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Research Article

Topological Influence-Aware Recommendation on Social Networks

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Users in online networks exert different influence during the process of information propagation, and the heterogeneous influence may contribute to personalized recommendations. In this paper, we analyse the topology of social networks to investigate users' influence strength on their neighbours. We also exploit the user-item rating matrix to find the importance of users' ratings and determine their influence on entire social networks. Based on the local influence between users and global influence over the whole network, we propose a recommendation method with indirect interactions that makes adequate use of users' relationships on social networks and users' rating data. The two kinds of influence are incorporated into a matrix factorization framework. We also consider indirect interactions between users who do not have direct links with each other. Experimental results on two real-world datasets demonstrate that our proposed framework performs better than other state-of-the-art methods for all users and cold-start users. Compared with node degrees, betweenness, and clustering coefficients, coreness constitutes the best topological descriptor to identify users' local influence, and recommendations with the measure of coreness outperform other descriptors of user influence.

1. Introduction

As the amount of information available online increases exponentially, it becomes more difficult for users to find the relevant information or contents in which they are interested, thereby resulting in an information overload problem. Recommender systems play an important role in tackling the problem of information overload and have attracted more attention in both academia and industry in recent years [1–7]. Such recommender systems have been used in many domains, including product recommendation on Amazon and movie recommendation on Netflix.

Collaborative filtering (CF) is one of the most popular techniques in recommender systems. Some CF methods that use only user-item ratings for recommendation confront cold-start problems. More specifically, for a new user in such recommender systems, because he/she has given few ratings, these CF algorithms perform poorly for the user. The situation is similar for a new item in recommender systems.

Given the rapid increase of online social networks and applications, users participate in online activities and produce a lot of social relationships, such as social friendships and trust relationships. In the real world, we always ask our trusted friends for movie and book recommendations. Social relationships provide an independent source of information for recommender systems in addition to user-item rating information. Social relationships among users can be incorporated into memory-based CF methods and matrix factorization methods in the recommendation process. Social influence theory in [8] indicates that correlations exist between two socially connected users; therefore, social relationship networks can be used for recommender systems. Social relationships provide opportunities to handle new users and improve the performance of recommender systems.

Some work has been done to exploit social relationship networks of users in recommender systems and improve the performance of recommender systems [9–14]. These methods assume that a user's taste can be affected by his/her trusted friends, and they take advantage of trusted relationships and friendships for recommendations in addition to user-item ratings. These methods incorporate direct trust relationships among users into matrix factorization to learn user preference vectors and item feature vectors. However, few works explore user influence in view of social network structure. Tang *et al.* [11] adopted PageRank algorithm on social networks to determine the reputations of users. Current social recommendation methods often use the rating similarity between users to measure the influence that a user exerts on his/her neighbours. However, it is not sufficient to consider the influence strength simply as the rating similarity. These methods do not take into account users' different roles in the network, which efficiently indicate users' influence in the process of information sharing through social networks.

In this paper, we investigate users' influence on their neighbours and the entire network, and we incorporate the influence into recommender systems. We exploit the topology of social networks to determine the local influence of each user and determine his/her global influence based on the number of his/her ratings. Both local and global influences are applied in the matrix factorization framework. In addition to the effect of trusted friends, we consider indirect interactions from users that have a high reputation. Experimental results demonstrate that our proposed algorithm outperforms other state-of-the-art recommendation models. Within this framework, the main contributions of this work include the following.

(i) We explore the topological influence of users according to their roles on social networks and incorporate the topological influence into recommendations.

(ii) In addition to the influence between socially linked users, we also consider the influence of indirect interactions among users, which can improve the recommendation performance.

(iii) Our proposed recommendation framework reduces recommendation errors, particularly for cold-start users.

The rest of this article is organized as follows. In Section 2, we provide an overview of several major approaches for recommender systems. In Section 3, we detail our proposed recommendation framework. The experimental results and empirical analysis are presented in Section 4. Section 5 presents the conclusions and suggestions for future work.

2. Related Work

In this section, we review several approaches for recommender systems, including (1) collaborative filtering systems that use only the user-item rating matrix and (2) social-based recommender systems that have attracted lots of attention recently.

Collaborative filtering is a widely used recommendation method. Generally, it is based on the assumption that similar users have similar preferences on common items. CF contains memory-based collaborative filtering [1, 15, 16] and model-based collaborative filtering [17, 18]. Memory-based CF methods use user-item ratings to calculate similarities between pairs of users or items and to identify neighbours of a target user or item and then make the prediction based on the weighted sum of ratings from neighbour users or items. However, memory-based methods are not efficient for highly sparse data as it is difficult to estimate the similarities accurately from the data. Model-based collaborative filtering methods train a predictive model based on patterns recognized from the known user-item ratings and then make recommendations via the predictive model. Among different model-based methods, low-rank matrix factorization (MF) techniques have attracted much attention [17–19] due to the advantages of scalability and accuracy.

Based on the assumption that users' tastes can be represented by a small number of latent factors, the MF method in [19] decomposes the $m \times n$ user-item rating matrix R into a user feature matrix $U \in R^{m\times d}$ and an item feature matrix $V \in R^{n\times d}$, shown as

$$R \approx UV^T, \tag{1}$$

where m and n are the number of users and items, respectively. The estimated rating of item j given by user i is $U_i V_j^T$. The matrices U and V can be learned by minimizing the sum-of-squared-errors objective function in

$$L = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}\left(R_{ij} - U_i V_j^T\right)^2 + \frac{\lambda}{2}\|U\|_F^2 + \frac{\lambda}{2}\|V\|_F^2, \tag{2}$$

where I_{ij} is the indicator function that equals 1 if user i has given a rating to item j and 0 otherwise. The regularization terms $\|U\|_F^2$ and $\|V\|_F^2$ are used to avoid overfitting. The optimization of (2) is generally solved by performing stochastic gradient descent.

Recently, some social recommendation methods based on matrix factorization techniques have been proposed to directly use trust relationships among users to provide better recommendations. These methods show substantial improvements [9, 12, 20–23] and relieve the cold-start problem [24–26]. One effective method for integrating social relationships into the MF model is to jointly factorize the user-item rating matrix and user-user social relationship matrix by sharing a common user feature matrix [9]. According to the same user feature matrix, information from social relationships can be transferred to improve the recommendation performance. However, an experimental analysis shows that this method is suitable for the membership links, but not very capable of handling the friendship links [27].

