Postprint: Matrix Factorization Recommendation Algorithm Integrating Implicit Trust and Item Correlations

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Abstract

With the development of social networks, recommendation systems incorporating social information have partially addressed the cold-start and data sparsity issues inherent in collaborative filtering recommendation systems; however, they still suffer from reduced recommendation accuracy when trust data is sparse. To this end, we propose a matrix factorization recommendation algorithm that integrates implicit trust and item correlation. First, we decompose trust data using a matrix factorization model to obtain a latent trusted matrix for users, upon which we introduce user influence to propose a recommendation model based on implicit trust. Then, to better leverage inter-item correlation information and reflect the directedness between items, we propose a recommendation model based on item correlation. Finally, we integrate these two recommendation models to construct a novel algorithm called TCRMF. Experimental results demonstrate that the proposed algorithm can effectively improve recommendation accuracy even under conditions of sparse rating and trust data, indicating promising application prospects.

Full Text

Preamble

Matrix Factorization Recommendation Algorithm Combining Implicit Trust and Item Correlation

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Abstract: With the development of social networks, recommendation systems that integrate social information have partially addressed issues such as cold-start and data sparsity in collaborative filtering recommendation systems. However, in cases of sparse trust data, recommendation accuracy still tends to decline. To address this problem, this paper proposes a matrix factorization recommendation algorithm that combines implicit trust and item correlation. First, the trust data is decomposed using a matrix factorization model to obtain users' potential trusted matrices, and user influence is introduced on this basis to propose a recommendation model based on implicit trust. Then, to better utilize the correlation information between items and reflect the directionality between items, a recommendation model based on item correlation is proposed. Finally, the two recommendation models are integrated to construct a recommendation algorithm called TCRMF.

Experimental results show that the proposed algorithm can effectively improve the accuracy of recommendation algorithms even when rating data and trust data are sparse, demonstrating good application prospects.

Keywords: recommendation system; collaborative filtering; social network; implicit trust; item correlation; matrix factorization

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0 Introduction

With the continuous development of network technology, resources and information on the Internet have expanded rapidly. Extracting effective information from massive data represents a significant challenge for ordinary users. Personalized recommendation systems provide the most effective solution to this problem. These systems analyze users' preferences to recommend information they may be interested in [1]. Existing recommendation methods can generally be divided into three categories: content-based methods [2], collaborative filtering methods [3], and hybrid methods [4]. Among these, collaborative filtering-based recommendation is the most widely applied approach, including user-based collaborative filtering, item-based collaborative filtering, and matrix factorization (MF) [5, 6]. However, these methods typically face problems such as cold-start, data sparsity, and poor algorithm scalability [7].

In recent years, with the development of social networks, trust relationships between users have emerged as important information in social networks, providing a basis for addressing data sparsity issues in recommendation systems [8]. Trust-based recommendation systems have alleviated problems such as sparse rating data to some extent, but they have also introduced new challenges. Currently, most trust metrics in social network-based systems are measured from the perspectives of user rating data or social trust graph data. However, in cases of sparse trust data, recommendation accuracy declines. Therefore, how to effectively mine trust relationships between users and measure trust values under sparse trust data conditions has become a critical issue for further improving social recommendation algorithms.

Meanwhile, in daily life, in addition to social relationships between users, certain correlation relationships also exist between items. These correlations between items also influence users' choices. Consequently, how to obtain correlation relationships between items and apply them to recommendation systems represents another challenging research problem.

To further improve recommendation algorithm performance, this paper proposes a matrix factorization algorithm that integrates implicit trust and item correlation. First, trust data is decomposed using a matrix factorization model to obtain users' potential trusted matrices. Next, user influence is introduced on this basis, and trust measurement methods for local implicit trust and global implicit trust are proposed along with corresponding recommendation models. Then, to better reflect the directed nature of correlations between items, a penalty coefficient is added to item Pearson similarity, and a recommendation model based on item correlation and popularity is proposed. Finally, a recommendation algorithm is proposed that comprehensively considers both user implicit trust and item correlation. Experimental results demonstrate that compared with other social recommendation algorithms, the algorithm proposed in this paper achieves more accurate recommendation results in terms of root mean square error and other metrics.

