Research on personalized recommendation method based on social impact theory

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Abstract. With the rapid development of computer technology, the personalized needs of users become more and more prominent. The complexity of online learning resources and social networks lead to sparse data sets and low recommendation efficiency. In this paper, the existing collaborative filtering recommendation algorithm does not distinguish the degree of user's trust when integrating the social impact theory. Therefore, in order to establish more accurate characteristics of user's social interaction, this paper integrates the trust mechanism in the social impact theory, brings the establishment, dissemination and socialization factors of trust into the research scope, and introduces them into personalized recommendation in the recommendation process of recommendation model, it is used to solve the problem of low recommendation effect and low quality of recommendation system on sparse data set. Experimental results show that the proposed personalized recommendation method can improve the recommendation effect and quality on sparse data sets.

1. Introduction
In recent years, data sparsity and cold start problems have a great impact on the performance and efficiency of recommendation. In addition to rating information, other factors that affect the quality of recommendation have become a hot topic for scholars, such as the social relationship between users and the attribute relationship of highly similar items. In the field of personalized recommendation, the user interest preference model based on human and social relationship brings a new opportunity to improve the recommendation performance. In order to solve the problem of information overload effectively and efficiently, more and more scholars begin to study the field of recommendation, and the recommendation system has entered a state of rapid development. Although the research of recommender system is booming, there are still some problems that affect the performance of recommender system, such as data sparsity, cold start, and scalability. Data sparsity is one of the key factors that affect the efficiency of recommender system. In 2008, Ma et al. [1] proposed SoRec model to decompose user's rating information and social information from a mathematical point of view, so as to model user's interest preference. The experimental results show that the recommendation performance is better than that of a single rating information recommendation system. The RSTE model proposed by Jamali [2] in 2010 combines the preferences of trusted friends with the interests of users, so as to realize the recommendation problem of unsatisfied items. The SocialMF model proposed by Irwin et al. [3] uses social information and trust transfer mechanism to get the trust relationship data that accurately evaluates
the user's interest characteristics. This method solves the problem that new users can't get recommendations. These scholars introduce the social impact theory into the recommendation system to improve the quality of the system effectively. However, most of the existing social recommendation algorithms are based on the trust interval value of 0-1, without considering the implicit trust relationship of users, and the obtained user preference characteristics are difficult to greatly improve the accuracy of the recommendation. Therefore, this paper integrates the trust mechanism of social influence theory, integrates the establishment, propagation and influencing factors of trust into the personalized recommendation model, and proposes a personalized recommendation algorithm to improve the efficiency of the recommendation system in the sparse data environment.

2. Related theories

2.1. Social impact theory
Social influence theory [4] emphasizes that knowledge comes from the construction of social meaning, and learners should actively interact in social situations. Everyone is in the society, people have social attributes, not isolated from the social existence of people, we are in the process of interaction with the society growing. Learners' learning mainly takes place through participating in social practice, including cooperative interaction, group work and family life. With the help of high-level learners, low-level learners can gradually master the previously unfamiliar knowledge or views. Therefore, social impact theory emphasizes the social attributes of human beings and advocates that learning should be constructed in a social environment. Online learning should also be guided by social constructivism, it needs to pay attention to students' social interaction, provide a harmonious and independent communication platform for students, and pay attention to students' common growth in cooperation.

2.2. Social networks
Social network [5] refers to the network structure connecting the social relationship between users, so the nodes representing users and the edges describing the social relationship between users are the basic elements of social network. In recent years, with the wide use of social media, tens of millions of users exchange information on social networks, and the information resources on social networks are growing exponentially, which brings unprecedented opportunities and challenges to the recommendation system. On the one hand, social network has a large number of social information resources for the recommendation process, which can lay a material foundation for the recommendation system to form a higher quality recommendation project. On the other hand, it can effectively analyse the user's behaviour in social network to help users realize the recommendation process. At present, social network analysis method is widely used in the research of recommendation system, and the correlation theory reflects why the data of social relationship between users can be used for recommendation to a certain extent. Therefore, using the users and social relationship in social network can effectively evaluate the interest preference of target users, so as to recommend for users.

2.3. Social recommendation method
Social recommendation method refers to the user's rating information and social information as input information, using the characteristics of the general association between users in social networks to deal with the problem that collaborative filtering cannot calculate the user similarity when the data is extremely sparse. The advantage of this method is that when the rating data is sparse, it can also build user preferences through social relations, so as to improve the performance of the recommendation system. Social recommendation methods include memory based social recommendation and model-based social recommendation [6]. Memory based social recommendation uses trusted friends to obtain user's interest characteristics. Therefore, the expected effect can be achieved through the target user's prediction of unsatisfied items. The prediction formula is $R_{st} = \frac{1}{F(m)} \sum_{m=1}^{F(m)} P_{st} R_{st}$, where $R_{st}$ is the prediction score, $R_{st}$ is the actual score, $F(m)$ is the set of trusted friends, and $P_{st}$ is the actual score it's
user social relationships. The model-based social recommendation method mainly uses the relevant model to learn from the user's social relationship data and rating data, so as to obtain the user's interest characteristics. The typical application is the social recommendation based on matrix factorization. Its basic idea is to use the excellent characteristics of matrix factorization to transform the recommendation into a multi relationship learning process. Based on the model-based social recommendation method, this paper proposes a personalized recommendation algorithm to improve the efficiency of the recommendation algorithm.