One more effective way to utilize social relations, as discussed in [9], is to introduce social regularization into the MF framework [12]. Social regularization constrains the difference between a user's latent vector and that of his/her friends. It is based on the assumption that a user's taste is similar to his/her directly connected friends. Experiments show that social regularization is more suitable for incorporating social relationships into MF than the joint factorization models. These recommendation models do not reflect the real-world process that users make decisions based on their own tastes and friends' influence. In [21], the authors incorporated the real-world decision-making process into recommendations and simultaneously fused the target user's interest and the interests of his/her trusted friends to predict the missing ratings. Using this method, the influence strength of friends is treated as the same. Recently, trust-ware recommender systems have focused on both online and offline trust relationships. A new trust-ware recommendation method USBN [28] combined online and offline social trust to improve the personal recommendation performance.

A few works have been done based on heterogeneous friends' influence in social recommendations [10, 29–31]. Friendships on social networks are different from trust relationships because friendships are bidirectional, and the interests of friends are heterogeneous [32]. In [10], the authors tried to treat friends separately according to rating similarities. They extended the regularization model by weighting each social link regularization term with the rating similarity between users. There are many kinds of relationships and interactions on online social networks [33, 34]. Therefore, it is not sufficient to consider the influence strength simply as rating similarities. For example, in a microblog network, direct interactions include users' mentions, reposts, and comments. In [30], Li and Xiong explored multiple direct interactions between users in a microblog network. They extended the regularization model by considering the direct interactions, and they inferred the influence by the number of mentions, reposts, and comments. In addition to user-item ratings and user-user relationships, some additional information from online user behaviours can also be combined with recommender systems. In [31], the authors considered different influences of friends and different levels of willingness to be influenced in social recommendations. The influence of friends and different levels of willingness to be influenced are generated by using a social influence propagation method on social networks.

3. Proposed Recommendation Framework

3.1. Local Social Influence. In the majority of cases, the influence between two users only takes effect at the local scale [23]. We define this type of influence as local influence (LI). In [35], the authors analysed the most influential nodes on social networks and found that coreness of nodes can represent the centrality and influence of nodes in network graphs more accurately than degrees and betweenness of nodes. Based on this theory, we first analyse the topological influence with respect to coreness and how this kind of influence is distributed in the chosen datasets; we then propose the calculation method of users' local influence according to their coreness in the network topology. In graph theory, a *k-core* of a graph G is the maximal connected subgraph of G in which degrees of nodes are at least k. Equivalently, it is one of the connected components of the subgraph of G formed by repeatedly deleting all nodes if their degrees are less than k. A node u has coreness c if it belongs to a c-core but not to any $(c+1)$-core.

Based on this definition of *k-core*, a node with a larger coreness means that it is at a location closer to the centre of the network, which implies that it may influence more users of the network and the influence may be strong because of its location in the network. If a hub exists at the edge position of the network, it will have a minimal impact in the influence propagation process of the network, whereas a less connected node placed in the core of the network will have a significant effect in the influence propagation process in the whole network. Thus, in this paper we define a node's influence proportional to its coreness. Figures 1(a) and 1(b) show the distribution of coreness of the two chosen datasets described in Section 4.1.

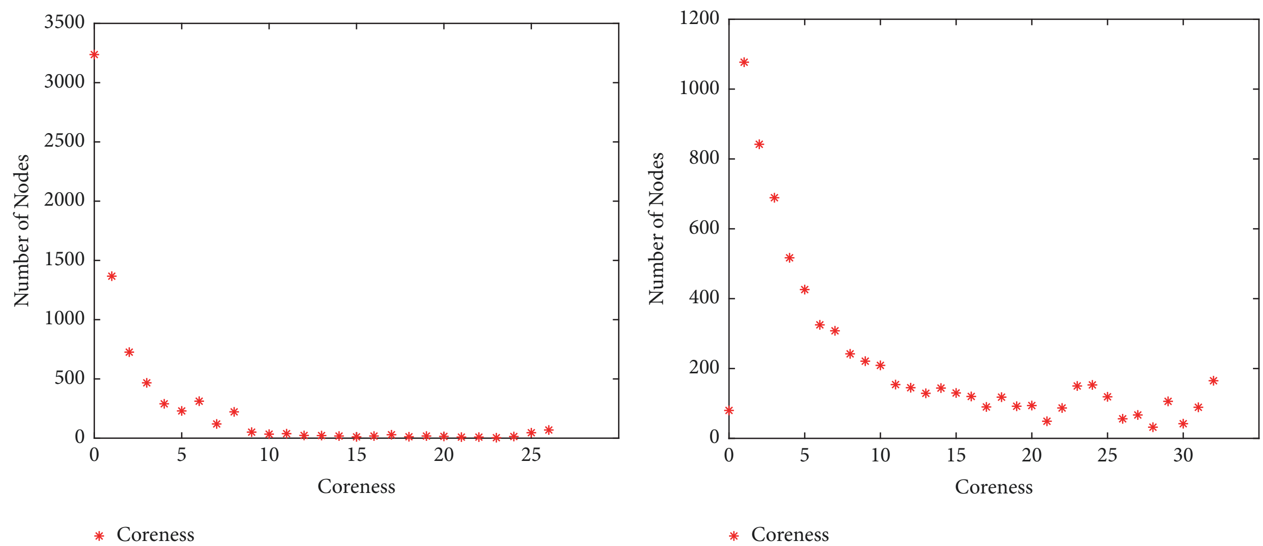
In the Epinions dataset, most nodes' coreness is smaller than 10, and the proportion is 94.75%. This distribution may be because this network fits the power-law distribution and a large long tail of users has a very small coreness. The smallest coreness is 0 and the biggest coreness is 26 in the Epinions dataset. Unlike the Epinions dataset, in the Ciao dataset, the proportion of nodes in which coreness is smaller than 10 is 65.05%, implying different network hierarchies and influence distributions of the two chosen datasets. The smallest coreness is 0 and the biggest coreness is 32 in the Ciao dataset.