1 Related Work

Typical collaborative filtering recommendation algorithms often face cold-start and data sparsity problems. With the rapid development of social networks, social information has introduced new data sources for traditional collaborative filtering algorithms. Consequently, an increasing number of researchers have investigated how to utilize social information to improve recommendation system quality. Massa et al. [9] first proposed a trust-based recommendation system, using similarity between users to represent trust values. Experimental results demonstrated that trust-based recommendation systems help improve recommendation quality. Wang et al. [10] proposed a collaborative filtering recommendation algorithm based on a one-hop trust model, defining direct and indirect social trust attributes based on user rating information to calculate trust between users. The recommendation algorithm designed based on this model improved recommendation accuracy. Zhao et al. [11] proposed a probabilistic matrix factorization algorithm based on trust propagation, defining three trust measurement methods based on in-degree and out-degree in trust graph models and integrating them into a probabilistic matrix factorization-based social recommendation model. Experimental results showed that the in-degree-based trust measurement method achieved better recommendation effects. Chen et al. [12] proposed a trust-based recommendation algorithm in social network environments, modeling trust relationships using the propagation property of trust and comprehensively considering similarity and trust to construct preference relationships between users based on rating data, thereby verifying the algorithm' s effectiveness. Guo et al. [13] utilized latent vectors obtained from probabilistic matrix factorization of the rating matrix to calculate similarity between users and friends, improving algorithm accuracy. However, the limitation of these recommendation algorithms is that when user rating data or social trust graph data is sparse, the calculated trust between users cannot accurately reflect the similarity relationships between users and their friends, adversely affecting recommendation accuracy.

In addition to social relationships between users, correlation relationships between items also provide a basis for introducing new data sources to collaborative filtering algorithms. Therefore, researching how to utilize correlation relationships between items to improve recommendation system accuracy represents a key current research problem. Wu et al. [14] used tag information to construct similarity relationships between users and items, integrating both into PMF to propose a neighbor-based probabilistic matrix factorization model. Yang et al. [15] used the Pearson correlation model as a similarity measurement model for users and items, optimized similarity through the Jaccard coefficient, and proposed a collaborative filtering model combining user and item predictions. Yu et al. [16] analyzed the tree structure composed of synonyms in semantic dictionaries such as Hownet, calculated semantic distances such as distance, depth, and density between items, performed semantic similarity-based clustering of items, and proposed a mobile application recommendation integrating social networks and item features. Sun et al. [17] used traditional similarity calculation methods to obtain rating similarity between items, combined item attributes to calculate attribute similarity, obtained final similarity between items through weighting factors, and proposed a recommendation algorithm based on item attributes and cloud filling. However, the limitation of these recommendation algorithms is that the similarity relationships between items are undirected, and the calculated correlation between items cannot well reflect the real correlation relationships, adversely affecting recommendation accuracy.

To address these two problems, this paper proposes a matrix factorization recommendation algorithm that integrates implicit trust and item correlation. The advantages of this algorithm are: a) It uses a matrix factorization model to decompose trust data to obtain users' potential trusted matrices, introduces user influence on this basis, and proposes measurement methods for local and global implicit trust and corresponding recommendation models, thereby partially solving the problem of reduced recommendation accuracy under sparse trust data conditions. b) It adds a penalty coefficient based on item Pearson similarity and proposes measurement methods for correlations between items from local and global perspectives through item correlation and popularity, thereby better reflecting the directed nature of correlations between items. c) It proposes a recommendation algorithm that comprehensively considers both user implicit trust and item correlation, further improving recommendation accuracy from both social network data and item correlation data perspectives.

2.1 Problem Description

In a recommendation system, let $U = \{u_1, u_2, ..., u_n\}$ denote the set of n users and $I = \{i_1, i_2, ..., i_m\}$ denote the set of m items. The user-item rating matrix is represented as $R \in \mathbb{R}^{n \times m}$. If user u has rated item i, then element r_{ui} in the rating matrix represents the corresponding rating value; otherwise, $r_{ui} = 0$ indicates that user u has not rated item i. In social networks, each user has N friends. The social relationship matrix is represented as $T \in \mathbb{R}^{n \times n}$. If users u and v have a social relationship, then element t_{uv} in the social relationship matrix represents the trust strength between users; $t_{uv} = 0$ indicates that users u and v have no social relationship.

