluate the mean average precision. First, the average precision of a single user u is defined as follows:

$$AP_u@K = \sum_{i=1}^{K} (Pre_u@i)/hit \tag{17}$$

where $Pre_u@i$ represents the precision when the recommended list length is i. *hit* represents the number of accurate predictions when the recommended list length is K. Generally speaking, MAP@K is the mean of AP@K for all users. So we can describe MAP@K as

$$MAP@K = \sum_{u \in u^{te}} (AP_u@K)/\left|u^{te}\right|. \tag{18}$$

4.4 Result analysis and discussion

In this section, we first show the recommended results of the data set divided by 50%/50%. By comparing the four indicators of the model (Pre@K, Rec@K, MRR @K and MAP@K), we draw a preliminary conclusion. Then, we try to find out the influence of different levels of social links and group links on recommendation performance by analyzing the level of social links and group links of users.

4.4.1 Recommendation performance comparison

Table 4 shows the recommendation performance of the compared methods in detail. We explain the results from the following three points. Firstly, it can be seen from the results that the proposed methods are obviously superior to the two benchmark methods. From the results of the two benchmark methods, we can see that for the traditional Bayesian personalized recommendation algorithm which only uses user-item interaction information, the integration of friend information improves the recommendation results. Similarly, the integration of group information can also improve recommendation results. Secondly, from the results of our three methods, G_SBPR is better than SGBPR, and SGBPR is better than GSBPR. From this result, we can see that the integration of group information and friend information into traditional recommendation system can make up for the problem of data sparsity. It is worth noting that group information and friend information are not as different as we naturally think. On the contrary, there is little difference between group information and fiend information. Compared with the hypothesis that friend feedback and group feedback are used to construct partial ordering relationship, the assumption that no partial ordering relationship is constructed can better improve the recommendation effect.

Furthermore, we compare the results of the three methods with that of G-BPR, trying to verify whether the improvement of recommendation results is entirely caused by group information. The results show that both G-BPR and SGBPR are better than GSBPR, while SGBPR and G-BPR have similar results, but SGBPR has three indicators better than G-BPR. From this result, we can conclude that the improvement of recommendation results comes not only from the integration of group information, but also from the integration of friend information. At the same time, we can see that S_GBPR is superior to GBPR in four indicators. This shows that although the influence of group information is greater, the strategy of undifferentiated fusion of group information and friend information is better than using group information only. We can see that the fusion of multiple information (group information and friend information) is better than that of single group information. The key is how to integrate. This is in line with our initial assumption that the

Table 4 Evaluations on the models

Methods	Pre@10	Rec@10	MRR@10	MAP@10
BPR	0.021574	0.009126	0.050496	0.010202
SBPR	0.037276	0.014186	0.081131	0.019337
G-BPR	0.042761	0.015664	0.092385	0.024346
SGBPR	0.042537	0.016277	0.092443	0.024360
GSBPR	0.039988	0.015336	0.091327	0.022534
G_SBPR	**0.043210**	**0.016384**	**0.093220**	**0.024489**

Bold value indicates best performance

Table 5 Social links and group links of users in training and testing sets

	Training set	Testing set
Numbers of user	3000	2452
Numbers of users with social links	1128	633
Numbers of users with group links	2476	1342

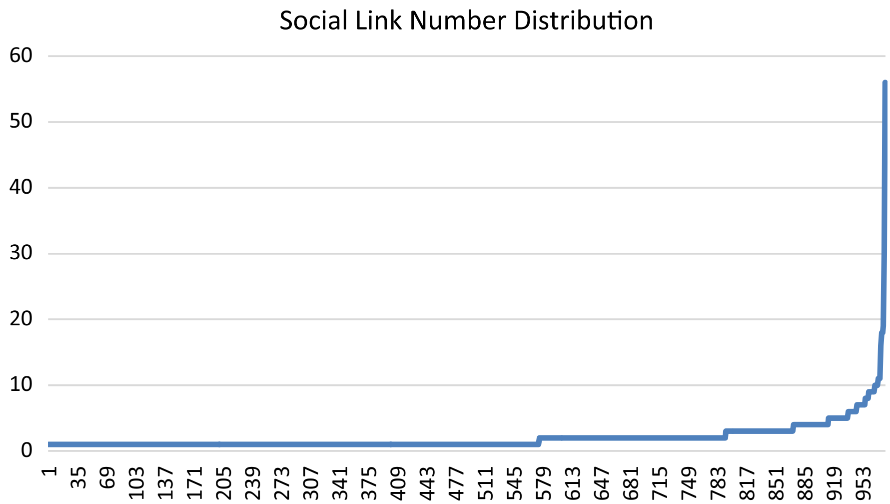

Fig. 2 Social link number distribution

group-adding behavior is spontaneously joined by users because of their common interests. In our data set, it is because users like the same artists or music that they spontaneously form groups. Because groups are formed based on users' personal preferences, items that users in the same group like are also likely to be users' preferences. Friend information is a result of users' two-way choice, and the preferences of friends can be regarded as the independently preferences of users themselves.