We define a user i's coreness as c_i. We normalize coreness before calculating the values of the local influence of the nodes in trust networks so that the values of local influence are in the $[0, 1]$ range. We use the notation nc_i to represent the normalized value of user i's coreness in trust networks. We use the notation LI_i to represent the value of user i's local influence in trust networks. It is obvious that LI_i should vary monotonously with nc_i. We define LI_i in

$$LI_i = \tanh(nc_i + \alpha). \tag{3}$$

If user i has a larger coreness, his/her friends are affected more strongly by him/her, leading to larger LI_i. The parameter α is an offset used to make the values of local influence of users above 0. The hyperbolic tangent function $f = \tanh(x)$ is chosen to map the coreness to the value of local influence nonlinearly and limit LI_i in the $(0, 1)$ range. We also investigate other generating functions of local influence and compare their effects on recommendations in Section 4.5.

3.2. Global Influence. A user's global influence indicates his/her reputation in the whole network. The user's reputation is a sort of status that gives additional powers and capabilities in recommender systems [11]. In the physical world, the user's reputation plays an important role in recommendation [36]. In [37], the authors found that suggestions from people with high reputations positively affect consumers' adoption of a brand. Massa [3] found that, in the online world, recommendations from users with high influence in entire networks are more likely to be trustworthy and reliable. In this paper, we use the notation GI_i to represent user i's global influence over the entire social network. On online shopping websites, we are more likely to trust those users who have bought more items or rated more items. Based on this intuition, in our proposed recommendation method, we use the number of ratings given by a user to measure the user's global influence. We define NoR_i as the number of ratings



(a) Epinions

(b) Ciao

Figure 1: The distribution of coreness in different datasets.

given by user i. We normalize NoR_i, and the expression of GI_i is presented in (4), analogous to (3):

$$GI_i = \tanh\left(NNoR_i + \alpha\right), \tag{4}$$

where $NNoR_i$ represents the normalized value of NoR_i and α is an offset to make the values of GI_i stay above 0. We investigate other generating functions of global influence in Section 4.5.

3.3. Indirect Interactions. In the real world, in addition to asking our friends for suggestions, we tend to take into account the suggestions of some persons who have high reputations in the community, even if they are not our friends and we have no direct interactions with them. In online networks, a celebrity's opinion is likely to affect the actions of other users even if they do not follow the celebrity. Indirect interactions between users will also affect users' actions, so indirect or implicit user connections should be emphasized [38]. For example, on Twitter, a celebrity's tweet that recommends a book may be retweeted by some users that are both the celebrity's followers and friends of the target user. When the target user sees the tweet, he/she may adopt the suggestion. Based on such a tendency, in our proposed recommendation method, we take into account indirect interactions between users. More specifically, if user j is not a trusted friend of user i but has high influence on the social network, user i's behaviours are likely to be influenced by user j. Therefore, for user i, those users who are not his/her trusted friends but have top-K coreness are considered to make recommendations for him/her.

3.4. Recommendation Approach. With LI and GI as previously defined, we present our method of recommendation with direct and indirect social influence (RDISI). Based on the idea that a user's taste is close to that of his/her trusted friends, we introduce a regularization term as shown in Eq. (5), which constrains a user's latent vector in terms of friends' local influence. The notation $F^{+}{}_{(i)}$ denotes the set of friends of user i:

$$\frac{\beta}{2}\sum_{i=1}^{m}\sum_{f\in F_{(i)}{}^{+}} LI_f \left\|U_i - U_f\right\|_F^{2}. \tag{5}$$

The parameter $\beta(\beta > 0)$ is used to control the importance of this regularization term. In terms of indirect interactions, as discussed in Section 3.3, users with high local influence can also affect other users' behaviours. Therefore, a user's taste is affected by such users and, in our method, a user's feature vector should also be close to that of the users with high local influence. In addition to the regularization term in (5), we also introduce another regularization term as shown in (6). $N_{(i)}{}^{K+}$ is the top-K users in terms of the value of local influence of users who are not user i's trusted friends:

$$\frac{\beta}{2}\sum_{i=1}^{m}\sum_{g\in N_{(i)}{}^{K+}} LI_f \left\|U_i - U_f\right\|_F^{2}. \tag{6}$$

As previously discussed, recommendations from users with high global influence are more likely to be trustworthy and reliable. Therefore, we use the values of users' global influence to weight the importance of their recommendations so as to incorporate global influence into MF. In the MF framework, the weight of R_{ij} in (2) is determined by I_{ij}, which is equal to 0 or 1. In RDISI, we also consider the global influence of user i, so we define the new weight for R_{ij} as $W_{ij} = \gamma \cdot I_{ij} \cdot GI_i$. Therefore, the importance of R_{ij} is controlled by W_{ij}, and parameter γ is used to control the importance of global influence.

The method incorporates two kinds of social influence into recommendation to improve the performance of recommender systems. The optimization problem minimizes

Input: List of training triples (user id, item id, rating), list of tuples (user id, trustee id), the dimensionality of user feature vector and item feature vector d, the learning rate η, the parameters γ, α, and β.
Output: User-user trust matrix, user-item rating matrix, local influence vector LI, global influence vector GI, user feature matrix U, and item feature vector V.
1: Generating user-item rating matrix and user-user trust matrix
for each triple (u_i, v_j, R_{ij}) **do**
    $train\_matrix(i, j) = R_{ij}$
end for
for each tuple (u_i, u_k) **do**
    $trust\_matrix(i, k) = 1$
end for
2: Calculating local influence and global influence
for $i = 1 : m$ **do**
    calculate nc_i
    calculate LI_i using Eq. (3)
    calculate $NNoR_i$
    calculate GI_i using Eq. (4)
end for
3: Initialize U and V randomly
while not convergence **do**
    calculate $\partial U/\partial L$ according to Eq. (8)
    calculate $\partial L/\partial V$ according to Eq. (9)
    update $U \longleftarrow U - \eta \cdot \partial L/\partial U$
    update $V \longleftarrow V - \eta \cdot \partial L/\partial V$
end while

Algorithm 1: The proposed recommendation method RDISI with direct and indirect social influence.