2.2 Low-Rank Matrix Factorization Model

To predict missing values in the user-item rating matrix R in recommendation systems, the matrix factorization model decomposes the high-order rating matrix R into two low-dimensional matrices: user matrix U and item matrix V, as shown in equation (1).

n12U={u,u,···,u}nm12I={i,i,···,i}m =uinmr Ruiuir=0uiruiuN ,=uvnnt Tuv,uvt,=0uvtuvnm Rnm RUVT RUV
···,]knn UUUUURiUik123=[„,···,]kmm VVVVVRjVjkij=Tijij RUVUV2111
(„)()2nmTijijijijf= RUVIR-UVijI=1ijIij=0ijI222111(„)()++222nmTUVijijijFFijf RUVIR-
UVUV0U 0V FUFVUVnm RSBWT SBW123=[„,···,]dnn BBBBBRiBid

The predicted rating of user u for item i can be expressed as $\hat{r}_{ui} = U_u^T V_i$. The squared error between the original rating and the predicted rating is used as the loss function, as shown in equation (2). By minimizing the loss function, matrices U and V are obtained.

To prevent overfitting, two regularization terms are added to equation (2) to constrain the parameters, as shown in equation (3). $\lambda_U > 0$ and $\lambda_V > 0$ are regularization parameters, and $\|\cdot\|_F$ denotes the Frobenius norm. The stochastic gradient descent method is used to obtain the user feature matrix U and item feature matrix V, which can accurately predict the missing values in the original rating matrix.

3.1 Implicit Trust-Based Recommendation Model

Under conditions where user rating data or social trust graph data is sparse, the trust calculated between users cannot accurately reflect the similarity relationships between users and their friends, adversely affecting recommendation accuracy. To address this, this section comprehensively considers measurement methods for local implicit trust and global implicit trust and proposes a comprehensive implicit trust-based recommendation model.

3.1.1 Local Implicit Trust

As analyzed in literature [18], given the user trust relationship matrix S, the matrix is decomposed through a low-rank matrix factorization model to obtain the user truster feature matrix B and trustee feature matrix W, as shown in equation (4).

123=[„,⋯,]dnn BBBBBRiBid

B represents the user truster feature matrix, where B_u denotes the d-dimensional latent feature vector of user u as a truster. W represents the user trustee feature matrix, where W_u denotes the d-dimensional latent feature vector of user u as a trustee. The predicted trust strength between users u and v can be expressed as $\hat{s}_{uv} = B_u^T W_v$. The squared error between the original trust strength and the predicted trust strength is used as the loss function, as shown in equation (5). By minimizing the loss function, matrices B and W are obtained.

To prevent overfitting, two regularization terms are added to equation (5) to constrain the parameters, as shown in equation (6). $\lambda_B > 0$ and $\lambda_W > 0$ are regularization parameters, and $\|\cdot\|_F$ denotes the Frobenius norm. The stochastic gradient descent method is used to optimize the above equation. The derivative formulas for B and W are shown in equations (7) and (8).

Through the matrix factorization algorithm, each user is mapped to a truster feature vector B_u and a trustee feature vector W_u. As analyzed in literature [19], in social networks, users with greater influence are more likely to be trusted by other users. Therefore, user influence is introduced through the user’ s trustee feature vector, as shown in equation (9).

The trust relationship between users is asymmetric. For example, your trust in a friend differs from that friend’ s trust in you. Therefore, to accurately measure different trust relationships between users, local implicit trust is introduced, as shown in equation (10).

The greater the influence of friend v, the more likely user u is to trust that friend, meaning that friends with greater influence have a larger effect on user u.

3.1.2 Global Implicit Trust

As analyzed in literature [12], global trust represents that a user’ s trust in a social network references the comprehensive evaluation of that user by all other nodes, reflecting the user’ s reliability and influence throughout the entire social network. To measure trust relationships between users from a global perspective, global implicit trust is introduced, as shown in equation (11).

The larger the influence of user u in the social network, the greater the user’ s global trust and the more they are trusted by others.

