A recommendation of pension service based on user preferences and trust relationships

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Abstract. Recommendation technology have been widely used in social networks and many e-commerce websites, but there are few recommendations of pension service and those recommendation results are not accurate enough. For more accurately recommending personalized pension services to users, this paper proposes a recommendation method of pension service based on the user preferences and the trust relationships between users. Firstly, by mining user socialization relationship information, the degree of trust relationships between users is calculated, and the Pearson correlation coefficient is used to obtain the user similarity, then their results are combined and used to find the neighbour user set of the target user. Secondly, a timeliness model of user ratings based on the user evaluation time are established, which is used to determine the user's preference for the service, and finally to predict the target user's rating value for the project. The experiment takes the Douban review data and the users social data as the case to verify the results. The experimental results show that compared with the traditional recommendation method, the recommendation method based on user preferences and trust relationships improves the accuracy of recommendation.

1. Introduction

With the rapid development of the Internet, more and more service information is available on the Internet. This makes it difficult for users to browse to the valid service information in a timely manner, and spends a lot of time in the invalid information[1]. Nowadays, recommendation systems are widely available in various e-commerce service websites, such as Amazon, CDNow, DangDang[2]. The purpose of these recommendation systems is to perceive the needs of users, provide service recommendations to users, and find the services that users really need from a large amount of information, thereby saving users' time and improving the efficiency of using information. However, the product recommendations of many websites that just recommend the current hot services directly to users, which not only ignores the user's individual needs, but also causes a large number of products to be forgotten by users. Not all the users have the same preferences as the mainstream users, but this type of product recommendation method cause that the product recommendation results obtained by all the users are roughly the same. This cannot satisfy the user's individual needs, and also loses the meaning of those recommendation results [3].

The recommendation system helps users to find projects they might be interested in from large amounts of data by mining binary relationships between users and projects, and generate personalized recommendations to meet individual needs. A good recommendation system can establish a close relationship with users. But how to accurately perceive user preferences, help users quickly find services that meet user needs in a large number of services is the focus and difficulty of current
research. Technically, personalized recommendations can be based on The actual needs and interests of users meet the different needs of different users [4].

At present, the widely used personalized recommendation algorithm is user-based collaborative filtering algorithm[5]. In this algorithm, a set of users are selected by calculating the similarity between the target users and other users, and then according to the history information of the service that this set of users are interested in, the recommendation results are provided for the target users. However, the typical user-based collaborative filtering algorithm does not accurately perceive the user's true preferences. This is because it does not take into account the social relationships and trust relationships between users, the effect of the timeliness of user ratings on the accuracy of recommendation results is not considered. So the final personalized recommendation results will be biased. Therefore, in order to solve the above problems, this paper proposes to explore the trust relationship between users through social networks first, and then calculate the final user preferences based on users ratings and their time stamps, so as to recommend more accurate personalized service information for target users.

2. Calculate user similarity

2.1. Pearson correlation coefficient

There are many methods to calculate user similarity, common methods include cosine similarity, Pearson coefficient and adjusted cosine similarity. The cosine similarity is to calculate the angle between two vectors, but there is no decentralization, which requires a certain value on every dimension of the vector. However, not every two users will rate the same project, so some dimensions are empty and cannot be calculated, the cosine similarity does not take into account the factor of different rating standards among different users. The difference between the Pearson correlation and the adjusted cosine similarity is that the decentralization method is different. The Pearson correlation coefficient considers the average of each item's score by the user, while the adjusted cosine considers the average value of each user who rates the item. This paper completes the user similarity calculation by combining the Pearson correlation coefficient, social and trust relationships among users. Calculate the similarity between user u and user v using Pearson correlation coefficient, and calculate the formula as follows (1):

$$sim(u,v) = \frac{\sum_i (r_{ui} - \bar{r}_u)(r_{vi} - \bar{r}_v)}{\sqrt{\sum_i (r_{ui} - \bar{r}_u)^2 \sum_i (r_{vi} - \bar{r}_v)^2}}$$

where $r_{ui}$ represents the rating of user u for item i, $\bar{r}_u$ represents the average rating of user u, $r_{vi}$ represents the rating of user v for item i, and $\bar{r}_v$ represents the average rating of user v, $I_u \cap I_v$ represents a service that user u and user v jointly comment on.

2.2. Calculation of trust between users

In the recommendation system, the traditional recommendation method only considers the similarity of users, ignoring the influence of the association between the recommended objects on the recommendation results in many application scenarios [6]. The degree of trust between users is related to the interaction experience, when the experience between two users is positive, the degree of trust between users will be increase; on the contrary, the degree of trust declines [7, 8]. So under the same hobbies as the two users, the user prefers the service recommended by the user who has a social relationship with himself. The recommendation to integrate social information has become a research hotspot in the recommendation field [9]. In the pension system, it is necessary to fully consider the elderly with similar interests and social relationships, they would have a relatively fixed social circles, information interaction ability is strong, they trust each other, so add credibility in similarity calculation, the recommended results will be more accurate.