the sum-of-squared-error objective function shown in the following:

$$\begin{aligned}\min_{U,V} L = {} & \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} W_{ij}\left(U_i V_j^T - R_{ij}\right)^2 \\ & + \frac{\beta}{2}\sum_{i=1}^{m}\sum_{f\in F_{(i)}^{+}} LI_f \left\|U_i - U_f\right\|_F^2 \\ & + \frac{\beta}{2}\sum_{i=1}^{m}\sum_{g\in N_{(i)}^{K+}} LI_f \left\|U_i - U_g\right\|_F^2 + \frac{\lambda}{2}\|U\|_F^2 \\ & + \frac{\lambda}{2}\|V\|_F^2\end{aligned} \tag{7}$$

A local minimum of the objective function given by (7) can be found by performing gradient descent in feature vectors U_i and V_j, as shown in the following:

$$\begin{aligned}\frac{\partial L}{\partial U_{\mathrm{i}}} = {} & \sum_{j=1}^{n} W_{ij}\left(U_i V_j^T - R_{ij}\right) V_j + \beta \sum_{f\in F_{(i)}^{+}} LI_f \left(U_i - U_f\right) \\ & + \beta \sum_{g\in F_{(i)}^{-}} LI_i \left(U_i - U_g\right) \\ & + \beta \sum_{h\in N_{(i)}^{K+}} LI_h \left(U_i - U_h\right) \\ & + \beta \sum_{p\in N_{(i)}^{K-}} LI_i \left(U_i - U_p\right) + \lambda U_i\end{aligned} \tag{8}$$

$$\frac{\partial L}{\partial V_j} = \sum_{i=1}^{m} W_{ij}\left(U_i V_j^T - R_{ij}\right) U_i + \lambda V_j, \tag{9}$$

where notation $F_{(i)}^{-}$ means user i's in-link friends and $N_{(i)}^{K-}$ is the set of users among whose nontrusted users user i is in the top-K list in terms of coreness.

3.5. Training and Prediction. Three steps are designed to train our proposed model.

Step 1. It is to generate the user-user trust matrix with trust relationships and then calculate coreness of each node in the trust network from the trust matrix. We normalize the values of coreness and then calculate the values of local influence according to (3).

Step 2. It is to generate the user-item rating matrix with rating data. We use the user-item rating matrix to calculate the number of ratings for each user. We then normalize the numbers of users' ratings and calculate the global influence using (4).

Step 3. It is to use stochastic gradient descent to find the optimal user feature matrix U and item feature matrix V.

The details of the steps are shown in Algorithm 1.

3.6. Complexity Analysis. The main cost in learning U and V is computing the loss function L and its gradients against feature vectors of users and items. Because of the sparsity of rating matrix R and trust relationships matrix T, the computational complexity of evaluating the loss function L is

$O(\epsilon_R d+\epsilon_T d+md)$, where d is the dimensionality of the feature vectors of users and items, m is the number of users, and ϵ_R and ϵ_T are the numbers of nonzero entries in matrices R and T, respectively. The computational complexities for gradients $\partial L/\partial U$ and $\partial L/\partial V$ in (8) and (9) are $O(\epsilon_R d + \epsilon_T d + md)$ and $O(\epsilon_R d)$, respectively. Therefore, the total computational complexity in one iteration is $O(\epsilon_R d + \epsilon_T d + md)$, which indicates that the computational time of our method is linear with respect to the number of users and the number of observations in the two sparse matrices. This complexity analysis shows that our proposal approach is very efficient and can scale to very large datasets. Moreover, the main cost of computing the influence is performing the *k-core* decomposition of the network to compute each node's coreness. The computational complexity of *k-core* decomposition is $O(\epsilon_T)$. Thus, if we compute the influence periodically because of the emergence of new influences, the computational cost is linear with the number of social relationships.

4. Experimental Analysis

In this section, we conduct several experiments to compare the recommendation qualities of our approach with other state-of-the-art recommendation models.

4.1. Datasets. We chose two real-world datasets to evaluate our proposed method: Epinions and Ciao. Each dataset has a trust network. The two datasets were collected from the websites http://www.epinions.com/ and http://www.ciao.co.uk/, respectively.

Epinions is an online product review website where users can read reviews about a variety of products (such as books, articles for daily use, cars, and home appliances) to help them make decisions on what to purchase. Users can also post a review after rating a product with integer scores from 1 to 5. Every member of Epinions establishes social relationships (i.e., trust relationships) with others to show his/her attitude to other users.

Ciao is an online shopping portal website in Europe. The site provides a network platform where registered users can review items and share their opinions on various products to help others make decisions. These reviews are available to the general public. Each user on Ciao also maintains a trust list to indicate his/her attitude to others.

The two datasets are crawled by Jiliang Tang et al. from two popular product review sites Epinions and Ciao in the month of May, 2011. The raw Epinions dataset contains 27 categories of items and the Ciao dataset contains 28 categories of items. These two datasets are published at Jiliang Tang's homepage at "https://www.cse.msu.edu/~tangjili/". Each of the two datasets is randomly extracted from the corresponding raw dataset so that they are not biased. The two chosen datasets have widely been used for performance evaluation.

Some statistics of these datasets are presented in Table 1. Rating data and social relationship data are both very sparse for the two datasets. The density of ratings is calculated by

$$\frac{\textit{the number of ratings}}{\textit{the number of users} \times \textit{the number of items}} \tag{10}$$

Table 1: Statistics of datasets.

	Epinions	Ciao
# of Users	7411	7267
# of Items	8728	11211
# of Ratings	276116	149147
Rating Density	0.0043	0.0018
# of Social Relationships	52982	110755
Social Relationship Density	0.00096	0.0021

The density of social relationships is calculated by

$$\frac{\textit{the number of trust relations}}{\textit{the number of users} \times \textit{the number of users}} \tag{11}$$

The statistics in Table 1 show that sparsity is quite noticeable in the two datasets, both for user-item rating matrices and user-user trust relationships. The rating data in the Ciao dataset is slightly sparser than those in the Epinions dataset. However, the social relationship density of Epinions is much sparser than that of Ciao. We divide users' rating data into the training set and test set. More specifically, for each rating dataset, we randomly choose 80% as the training set and the remaining 20% as the test set. We generate 5 random data splits of the training and test set and report the average result over the 5 splits.