3.1.3 Comprehensive Implicit Trust-Based Recommendation Model

Under sparse trust data conditions, the recommendation model that integrates local implicit trust and global implicit trust can more accurately reflect similarity relationships between users and their friends. Therefore, a comprehensive recommendation model is proposed that combines both types of implicit trust, as shown in equation (12).

Parameter α controls the impact of users' local implicit trust and global implicit trust on the recommendation algorithm.

3.2 Item Correlation-Based Recommendation Model

The correlation relationships between items are one of the important factors influencing user decision-making in recommendation systems. This paper measures correlations between items from the perspectives of item correlation and popularity.

3.2.1 Item Correlation

Pearson similarity or cosine similarity, commonly used to measure item similarity, has symmetry, i.e., the similarity between items p and q equals the similarity between items q and p [20]. However, in real life, to consider the differences in mutual influence between items, the similarity between items p and q differs from the similarity between items q and p. Therefore, to accurately describe correlation relationships between items, a penalty coefficient is added to Pearson similarity without considering other item-related information. The correlation of item p to item q is shown in equation (13).

N_p represents the number of users who rated item p in the recommendation system, and N_q represents the number of users who rated item q. Parameter γ is a penalty factor, typically in the range $[0.5, 1]$, controlling the directed nature of correlations between items.

3.2.2 Item Popularity

Item popularity represents the popularity degree of an item among all items from a global perspective. In recommendation systems, item popularity generally exhibits large differences. From item popularity, we can infer the likelihood of a user' s interest in an unrated item. The higher the item' s popularity, the greater the possibility that the user will be interested in the unrated item. As analyzed in literature [21], item popularity is proportional to the number of users who have browsed the item, and vector normalization is performed when calculating each item' s popularity, as shown in equation (14).

N_p represents the number of users who rated item p, and I represents the set of all items.

3.2.3 Comprehensive Correlation-Based Recommendation Model

Item correlation obtains directed correlation relationships between items from a local perspective, while item popularity corrects this relationship from a global perspective to more accurately reflect correlations between items. Therefore, a comprehensive correlation-based recommendation model is proposed, as shown in equation (15).

Parameter β controls the impact of item correlation and item popularity on the recommendation algorithm.

3.3 Fusion Model Combining Implicit Trust and Item Correlation

The implicit trust-based recommendation model analyzes trust between users from a social network perspective to improve recommendation system accuracy, while the item correlation-based recommendation model analyzes correlations between items from an item correlation perspective to improve recommendation system accuracy. Therefore, considering both methods, a fusion model combining implicit trust and item correlation is proposed, as shown in equation (16).

Parameters σ and ρ represent the impact of social relationships and item correlation relationships on the recommendation algorithm, respectively. The stochastic gradient descent method is used to optimize the above equation. The derivative formulas for U and V are shown in equations (17) and (18).

3.4 Algorithm Description

The Matrix Factorization Recommendation Algorithm Combining Implicit Trust and Item Correlation (TCRMF) proceeds as follows:

Input: User-item rating matrix R, user-user social matrix S, latent feature dimensions d and k, regularization coefficients λ_U and λ_V, hyperparameters α, β, σ, and ρ, penalty factor γ, learning rates μ_1 and μ_2, maximum iteration counts L_1 and L_2.

Output: Truster feature matrix B, trustee feature matrix W, user feature matrix U, and item feature matrix V.

The time complexity of the TCRMF algorithm is primarily calculated based on the objective functions f_1, f_2 and the solution of their corresponding partial derivatives. The time complexity of objective function f_1 is $O(nr_kd + nt_kd)$, and the time complexity of objective function f_2 is $O(nr_kd + nt_kd)$. The time complexity of calculating partial derivatives $\frac{\partial f}{\partial B}$ and $\frac{\partial f}{\partial W}$ is $O(nt_kd)$, and the time complexity of calculating partial derivatives $\frac{\partial f}{\partial U}$ and $\frac{\partial f}{\partial V}$ is $O(nr_k d)$. Since r_k, t_k, d, and k are relatively small, the calculation of partial derivatives is relatively fast and linearly proportional to the total number of users n. Therefore, the time complexity of objective function and gradient calculation is $O(n(r_k+t_k)d)$. The algorithm' s time complexity is mainly affected by the number of users n, making it applicable to large-scale datasets.