4.4.2 The impact of friends and groups on recommendation performance

We make a simple analysis of social links (user–user link in the friend relations) and group links (user–user link in the group relations) of users in training and testing sets, as shown in Table 5.

Table 5 reflects the basic situation of our experimental data. The users of the testing set are all from the users of the training set. Our experiment is based on the training model to get the recommendation list of all users and compares with the actual list of users in the testing set. Thus, we can only consider the friend information and group information of users in the testing set.

Figures 2 and 3 show the number distribution of social links and group links, respectively. From Fig. 2, we can see that the distribution of social links is very centralized, the vast majority of links are less than or equal to 2, and users with more

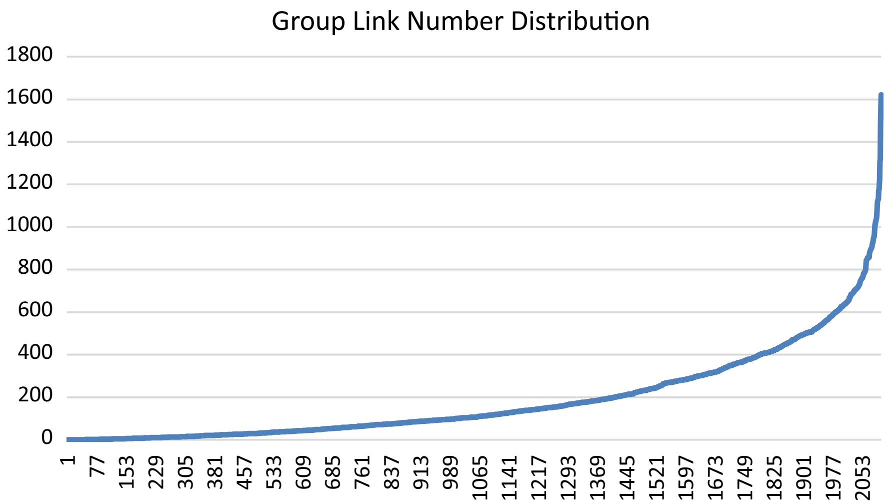

Fig. 3 Group link number distribution

than 5 links are very rare. From Fig. 3, we can see that the distribution of group links is relatively scattered.

To ensure the statistical significance of the analysis, we only consider the links of at least 30 users. Therefore, we set the social link level to [1–4], and observe performance of G_SBPR under different social link levels. The results are shown in Fig. 4.

From the results in Fig. 4, with the number of friends increasing, the recommended indicators have an approximate trend of getting better and better. From the Pre@10 ranking index, the recommendation performance is best when the number of friend links is 4. From the Rec@10 ranking index, the recommendation

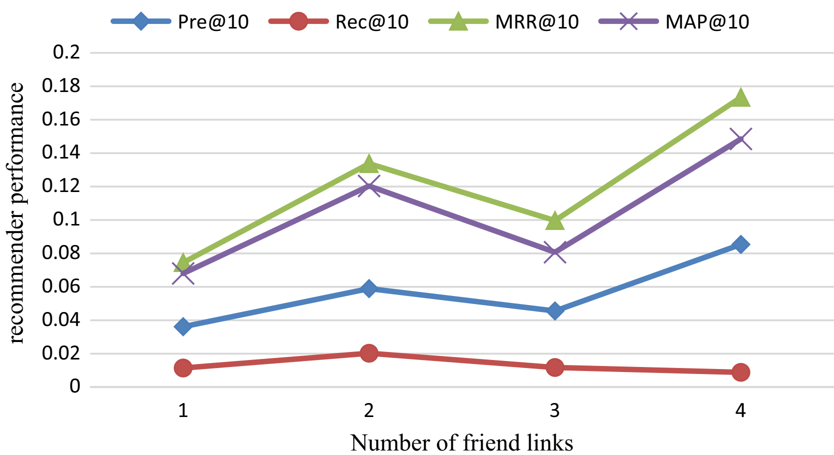

Fig. 4 G_SBPR model performance at different friend link levels

performance is better when the number of friend links is 2. From the MRR@10 ranking index, the recommendation performance is better when the number of friend links is 4. From the MAP@10 ranking index, the recommendation performance is better when the number of friend links is 4.