4.2. Metrics. We choose four well-known metrics to measure the performance of our proposed approach in comparison with other collaborative filtering and trust-aware recommendation models. They are mean absolute error (MAE), root mean square error (RMSE), precision, and recall. The metric MAE is defined as

$$MAE = \frac{1}{T}\sum_{i,j}\left|R_{ij} - \hat{R}_{ij}\right|, \tag{12}$$

where R_{ij} denotes the rating that user i has given to item j, $\hat{R}_{ij}$ denotes the predicted rating that user i gives to item j, and T denotes the number of test ratings. The metric RMSE is defined as

$$RMSE = \sqrt{\frac{1}{T}\sum_{i,j}\left(R_{ij} - \hat{R}_{ij}\right)^2}. \tag{13}$$

From the definitions, we can see that a smaller MAE or RMSE value means a better performance.

The metric precision is defined as

$$precision = \frac{1}{m}\sum_{i=1}^{m}\frac{N_r^i}{L}, \tag{14}$$

where N_r^i is the number of recovered items in the recommendation list for user i and L is the length of recommendation list. The recommendation list for user i consists of the L items with the highest predicted score generated by the recommendation algorithm.

The metric recall is defined as

$$recall = \frac{1}{m}\sum_{i=1}^{m}\frac{N_r^i}{N_p^i}, \quad (15)$$

where N_p^i is the number of items collected by user i in the testing set. Assuming the length of recommendation list, L, is fixed, a greater precision or recall means a better performance.

4.3. Comparisons. In this section, to show the effectiveness of our proposed recommendation approach, we compare our recommendation method RDISI with the following representative models.

Probabilistic Matrix Factorization (PMF) [18]: This studies a low dimensional user feature matrix and item feature matrix to predict the ratings. This method only uses the user-item rating matrix for recommendation.

RSTE [21]: This method linearly combines a basic matrix factorization model and a trust-based neighbourhood model together and simultaneously fuses the user's interest and interests of his/her trusted friends to predict the missing ratings.

SoRec [9]: This method is based on matrix factorization and exploits local social context by performing a factorization on the social relationship matrix. The method jointly factorizes the user-item rating matrix by UV^T and the social relationship matrix by UZ^T, where U is the user feature matrix and Z is the factor feature matrix with no realistic implications.

SocialMF [12]: This method takes into account the interests of trusted friends by incorporating a regularization term into the objective function. The regularization term controls the distance between user i's feature vector and the combinational feature vector of his/her trusted friends.

SoReg [10]: This method incorporates the social regularization term into MF by weighting each social link regularization with the rating similarity between users. User similarities are used to control the distance of feature vectors between user i and his/her trusted friends.

4.4. Parameter Settings. For our method, we select optimal parameters for both datasets. Because the two datasets have different data statistics, different parameters are needed for training. The parameter α is determined through cross-validation. For the Epinions dataset, we determine the parameters $\alpha = 0.3$ and $\beta = 0.05$. Parameter γ is set as 3. For the Ciao dataset, we set the parameters $\alpha = 0.5$, $\beta = 0.04$, and $\gamma = 3$. The learning rate η is 0.0004 and $K = 1000$ in our proposed method for both datasets. The parameters of the compared recommendation methods are shown in Table 2. We set the number of latent factors as $d = 20$ and set the length of recommendation list $L = 100$ for all experiments.

4.5. Experimental Results. We randomly select 80% of data for each dataset as training data to verify our proposed method. The experiment results are shown in Table 3. The percentages in Table 3 are the improvements of our RDISI method over the corresponding approaches.

As shown in Table 3, in the Epinions dataset, SocialMF does not perform better than SoRec; SocialMF even has larger RMSE than PMF in Epinions. There may be two reasons for this: (1) the Epinions dataset has some noises, and SocialMF fails to deal with these noises well, and (2) the social relationship density of Epinions is very small, as shown in Table 1, so that SocialMF cannot take advantage of trust relationships well. From the results, we can observe that our proposed recommendation method performs better than the comparison partners.

As discussed in Section 3.4, the definition of W_{ij} is $W_{ij} = \gamma \cdot GI_i \cdot I_{ij}$. If γ is extremely large, the weight of a rating dominates in determining users' feature vectors. A very small γ means that local influence dominates in that process. To determine the best value of γ, we fix parameter β and observe the performance versus γ. In each dataset, we change the ratio of training data to 60%, 70%, and 80%. The parameters are the same for different training ratios in each dataset. In the Epinions dataset, we set $\beta = 0.05$. Awe then adjust the parameter γ in the $[0.5, 3.5]$ range. The result is illustrated in Figure 2(a). In the Ciao dataset, we set $\beta = 0.04$. The result is illustrated in Figure 2(b). Moreover, when we set the parameter γ at 4 in the Epinions dataset and 4.5 in the Ciao dataset, the values of MAE are both infinite, indicating that a very large weight of GI greatly damages the recommendation performance. The results show that the variations of MAE are similar in both datasets with different ratios of training data, and MAE achieves the lowest value in the interval $[2.5, 3]$ of γ. Therefore, the optimal value of γ does not closely correlate with the datasets, and the complexity of our method can be reduced.

Parameter β indicates the importance of trustees and celebrities. We also use three ratios of training data (i.e., 60%, 70%, and 80%) in each dataset. First, we set the other parameters at optimal values in both datasets and then adjust parameter β in the $[0.01, 0.09]$ range. The results are shown in Figure 3. The results demonstrate that an appropriate combination of influence of trustees and celebrities can improve the recommendation performance. The best value of β is similar in both datasets, implying that the parameter can be easily determined independently of the datasets.

To verify whether coreness is more effective than other indicators (e.g., node betweenness, node degrees, and clustering coefficients) on determining local influence in recommender systems, we conduct experiments to compare the performance of RDISI using betweenness, degrees, clustering coefficients, and coreness to determine users' local influence, respectively. In these comparison experiments, we merely replace nc_i in (3) with normalized node betweenness, node degrees, and node clustering coefficients, respectively. The comparison results are shown in Table 4.