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4 Experimental Results and Analysis

This section primarily introduces the impact of the TCRMF algorithm compared with other related algorithms on recommendation results. First, the datasets and evaluation methods used in the experiments are introduced, followed by the design of the experiments.

4.1 Datasets

To compare the impact of different information on recommendation results, this paper selected two public datasets for algorithm testing: Epinions (http://www.trustlet.org/epinions.html) and Ciao (http://www.cse.msu.edu/~tangjili/trust.html). Both datasets contain user rating information and social relationship information. The detailed statistical characteristics of the two datasets are shown in Table 1 .

4.2 Evaluation Metrics

To evaluate the performance of recommendation algorithms, this paper uses Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These two evaluation metrics measure the accuracy of recommendation results by calculating the error between real ratings and predicted ratings. Smaller values indicate higher recommendation accuracy. The calculation formulas for the two evaluation metrics are shown in equations (19) and (20).

N_T represents the number of ratings in the test set, R_{ij} represents the real rating value, and $\hat{R}_{ij}$ represents the predicted rating value.

4.3 Experimental Results Analysis

To verify the prediction accuracy of the TCRMF algorithm, it is compared with the Matrix Factorization algorithm (MF), the social recommendation algorithm based on trust propagation proposed by Jamali et al. [22] (SocialMF), and the social regularization-based recommendation algorithm proposed by Ma et al. [23] (SoReg).

Experiment 1: Analysis Under Different Feature Vector Dimensions

This experiment compares the performance of various algorithms on the Epinions and Ciao datasets. For all matrix factorization-based recommendation algorithms, the latent feature dimensions are set to 5 and 10, and the accuracy of each algorithm is verified. The experimental results are shown in Table 2 and Table 3 .

a) The MAE and RMSE values of SocialMF and SoReg algorithms are smaller than those of the MF algorithm, indicating a certain improvement in recommendation accuracy. This demonstrates that social information helps improve the prediction accuracy of traditional matrix factorization recommendation algorithms.

b) Compared with SocialMF and SoReg social recommendation algorithms, the TCRMF algorithm proposed in this paper achieves further improvements in both MAE and RMSE values. This indicates that fusing item correlation information on top of social information can further improve recommendation algorithm prediction accuracy.

Experiment 2: Analysis Under Different Rating Sparsity Levels

To test the performance of various algorithms under different rating sparsity levels, different rating quantities are divided into six groups: 0-20, 21-50, 51-100, 101-300, 301-500, and above 500. The RMSE values for both Epinions and Ciao datasets are calculated separately. The experimental results are shown in Figure 1 [Figure 1: see original paper].

a) Under different rating sparsity levels, the accuracy of SocialMF, SoReg, and TCRMF algorithms is significantly better than that of the MF algorithm. This indicates that utilizing social information helps improve algorithm accuracy.

b) For dense rating data (rating quantity > 300), the TCRMF algorithm is significantly superior to other social information-based recommendation algorithms. This shows that as the number of ratings increases, the proposed algorithm can effectively mine correlation relationships between items, thereby further improving recommendation algorithm accuracy.

Experiment 3: Analysis Under Different Trust Sparsity Levels

To test the performance of various algorithms under different social relationships, different social relationship quantities are divided into six groups: 0-5, 6-15, 16-30, 31-50, 51-100, and above 100. This experiment only compares three social information-based recommendation algorithms: SocialMF, SoReg, and TCRMF. The RMSE values for Epinions and Ciao datasets are calculated separately. The experimental results are shown in Figure 2 [Figure 2: see original paper].

a) Under different trust sparsity levels, the accuracy of the TCRMF algorithm is superior to that of SocialMF and SoReg algorithms. This indicates that fusing item correlation data on top of social network data helps improve algorithm accuracy.

b) Under sparse trust data conditions (trust data < 15), the TCRMF algorithm is significantly superior to other social information-based recommendation algorithms. This indicates that performing matrix factorization on trust data through a recommendation model that integrates local implicit trust and global implicit trust can effectively improve the accuracy of social recommendation algorithms.