3. Personalized recommendation method based on social impact theory

3.1. Social impact factors

Social impact factor refers to the factors that affect personalized recommendation methods, including user trust, social interaction influence and project relevance. In the recommendation system, the trust relationship is often described as two users, user1 and user2, in the social network. If user user1 can help user user2 to provide products or services, and this product or service has certain value, then user user2 trusts user user2. Therefore, trust relationship is very valuable information in the process of recommendation, which can be obtained in the trust network. User trust network is composed of user and trust relationship information. The trust value obtained in the user trust network is 0-1, where 1 represents trust and 0 represents distrust. Because the obtained trust relationship matrix is extremely sparse, the trust relationship between users is missing items in most cases. In order to establish the trust relationship of missing items and more accurately model the user interest, we can use the trust propagation method to calculate the explicit trust relationship and implicit trust relationship between users, so as to obtain the trust relationship between users' degree. Formula (1) is the calculation method of explicit trust relationship ($T_{uw}$), where $L_{max}$ is the longest distance of user trust transfer, $L_{uw}$ is the actual distance between users, formula (2) is the calculation formula of implicit trust relationship ($T_{nu}$), where $P_{uu}$ is the intersection of scoring items, $R_{uu}$ and $R_{uw}$ are the specific scoring values of users for items, and $Q$ is the scoring range.

$$T_{uw} = \frac{L_{max} - L_{uw} + 1}{L_{max}}$$

$$T_{nu} = \sum_{u \in P_{uu}} \left(1 - \frac{1}{Q} \left|R_{uu} - R_{uw}\right|\right) / P_{uu}$$

Social interaction influence is used to evaluate the credit degree of users, which effectively reflects the importance of users in the social network. Therefore, in the recommendation system, the number and quality of linked web pages are taken as the basic reference to get the importance of web pages, so as to use the page ranking algorithm to effectively calculate the social influence of users in the social network. If more users are linked in the trust network, the influence of this user is higher than that of other users. Formula (3) is the calculation method of social interaction influence ($GR(u)$), where is the probability value of users from the current node to the next node, $M$ is the number of users, and $D_x$ is the set of trusted users.

$$GR(u) = \frac{1}{M} + (1 - k) \cdot \sum_{x \in D_x} \frac{1}{D_x} \cdot GR(x)$$

Project relevance refers to the inherent attributes and connections between projects. It is an important information and data source of recommendation system. Therefore, establishing the connection between projects has a positive impact on the quality of recommendation. Item relevance is to establish the relationship between items by analysing the scoring information of users. Because the items that users like usually have some attribute characteristics, the scored items can reflect the corresponding statistical
characteristics to a certain extent. The project association degree \( H_{K_iK_j} \) is calculated by using the keyword \( S_x \in K_n \). The association result is obtained by formula \( H_{K_iK_j} = \sum_{a=1}^{n} (S_{K_ia}, S_{K_ja}) / n \), where \( S_{K_i,a} \) and \( S_{K_j,a} \) are the different attribute characteristic values of the project. When \( S_{K_i,a} = 1 \), it means that the project does not have attribute characteristics, \( n \) is the number of projects, \( H_{K_iK_j} \) is the association degree of the project, and its value range is 0-1, the larger the data, the higher the similarity between projects.

3.2. Personalized recommendation algorithm model

Personalized recommendation algorithm model is based on matrix factorization technology, which has good expansibility and efficiency in processing high-dimensional rating information data. Because the traditional PMF model is a widely used model, but this model only considers the score information of user and project interaction, and does not integrate the social influence factors. Therefore, this paper improves the PMF model, integrates the user trust relationship, social interaction influence and project relevance into the PMF model, and forms the personalized recommendation algorithm model proposed in this paper. The implementation steps of personalized recommendation algorithm proposed in this paper are divided into four steps.