The results in Table 4 clearly indicate that coreness is more effective than node betweenness, node degrees, and node clustering coefficients. Therefore, we use coreness to represent users' local influence in our recommendation method RDISI.

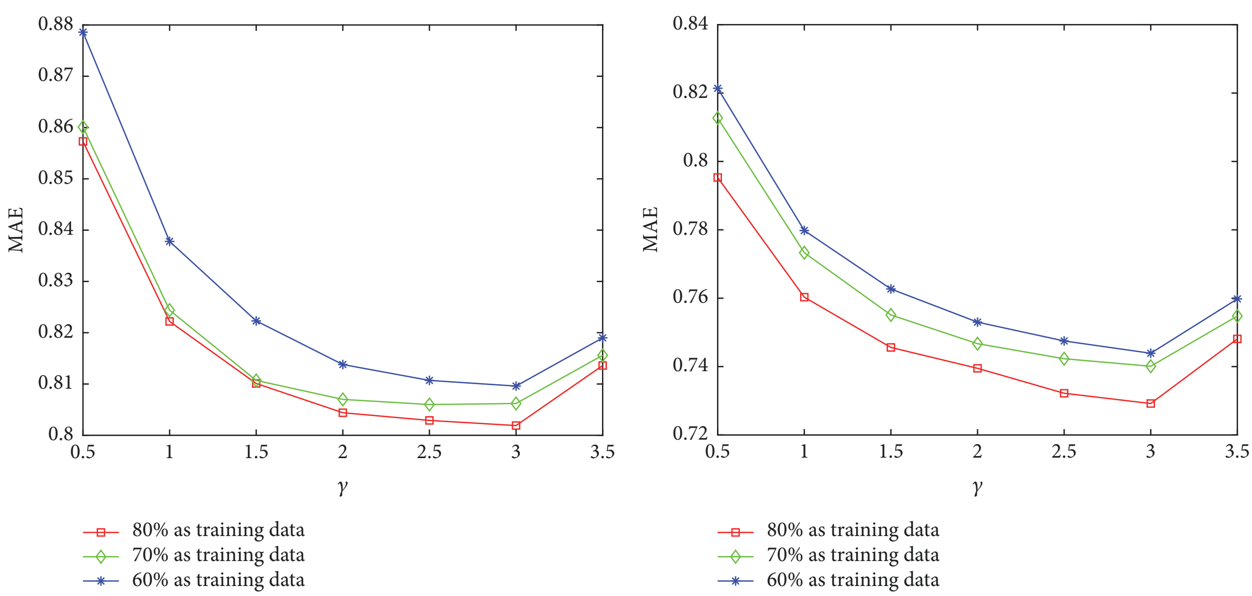
In the Epinions and Ciao datasets, some users have rated lots of items, but most users have rated only a few items. We select those users who have rated no more than 10 items in the training set as cold-start users. We conduct experiments

Table 2: Parameter settings of compared recommendation methods.

Datasets	Algorithms	Parameters
Epinions	PMF	$\eta = 0.001, \lambda = 0.08$
	RSTE	$\eta = 0.035, \lambda = 0.001, \alpha = 0.9$
	SoRec	$\eta = 0.005, \lambda = 0.003, \lambda_Z = 0.01, \lambda_C = 0.01$
	SocialMF	$\eta = 0.02, \lambda = 0.001, \lambda_T = 0.3$
	SoReg	$\eta = 0.0004, \lambda = 0.1, \beta = 5$
Ciao	PMF	$\eta = 0.01, \lambda = 0.08$
	RSTE	$\eta = 0.04, \lambda = 0.001, \alpha = 0.9$
	SoRec	$\eta = 0.02, \lambda = 0.001, \lambda_Z = 0.01, \lambda_C = 0.01$
	SocialMF	$\eta = 0.02, \lambda = 0.001, \lambda_T = 1$
	SoReg	$\eta = 0.0004, \lambda = 0.1, \beta = 5$

Table 3: Performance comparisons (MAE and RMSE).

Dataset	Metrics	PMF	SoRec	RSTE	SocialMF	SoReg	RDISI
Epinions	MAE	0.8680	0.8467	0.8564	0.8651	0.8232	**0.8011**
	Improve	7.71%	5.39%	6.46%	7.40%	2.68%	
	RMSE	1.0922	1.1105	1.1475	1.1903	1.0655	**1.0392**
	Improve	4.85%	6.42%	9.44%	12.70%	2.47%	
Ciao	MAE	0.8841	0.7991	0.7786	0.7858	0.7491	**0.7308**
	Improve	17.34%	8.55%	6.14%	7.00%	2.44%	
	RMSE	1.1353	1.1071	1.0859	1.1230	0.9904	**0.9721**
	Improve	14.38%	12.19%	10.48%	13.44%	1.85%	