Trust between users is divided into direct trust and indirect trust. According to the user's social
information, direct attention and interactive behavior is called direct trust. As shown in figure 1(a), A has a direct trust relationship with B. In social information, users have indirect trust with friends of people they following, as shown in figure 1(b), there is an indirect trust relationship between A and C. Because the multi-layer indirect trust relationship is not reliable, so this paper only considers the two-layer indirect trust relationship. The direct trust of user u to user v is expressed as $t'(u,v)$, the indirect trust of user u to user v is expressed as $t''(u,v)$. The value of the trust is directly related to the number of interactions between users. The interaction behavior includes comments, likes and forwarding. Such data shows that users are more interested in a pension institution or a certain aged care service. By collecting and excavating such information in the pension service platform, it is more accurate to perceive the preferences of the elderly in order to recommend the pension institutions and service types that the elderly need. The formula for calculating the direct trust of user u to user v is as follows (2):

$$t'(u,v) = \frac{\sum C_{uv} \cup L_{uv} \cup F_{uv}}{N_u}$$  \hspace{1cm} (2)$$

where $C_{uv}$, $L_{uv}$, and $F_{uv}$ respectively indicate user u to comments, likes, and number of forwards to the user v, and $N_u$ represents the total number of user u interaction information. The calculation formula for the indirect trust of user u to user v is as follows (3):

$$t''(u,v) = \frac{\sum C_{u,h} \cup L_{u,h} \cup F_{u,h} \sum C_{v,h} \cup L_{v,h} \cup F_{v,h}}{N_u}$$  \hspace{1cm} (3)$$

where h represents the intermediate user of user u and v, the user who is concerned by user u and who is pay attention to the user v. This paper considers that the similarity between user u and user v is expressed as follows (4):

$$\begin{align*}
    \text{sim}(u,v) &= \frac{t'(u,v) + t''(u,v)}{2}, \text{direct trust relationship} \\
    \text{sim}(u,v) &= \frac{t'(u,v) + t''(u,v)}{2}, \text{indirect trust relationship} \\
    \text{sim}(u,v) &= 0, \text{there is no trust relationship}
\end{align*}$$  \hspace{1cm} (4)$$

From this, the number of K users with the highest similarity to the user u are calculated as their adjacent user sets, which are denoted as $S(u)$.

3. Forecast user rating

3.1. Establish the timeliness model of user rating

In the recommendation system, the user's preferences are constantly changing over time, and the similar types of recommendations over a period of time can reduce the user's satisfaction, so the recommendations should be made according to the dynamic user's preferences. In this section, it is believed that there is a non-linear diminishing trend of user preference for services over time. It is possible to recommend more accurate services for the elderly according to their dynamic user's preferences. The longer the time bucket from that user finished service evaluation to the current time, the lower the interest, and for the services that users have recently evaluated, they are more interested. So, the timeliness model of user rating should be established. However, the user's preference for a service is not directly proportional to the satisfaction after using the service. Some users are interested
in a service, but after using it, the service experience is not good, so in this paper, the timeliness of user rating and the user rating are combined to calculate the user's preference value for the service as a formula (5):

\[ P_{r^i} = \exp\left(\frac{-\text{time}(u,i)}{\text{time}}\right) \times r_{r^i} \]  

(5)

In the pension service recommendation, \( \text{time}(u,i) \) indicates the timeliness of user rating of that the user \( u \) evaluate the service \( i \), when the service evaluation time is in the most recent cycle, the value of \( \text{time}(u,i) \) is 0, when the service evaluation time is in the penultimate period, its value is 1 and so on. From the formula, it can be concluded that the closer the user evaluation time is to the current time, the smaller the \( \text{time}(u,i) \) value is, and the value of \( \exp\left(\frac{-\text{time}(u,i)}{\text{time}}\right) \) approaches 1. \( \text{time} \) indicates the user evaluation period. The shorter the user evaluation period, the faster the interest declines. Therefore, the newer evaluation, the higher the preference value. \( r_{r^i} \) indicates the actual rating of user \( u \) for service \( i \).