Step 1: determine the PMF model \([7]\). The PMF model uses the user interest characteristics and the inherent characteristics of the two implicit feature matrices \( U \in R^{m \times m} \) and \( V \in R^{n \times n} \) to learn the prediction score \( U^TV \), combines the probability analysis and the relationship between the prediction score \( U^TV \) and the real score \( R \), and finally derives a minimum objective function combined with bayesian rules. Formula (4) is the calculation method of \( R \) gaussian distribution of scoring matrix, where \( N(R|G(U^TV)) \) is the probability density function, \( h \) is the identification matrix, formula (5) is the calculation formula of minimization objective function, and figure 1 is the original model of PMF.

\[
Q(R|U,V,\beta^2) = \prod_{i=1}^{a} \prod_{j=1}^{b} \left[ N(R_{ij}|G(U^TV)) \right]^{\frac{h_{ij}}{2}} \tag{4}
\]

\[
L(R,U,V) = \frac{1}{2} \sum_{i=1}^{a} \sum_{j=1}^{b} h_{ij} \left[ R_{ij} - G(U^TV) \right]^2 + \frac{\xi}{2} \left\| U \right\|_F^2 + \frac{\xi}{2} \left\| V \right\|_F^2 \tag{5}
\]

Step 2: integrate user trust into PMF model. By using the scoring information and trust relationship to learn the user's interest feature space \( U \), and then by evaluating the trusted friends in the social network to obtain the hidden feature vector \( U = \sum_{k \in R_d U_i} \), finally get the integrated model. Formula (6) is a calculation method integrating user trust relationship.

\[
Q(U_k|R,\alpha^2,\beta^2) = \prod_{a=1}^{m} K(U_k|U,\beta^2) \prod_{b=1}^{m} (U_k|0,\beta^2) \tag{6}
\]

Step 3: integrate social interaction influence into PMF model. Through bayesian rules, the social interaction influence is integrated into the improved model, and the improved calculation method is obtained.

\[
Q(U,V|R,\alpha^2,\beta^2) = \prod_{a=1}^{m} \prod_{b=1}^{m} \left[ N(R_{ij}|G(U^TV)) \right]^{\frac{h_{ij}}{2}} \cdot \prod_{a=1}^{m} N(U_k|0,\beta^2) \cdot \prod_{b=1}^{m} N(U_j|0,\beta^2) \tag{7}
\]

Step 4: integrate project relevance into PMF model. In order to improve the quality of recommendation, the inherent characteristics of attribute association are introduced, and the matrix decomposition calculation method of social interaction impact probability and the minimum objective function calculation method are obtained. Figure 2 is the improved personalized recommendation algorithm model.
Figure 1. PMF original model.

Figure 2. Improved personalized recommendation algorithm model.

4. Simulation experiment and results
In order to verify the effectiveness of the algorithm proposed in this paper, the system is verified on two open-source datasets Epinions and Douban, which are two classic open-source datasets of social network recommendation, including user rating data and trust relationship. Data set Epinions contains 26149 feedback from 8724 users on 16542 projects the Douban data set contains 887478 score records of 7421 user pairs and 34125 items. This paper compares the algorithm with PMF, SoRec, SocialMF and other algorithms to observe the top-N recommendation ability of the algorithm. In order to ensure the consistency of the test environment, we choose the results when the parameters are optimal on two open-source datasets. Therefore, we set $\xi_v = 12$ and $\xi_i = 6$ in Epinions, $\xi_v = 17$ and $\xi_i = 13$ in Douban to get the final test results. Table 1 is the test results of different algorithms in Epinions, and table 2 is the test results of different algorithms in Douban. Figure 3 is the comparison of algorithms in Epinions and figure 4 is the comparison of algorithms in Douban.

Table 1. Test results of different algorithms in Epinions.

| Algorithm | MAE    | RMSE  |
|-----------|--------|-------|
| PMF       | 0.921  | 1.17  |
SoRec 0.823 1.18
SocialMF 0.864 1.02
Improved algorithm 0.771 0.968

| Algorithm   | MAE  | RMSE |
|-------------|------|------|
| PMF         | 0.813| 1.022|
| SoRec       | 0.801| 1.017|
| SocialMF    | 0.783| 0.993|
| Improved algorithm | 0.691| 0.951|

Table 2. Test results of different algorithms in Douban.

Figure 3. Comparison of algorithms in Epinions.

Figure 4. Comparison of algorithms in Douban.

It can be seen from figure 3 and figure 4 that the test results of PMF algorithm in two datasets are higher than other algorithms, which indicates that the recommendation performance of PMF algorithm is worse than other algorithms, and the test results of the algorithm proposed in this paper are lower than
other algorithms, which indicates that the recommendation performance of this algorithm is better than other algorithms. Therefore, it verifies the effectiveness of the improved recommendation algorithm, which integrates the social influence factors such as user trust, social interaction influence and project relevance, and improves the recommendation effect and quality of sparse data.

5. Conclusion
In this paper, the problem of low recommendation efficiency and quality caused by the current sparse data problem is studied. The social impact theory is integrated into the recommendation algorithm. The personalized recommendation algorithm model is constructed by using the user trust relationship, social interaction influence and project relevance in the social impact factors, and a personalized recommendation algorithm is proposed. Finally, the algorithm is verified by experiments, this method improves the accuracy of recommendation and improves the low quality of recommendation in sparse data environment.

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