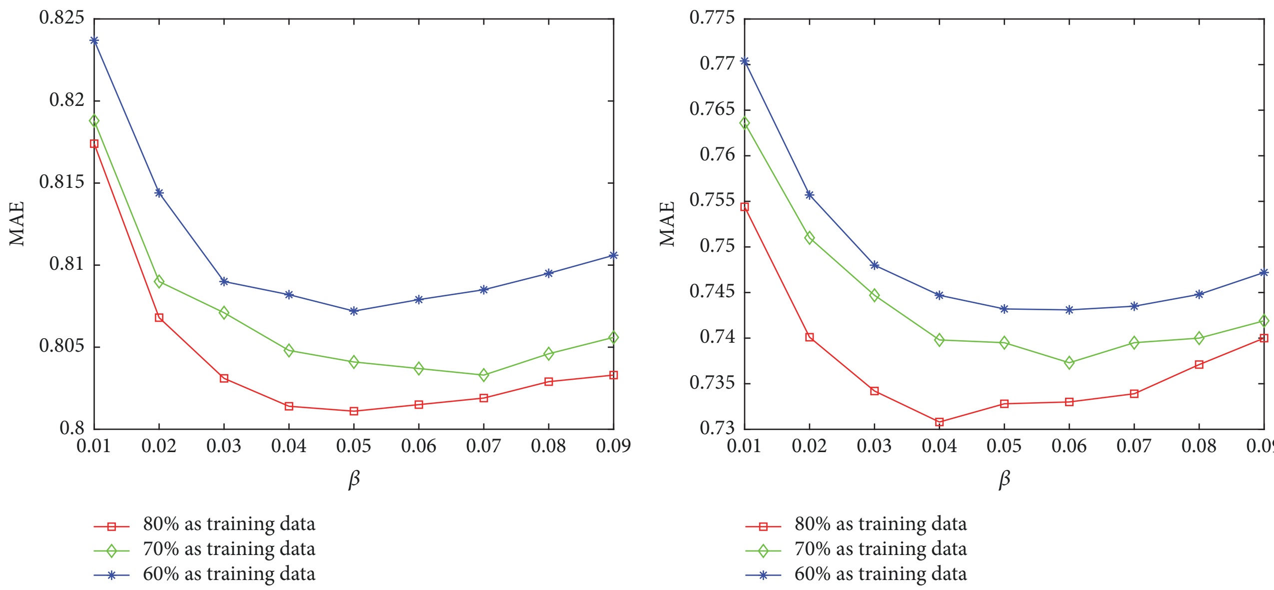
(a) Epinions

(b) Ciao

Figure 2: The effect of parameter γ in different datasets.

Table 4: Performance comparisons with other indicators (dimensionality=20).

Dataset	Metrics	Betweenness	Degree	Clustering Coefficient	Coreness
Epinions	MAE	0.8155	0.8139	0.8060	0.8011
	RMSE	1.0605	1.0581	1.0466	1.0392
Ciao	MAE	0.7382	0.7335	0.7336	0.7308
	RMSE	0.9818	0.9763	0.9762	0.9721



(a) Epinions

(b) Ciao

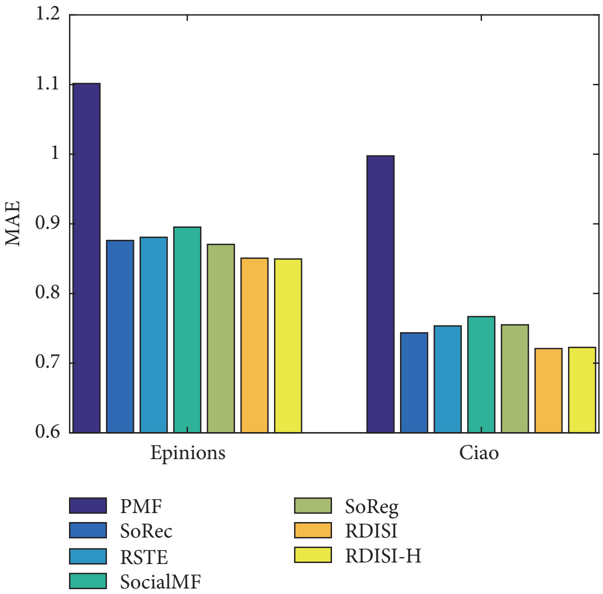
Figure 3: The impact of parameter β.

to verify whether our method RDISI performs better than other state-of-the-art recommendation models. In addition to coreness, node's *h-index* can also represent its local influence. According to Hirsch [39], a scientist who has index h means that h of his/her *Np* papers have at least h citations each, and the other (*Np*-*h*) papers have fewer than h citations each. Based on this original definition, we define the user's *h-index* in trust networks. A user i has index h if h of his/her in-link friends (i.e., the users who trust i) have at least h in-link friends each, and the other in-link friends of i have fewer than h in-link friends. Inspired by this, we propose a variant of RDISI named RDISI-H in which the user's local influence is determined by his/her *h-index* on social networks. We verify the performance of RDISI-H on cold-start users here.

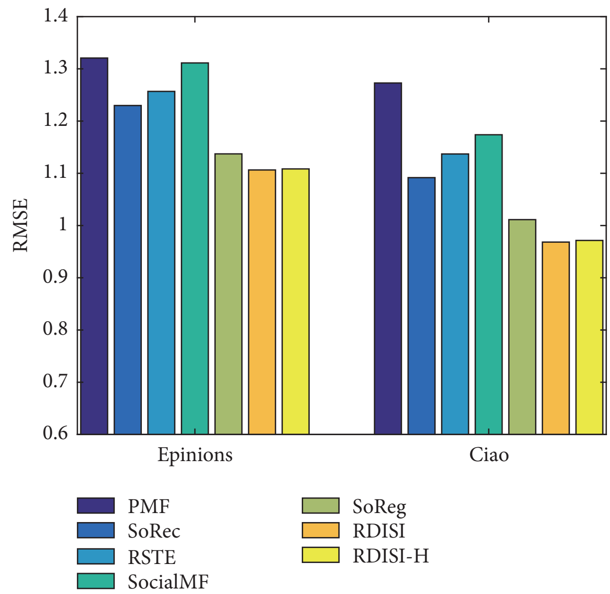
The comparison results for MAE and RMSE on cold-start users are shown in Figure 4, which indicates that our recommendation methods RDISI and RDISI-H outperform other models on cold-start users. Among the comparison models, SoReg performs the best in both datasets. In Epinions, the improvements in terms of MAE for RDISI and RDISI-H are 2.27% and 2.41%, respectively. In Ciao, the improvements in terms of MAE for RDISI and RDISI-H are 4.52% and 4.29%, respectively. Although the improvements are from the view of cold-start users, it seems that the *h-index* is an effective indicator of influence of users in the recommendation process.

Inspired by [40], we consider that local influence of nodes is not linear with coreness of nodes. Local influence initially increases rapidly with the increase of coreness, but it gradually becomes relatively stable. We also consider a similar relationship between global influence and the number of user ratings. In this paper, we limit the values of user influence in the $[0, 1]$ range. Based on these assumptions, we choose the hyperbolic tangent function $f(x) = \tanh(x)$ or the variant of logistic function $f(x) = (1 - e^{-x})/(1 + e^{-x})$ as the generation function of local influence and global influence. Even if a user's coreness is very small, he/she can still contribute to the information propagation to a certain extent; therefore, the user's local influence cannot be ignored. Even if a new user has not rated any item, he/she can still take part in online activities through which he/she still affects other users' preferences. Therefore, when the number of ratings given by a user is very small or even equal to 0, the value of his/her global influence is not 0. Therefore, we adjust the two preceding functions to meet this condition. The new functions are $f_1(x) = \tanh(x + \alpha)$ and $f_2(x) = (1 - e^{-(x+\alpha)})/(1 + e^{-(x+\alpha)})$, where α is the offset used to make the values of users' influence above 0. We first choose $f_1(x)$ as the generation function of local influence and global influence. We replace either the generation function of local influence or global influence with the variant logistic function $f = (1 - e^{-(x+\alpha)})/(1 + e^{-(x+\alpha)})$ while fixing the other one. The experiment results are shown in Table 5. The results indicate that recommendations using $f_1(x)$ perform better. Therefore, we choose $f = \tanh(x+\alpha)$ as the generation function of local influence and global influence.