From these results, with the increase of the number of links to friends, Pre@10, MRR@10 and MAP@10 fluctuate upward for the level of links to friends. For this data set, the best recommendation is when the number of friend links is 4.

Next, let's look at group links. The distribution of group links is more uniform. We divide them into the following intervals: [0,150), [150,300), [300,450), [450,600), [600,750), [750,900), [900, 1050), [1050, 1200), [1200, 1350), [1350, 1500), [1500, 1650). Similarly, we only consider the group links of at least 30 users. Then we oberve the performance of G_SBPR at these group link levels. The results are shown in Fig. 5.

From the results in Fig. 5, the performance of the model at different levels of group links is similar to that of social links. As we can see, with the increase of group links, the recommended indicators have an approximate trend of getting better and better. From the Pre@10 ranking index, the recommendation performance is better when the number of group links is in the range of [600,750). From the Rec@10 ranking index, the recommendation performance is the best when the range of group links is [600,750) and [300,450); from the MRR@10 ranking index, when the range of group links is [600,750], the recommendation performance is better; from the MAP@10 ranking index, the range of group links is [600,750], the recommendation performance is better.

Generally speaking, when the horizontal range of group links is [600,750], the recommendation performance of group links is the best. And with the increase of group links, the four indicators show an upward trend of fluctuation.

In summary, the recommendation effect is affected by the level of social links and group links. Similarly, the experimental results are realistic. In the real world, the number of personal friends relative to the total number of users is very sparse,

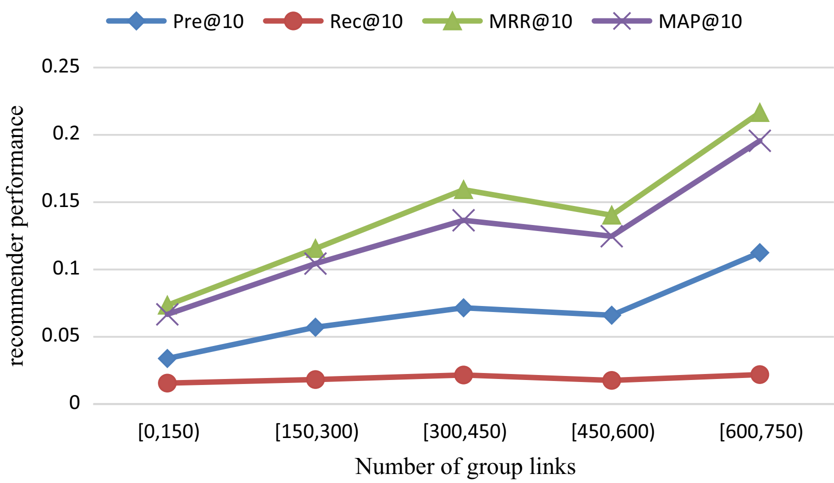

Fig. 5 G_SBPR model performance at different group link levels

only a few people have relatively more friends. Friendship, as a mutual choice, is a way to reflect the diversity of user preferences. There are many things a user likes, so a user's preferences need to be expressed from multiple dimensions. Therefore, the more friends, the more comprehensive the user's personal preferences can be expressed through his friends. The reason why the fluctuation is rising is that the preferences between people are different and dynamic. There are also some characteristics unique to friends, which will cause some interference to users' preferences. Similarly, groups tend to be of interest to users. Some users join fewer groups and some users join more groups. Relatively speaking, the larger the number of users, the more comprehensive the user preferences will cover. If the number of users is small, it is likely that there are potential interest groups that have not been found. Therefore, the more group links, the user preferences can be expressed more front. The reason for the rise in volatility is similar to that of social friends.

4.4.3 Comparison of results under different sparsity level

In order to prove the validity of the experiment, we supplement the data set on 20%/80% partition. Similarly, we divide the data set s into two parts. First, we determine whether the user's interaction item is greater than or equal to 5. For users with no less than five interactive projects, we divide each user's project into 80% training set and 20% testing set. For users whose interaction items are less than 5 items, we allocate them into training sets. Finally, the training set and testing set of the experiment are obtained. In addition, according to the training set, we can get friend feedback set and group feedback set. The experimental results are similar to the 50%/50% partition, but the improvement effect is different compared with the benchmark method. The performance improvement effect is shown in Table 6.