3.2. Predict user ratings for services

Through the steps described above, firstly we calculate K users that are most similar to the target user \( u \), and calculate the degree of preference of these users to the target service, thereby the rating value of the target user \( u \) for the service is predicted, and finally the platform will recommend set of services with the top rating value for the user. The predicted scores of the target user \( u \) for the services can be calculated by the following (6):

\[ S(u, i) = \sum_{v \in \text{nearest}} P_{r^v} \times \text{sim}(u, v) \]

\[ \frac{\sum_{v \in \text{nearest}} \text{sim}(u, v)}{\text{sim}(u, v)} \]  

(6)

4. Experimental results and analysis

This paper introduces the data used in the experiment, explains the test method and evaluation criteria, and gives the experimental results based on user trust and user evaluation time recommendation algorithm, and compares it with the user-based collaborative filtering recommendation algorithm.

4.1. Experimental data set

In this paper, the experimental data sources are the user data and movie evaluation data of Douban. The original data contains about 80,000 ratings of 986 users, and about 50,000 social behavior data of these users. All the scores of the movie are 1 to 5, and the higher the user evaluation score, the more the user likes it. In the movie data, the movie data attributes are mapped to the aged service data. The evaluation time of the movie indicates the user's evaluation time of the aged care service in the pension service platform, the movie user score indicates the old person's score on the aged care service, and the movie user social information indicates the social information between the elderly.

4.2. Experimental evaluation criteria

By collecting the user's evaluation data one week ago, by referring to the user's recommendation service, according to the user's next week's score record, it is judged whether the recommendation data is accurate, and the percentage of the recommended service in the service used by the user. In this paper, the average absolute error MAE is used to evaluate the prediction accuracy of the recommendation algorithm. The average absolute error of the user \( u \) is calculated as a formula (7):

\[ MAE_u = \frac{1}{n} \sum_{i} |P_{r^i} \cdot R_{r^i}| \]  

(7)

where \( n \) represents the number of recommended services that the user \( u \) has used and scored, and \( P_{r^i} \) and \( R_{r^i} \) represent the predicted score value and the actual score value of the user \( u \) for the service \( i \).
4.3. Experiment process
The experimental code is implemented in Java and Python. The experiment process is as follows: First, the crawled data is processed, and each user evaluates the movie with no less than 20 data, and deletes illegal characters and sensitive information such as personal information. Secondly, the Pearson similarity between users is calculated based on the obtained score data, the social information of the user is found, and the degree of trust between the users is calculated. Third, the number of adjacent user sets is 10, 20, 30, 40, and 50, calculate the MAE changes when selecting different numbers of similar users. Fourth, the user evaluation period $time_i$ is selected as 10, indicating the length of the period in which the user evaluates the service in the pension service platform. Finally, the preference is calculated based on the evaluation time of the selected K similar users for the target service, predicting the predicted score value of the target user for the target service. The experimental results show that when K is 50, the experimental results are the best.

4.4. Experimental result
In this experiment, the user-based collaborative filtering algorithm is compared with the proposed algorithm. The user history evaluation data is used to predict the user's rating value for the service next week, and the recommendation accuracy of the two algorithms is judged according to the value of MAE. The experimental comparison data is shown in figure 2. Observing the two polylines in the figure 2 as shown in the figure 2 can be concluded that the recommended accuracy of the proposed algorithm is higher, and the larger the value of K, the smaller the value of MAE, the more accurate the recommendation.

![Comparison of the results of the two algorithms](image)

**Figure 2.** Comparison of the results of the two algorithms.

5. Conclusion
In this paper, the trust degree between users is calculated according to the social information of users, and the trust degree and the evaluation score are used as indicators for calculating the similarity of users. And we establish the timeliness model of user rating to calculate user preferences, and the scenario of that the user's preference for the service changes with time is fully considered, thereby a more accurate service is recommended for the user. It is proved by experiments that this method can obtain more accurate recommendation results compared with the traditional recommendation algorithm.

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References

[1] X.Y. Huang, R. Lu, Z.H. Wang, Z.F. Zhu, ICNC, 591-596 (2017)
[2] P. Wang, H.W. Ye, ICIIS, 152-154 (2009)
[3] R. Zhu, H.M. Wang, D.W. Feng, Journal of Software, 22, 852-864 (2011)
[4] G.J. Zou, J.S. Wang, H.L. Yuan, ICIEA, 1643-48 (2018)
[5] X. Wu, B. Cheng, J. Chen, IEEE Transactions on Services Computing, 1 (2017)
[6] L. Duan, H, Tian, Future Internet, 9, 63 (2017)
[7] W. Sherchan, S. Nepal, C,Paris, CSUR, 45, 47 (2013)
[8] X. Xia, J. Yu, S. Zhang , Security & Communication Networks, 9, 1-9 (2017)
[9] H.F. Liu, L.P. Jing, J. Yu, Journal of Software,29, 340-362 (2017)