Experiment 4: Analysis of Different Item Correlation Calculation Methods

To evaluate the impact of different item correlation calculation methods on recommendation algorithm accuracy, item correlations are first calculated based on Pearson similarity, and the undirected correlation relationships between items are combined with MF to obtain an improved recommendation algorithm called UCMF. Then, item correlations are calculated using the item correlation measurement method proposed in this paper, and the directed correlation relationships between items are combined with MF to obtain an improved recommendation algorithm called DCMF. Finally, the test results of the two improved algorithms on Epinions and Ciao datasets are compared. The latent feature dimensions are set to 5 and 10, and the RMSE values of both algorithms are calculated. The experimental results are shown in Table 4 .

a) Compared with the MF algorithm in Tables 2 and 3, the RMSE values of the UCMF algorithm that incorporates undirected correlation relationships between items are smaller than those of the MF algorithm, because fusing item correlation relationships helps improve algorithm accuracy.

b) Compared with the UCMF algorithm, the recommendation accuracy of the DCMF algorithm that incorporates directed correlation relationships between items has improved to varying degrees. This is because compared with undirected correlation relationships, the proposed method better reflects the real correlation relationships between items.

Experiment 5: Impact of Parameters on RMSE

To illustrate the impact of parameters in the TCRMF algorithm on recommendation results, this paper takes the Epinions dataset as an example, extracting 80% as the training set and comparing recommendation effects under various parameters. The experimental results are shown in Figure 3 [Figure 3: see original paper].

a) Parameter α controls the impact of users' local implicit trust and global implicit trust on the recommendation algorithm. From Figure 3(a), when $\alpha = 1$, the algorithm only considers users' local implicit trust information; when $\alpha = 0$, the algorithm only considers users' global implicit trust information. When $\alpha \in (0, 1)$, the algorithm comprehensively considers both local and global implicit trust information. As the value of α increases, the algorithm' s RMSE value first decreases and then increases, and recommendation accuracy first increases and then decreases. When

$\alpha = 0.5$, recommendation accuracy is optimal.

b) Parameter β controls the impact of item correlation and popularity on the recommendation algorithm. From Figure 3(b), when $\beta = 1$, the algorithm only considers item correlation information; when $\beta = 0$, the algorithm only considers item popularity information. When $\beta \in (0, 1)$, the algorithm comprehensively considers both item correlation and popularity information. As the value of β increases, recommendation accuracy first increases and then decreases. When $\beta = 0.4$, recommendation accuracy is optimal.

c) Parameter σ represents the impact of users' social relationships on the recommendation algorithm. From Figure 3(c), as the value of σ increases, the proportion of users' social relationships in the TCRMF algorithm gradually increases, and recommendation accuracy first increases and then decreases. When $\sigma = 0.1$, the algorithm achieves better recommendation accuracy.

d) Parameter ρ represents the impact of item correlation relationships on the recommendation algorithm. From Figure 3(d), as the value of ρ increases, the proportion of item correlation relationships in the TCRMF algorithm gradually increases, and recommendation accuracy also first increases and then decreases. When $\rho = 0.1$, the algorithm achieves optimal recommendation accuracy.

5 Conclusion

This paper proposes a matrix factorization algorithm that integrates implicit trust and item correlation. The trust data is decomposed using a matrix factorization model to obtain users' potential trusted matrices. Based on this, user influence is introduced to propose a recommendation model that integrates local implicit trust and global implicit trust. This model improves recommendation system accuracy when trust data is sparse. To consider the differences in mutual influence between items, a penalty coefficient is added to item Pearson similarity to introduce item correlation, while item popularity is considered from a global perspective to correct item correlation, proposing a comprehensive correlation-based recommendation model. This model can better reflect the directed relationships between items without relying on other external item information. Experimental results show that the proposed algorithm outperforms existing social recommendation algorithms for sparse trust data, and fusing item correlation information on top of social information can further improve recommendation algorithm prediction accuracy, achieving more significant effects. In future work, the focus will be on integrating contextual information such as geographical location into the proposed recommendation model to predict target users' preferences for items, with the aim of further improving the recommendation algorithm' s accuracy.

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Note: Figure translations are in progress. See original paper for figures.