In trust networks, in general, relational information is not static. The effect of the emergence of new influencers and new trends should be discussed. Specifically, the number of the users in a social network is increasing, and new trust relationships among users have been emerging. To verify the performance of our proposed algorithm with the effect of the emergence of new influencers and new trends, we conduct a new experiment. In this experiment, we use a larger Epinions dataset which is named Epinions_ext dataset. The Epinions_ext dataset contains 390732 ratings of 13209 users for 14027 items and 145927 trust relations among users. Specifically, the Epinions dateset we used and described



(a) MAE



(b) RMSE

Figure 4: Performance comparisons of cold-start users (dimensionality=20).

Table 5: Performance comparisons using different generation functions.

Dataset	Generation function of local influence	Generation function of global influence	Performance (MAE)
Epinions	$f_1(x)$	$f_1(x)$	0.8011
	$f_2(x)$	$f_1(x)$	0.8056
	$f_1(x)$	$f_2(x)$	0.8042
Ciao	$f_1(x)$	$f_1(x)$	0.7308
	$f_2(x)$	$f_1(x)$	0.7348
	$f_1(x)$	$f_2(x)$	0.7319

in Section 4.1 is a subset of Epinions_ext dataset, which means that there are new uses and new trust relationships in addition to that of the Epinions dateset we used and described in Section 4.1. We also select optimal parameters for the Epinions_ext dataset. The experiment results compared with the comparison methods are shown in Table 6.

When we conduct experiments on the Epinions_ext dataset, we get smaller MAE and RMSE, which means that our proposed model even performs better when the social relationships and the number of users in the network are increasing. It is also noticeable that our proposed model gets larger improvement than the comparison methods when using the Epinions_ext dataset and our proposed model is scalable with the size of the dataset.

Our proposed model is focusing on rating prediction so that we select the metrics MAE and RMSE to evaluate the performance of our proposed recommendation model. To verify whether our proposed method is effective in the ranking, which is another task of recommender systems, we conduct extended experiments to verify the performance of our proposed method in the ranking task by using the metrics precision and recall that are both defined in Section 4.2. We also select optimal parameters for the experiments in this section. The experiment results are shown in Table 7.

Our proposed model and the comparison methods in this paper are focusing on rating prediction so that these methods do not perform well in the ranking task of recommender systems, which can be verified by the values of precision and recall. However, our proposed method performs better than the comparison partners in ranking task.

5. Conclusions

With the popularization of online social networks, exploiting social relationships provides a reliable source that can be utilized to improve the performance of recommender systems. In this paper, we exploited users' trust relationships and calculated each user's coreness, which determines the user's local influence on social networks. A user's global influence is determined by the number of ratings he/she has given. Incorporating local and global influence, we propose the recommendation method RDISI. In addition to direct influence, the method also considers indirect interactions between users who do not have direct links. Experimental results from the real-world datasets Epinions and Ciao demonstrate that our method performs better than some state-of-the-art social recommendation models. Moreover, as analysed beforehand and shown in Figure 1, the structures

Table 6: Performance comparisons (dimensionality =20).

Dataset	Metrics	PMF	SoRec	RSTE	SocialMF	SoReg	RDISI
Epinions_ext	MAE	0.9230	0.8923	0.8580	0.8559	0.7571	**0.7364**
	Improve	20.21%	17.47%	14.17%	13.96%	2.73%	
	RMSE	1.1543	1.1982	1.1567	1.1903	1.0087	**0.9588**
	Improve	16.94%	19.98%	17.11%	19.45%	4.86%	

Table 7: Performance comparisons (precision and recall).

Dataset	Metrics	PMF	Social MF	SoReg	RSTE	SoRec	RDISI
Epinions	precision	4.8e-4	5.5e-4	5.8e-4	6.2e-4	6.7e-4	**7.0e-4**
	Improve	45.83%	27.27%	20.69%	12.90%	4.48%	
	recall	0.0065	0.0072	0.0072	0.0081	0.0091	**0.0101**
	Improve	55.38%	40.28%	40.28%	24.69%	10.99%	
Ciao	precision	1.8e-4	2.2e-4	2.2e-4	2.4e-4	2.6e-4	**2.7e-4**
	Improve	50.00%	22.70%	22.70%	12.50%	3.85%	
	recall	0.0038	0.0046	0.0044	0.0047	0.0054	**0.0058**
	Improve	52.63%	24.09%	31.82%	23.40%	7.41%	
Epinions_ext	precision	0.0011	0.0014	0.0015	0.0016	0.0016	**0.0017**
	Improve	36.36%	21.43%	13.33%	6.25%	6.25%	
	recall	0.0257	0.0267	0.0287	0.0303	0.0307	**0.0321**
	Improve	24.90%	20.22%	11.85%	5.94%	4.56%	

of user relations in the two datasets are different, but our method managed to improve the performances in both cases. Coreness constitutes the best topological descriptor for identifying users' local influence, and recommendation using coreness outperforms that using node degrees, betweenness, and clustering coefficients.

In this paper, we only investigate how trust relationships affect users' preferences and how they can be fused into the MF recommendation model to make better recommendations. However, distrust relationships in social networks are also critical in the social recommendation process. Even very few distrust links can have a great impact on social recommendations. Thus, it is worth conducting research using a dataset that contains both trust and distrust relationships as some networks allow users to express distrust of others.

Data Availability

The data used to support the findings of this study are available from "http://www.cse.msu.edu/~tangjili/trust.html".

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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