From this table, we can see that the performance improvement for 50%/50% data set is better than the data set divided by 80%/20% data set. It is demonstrated

Table 6 The performance improvement effect under different sparsity level

	BPR	SBPR	**G_SBPR**	Improve(BPR) (%)	Improve(SBPR) (%)
50% training set and 50% testing set					
Pre@10	0.021574	0.037276	0.043210	***100.28***	***15.92***
Rec@10	0.009126	0.014186	0.016384	***79.54***	***15.49***
MRR@10	0.050496	0.081131	0.093220	***84.61***	***14.90***
MAP@10	0.010202	0.019337	0.024489	***140.05***	***26.64***
80% training set and 20% testing set					
Pre@10	0.016503	0.028159	0.031209	**89.10**	**10.83**
Rec@10	0.015133	0.023908	0.026107	**72.52**	**9.20**
MRR@10	0.049732	0.070853	0.090704	**82.38**	**28.02**
MAP@10	0.009698	0.01564	0.201159	**107.43**	**28.62**

Bold value indicates the percentage of improvement

Italic values are used to distinguish different divisions of data that when the data is more sparse, the effectiveness of adding friend and group information is better.

4.5 Robustness analysis

In this part, we analyze the robustness of K value of four experimental evaluation metrics. The experimental results are shown in Table 7.

From the results, we can see that the length of the recommended list K has a certain impact on the results, but the overall impact is small. When K is 5, G_SBPR performs best in the evaluation indicators Pre@K, MRR@K and MAP@K; when K is 10 and 15, G_SBPR performs best in the four evaluation indicators; and when K is 20, G_SBPR performs best in the evaluation indicators Rec@K and MRR@K. In conclusion, G_SBPR is less affected by K value. The proposed method G_SBPR has good performance at different K values.

Table 7 The impact of K on the models

		K=5	K=10	K=15	K=20
Pre@K	BPR	0.023369	0.021574	0.020636	0.019647
	SBPR	0.040131	0.037276	0.034625	0.033044
	G-BPR	0.047431	0.042761	0.039033	0.036419
	SGBPR	0.047838	0.042537	0.038377	**0.037551**
	GSBPR	0.045392	0.039988	0.036909	0.034074
	G_SBPR	**0.048532**	**0.043210**	**0.039084**	0.036327
Rec@K	BPR	0.005294	0.009126	0.013033	0.016370
	SBPR	0.008159	0.014186	0.019577	0.024796
	G-BPR	0.009179	0.015664	0.021240	0.025769
	SGBPR	**0.010060**	0.016277	0.021438	0.021493
	GSBPR	0.008786	0.015336	0.020727	0.025022
	G_SBPR	0.009775	**0.016384**	**0.021465**	**0.025779**
MRR@K	BPR	0.045378	0.050496	0.052757	0.053892
	SBPR	0.073974	0.081131	0.083567	0.085002
	G-BPR	0.086429	0.092385	0.094656	0.095921
	SGBPR	0.085794	0.092443	0.094621	0.094453
	GSBPR	0.085056	0.091327	0.093357	0.094283
	G_SBPR	**0.087051**	**0.093220**	**0.095293**	**0.096469**
MAP@K	BPR	0.013458	0.010202	0.008883	0.008197
	SBPR	0.025241	0.019337	0.016789	0.015429
	G-BPR	0.031610	0.024346	0.020042	0.019009
	SGBPR	0.032044	0.024360	0.020796	**0.020005**
	GSBPR	0.030099	0.022534	0.019373	0.017511
	G_SBPR	**0.032047**	**0.024489**	**0.020860**	0.018900

Bold value indicates best performance

5 Conclusion and future work

In this paper, we proposed a social recommendation framework to leverage friend and group information to improve the recommendation performance. We introduce three Hypotheses to consider different feedbacks and extend the BRP method from different perspectives. In addition, we have showed the effectiveness of friend and group information on recommendation performance. We gave a deep analysis on how the friend information and group information affect the performance. Finally, the G_SBPR achieved the best performance. Our model has an improvement of more than almost 80% in terms of BRP method and almost 15% in terms of SBPR method at 50/50 data set. Our model also has an improvement of more than 70% in terms of BRP method and 9% in terms of SBPR method at 80/20 data set.

At the same time, our research has practical business value. As an effective tool to promote the development of socialized commerce, social recommender system can provide targeted products and services to users and improve their satisfactions. The research in this paper extends the social recommender system well, making the social recommendation more accurate and the social communication more effective. Experiments show that when we make good use of social information (friends and group information in this research), we can improve the accuracy of social recommendation and better promote the development of social commerce.

However, our research still has some limitations. Firstly, our data only contain 3000 users and it is limited. We will enlarge the data set and conduct large scale experiments to make our findings more strong. Secondly, only friend and group information are considered in this paper. There may be other kinds of social information in online social networks. We will consider more social information and design better social recommender system. Thirdly, deep learning is very hot in recent and we will consider deep learning models to build the social recommender system.

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