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Online Learning of Social Science Courses Based on Personalized Recommendation Algorithm

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The recommendation algorithm has been used to find the course of interest in the vast amount of online learning resources. This paper analyzed the recommendation algorithm briefly and designed an improved user-based collaborative filtering recommendation algorithm (UCFRA) recommendation algorithm based on UCFRA by improving its matrix filling based on the item attribute. It was found that when the number of K nearest neighbors was 80, the precision rate of the improved UCFRA was 0.5387 for the MovieLens 100K dataset, which was 5.13% higher than that of the UCFRA. For the social science course dataset, the highest precision rate of the improved UCFRA was 0.5429, and the highest coverage rate was 0.4559, both of which were better than the UCFRA. The experimental results verified that the reliability of the designed recommendation algorithm for social science course recommendation. The algorithm can be further applied.

Keywords: recommendation algorithm, social science course, online learning, collaborative filtering

1. INTRODUCTION

With the rapid development of the Internet (Chen et al., 2021), more and more online resources have become available. Through the Internet, users can access various resources such as movies, books, and music they want anytime and anywhere, but at the same time, the huge amount of resource material also increases the difficulty of finding specific content of interest to the user. The emergence of personalized recommendation algorithms (Wang et al., 2022) alleviates this problem. Personalized recommendation algorithms are applied effectively in many fields such as online shopping (Jiang et al., 2021) and music recommendation (Shi, 2021).

Zarzour et al. (2018) designed a two-stage recommendation system combining dimensionality reduction and clustering techniques, and found that the method could generate accurate and efficient recommendations. Zhao et al. (2018) designed a low-rank and sparse cross-domain (LSCD) recommendation algorithm, demonstrating the method's effectiveness through experiments on real-world datasets. Zhu et al. (2018) designed a multi-constrained path recommendation algorithm combined with knowledge graphs, applied it to resource recommendation for online learners, and found through experiments that there was a similarity between learner self-organization paths and recommendation paths. Wang et al. (2021) designed a recommendation algorithm that combined temporal factors and emotional tendencies for the information expiration problem. Through experiments, they found that the method could solve the problem of temporal effects and sentiment analysis in the recommendation to improve model prediction performance. With the development of informatization in the education domain, more and more people are being attracted to online learning. Recommendation algorithms have been applied to help users find the learning resources they need (Wang, 2021). This paper designed a recommendation algorithm for the online learning of social science courses. Experiments conducted on an actual data set confirmed the method's reliability in terms of accuracy. The proposed recommendation algorithm can be further applied in actual online learning.

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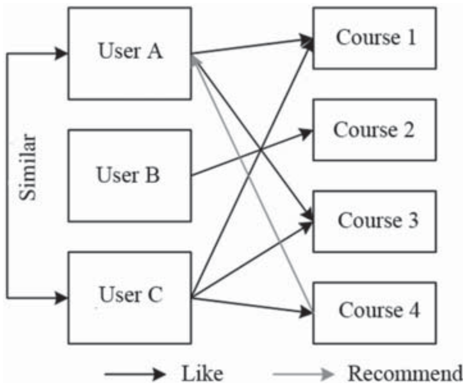


Figure 1 Example of UCFRA.

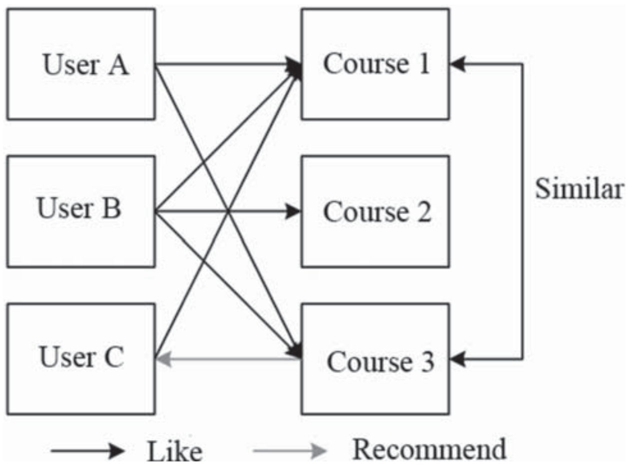


Figure 2 An example of ICFRA.

2. PERSONALIZED RECOMMENDATION ALGORITHM

Recommendation algorithms address the problem of how to recommend the content of interest to users in the presence of information overload (Alhijawi and Al-Naymat, 2022), and the collaborative filtering recommendation algorithm (CFRA) is one of them. CFRA consists of two main types, one is user-based CFRA (UCFRA) (Wang et al., 2021), and the other is item-based CFRA (ICFRA) (Iwendi et al., 2022).

The principle of UCFRA is shown in Figure 1.

According to Figure 1, user A likes courses 1 and 3, user B likes course 2, and user C likes courses 1, 3, and 4. Users A and C both like courses 1 and 3, so user A and user C are considered similar, and therefore, course 4, which user C likes, is recommended to user A. The specific steps of UCFRA are as follows.

(1) A user-item scoring matrix is established:

$$R\left(m,n\right)=\begin{bmatrix} R_{1,1} & R_{1,2} & \cdots & R_{1,n} \\ R_{2,1} & R_{2,2} & \cdots & R_{2,n} \\ \cdots & \cdots & \cdots & \cdots \\ R_{m,1} & R_{m,2} & \cdots & R_{m,n} \end{bmatrix},$$

where $R_{i,j}$ refers to the score given to item j by user i.

(2) A user similarity matrix is established to determine the similarity between users.

(3) Users are ranked according to their similarities. Top K users are used as the set of nearest neighbor users, U_k.

(4) The item in which the nearest-neighbor users have been rated and the target users have not been rated is predicted:

$$P_{A,i}=\overline{R_A}+\frac{\sum_{B\in U_k} sim(A,B)(R_{B,i}-\overline{R_B})}{\sum_{B\in U_k} sim(A,B)},$$

where $\overline{R_A}$ and $\overline{R_B}$ refer to average scores of users A and B and sim(A, B) refers to the similarity between users A and B.

The principle of ICFRA is shown in Figure 2.

As shown in Figure 2, users who like course 1 are A, B, and C, the user who likes course 2 is B, users who like course 3 are A and B, the user who likes courses 1 and 2 is B, users who like courses 1 and 3 are A and B, and the user who likes courses 2 and 3 is B. It is assumed that courses 1 and 3 are similar, so course 3 is recommended to user C, who does not rate course 3. Similar to UCFRA, the specific steps of ICFRA are as follows.

(1) A user-scoring matrix is established.

(2) The similarity between different items is calculated to build an item similarity matrix.

(3) The items are ranked according to their similarity. Top K items are used as the set of nearest neighbor items, I_k.

Table 1 Users, item scores, and item attributes.

	I_1	I_2	I_3	I_4
U_1	0	2	2	5
U_2	1	1	2	1
U_3	2	0	1	2
U_4	5	3	4	2
p_1	0	1	1	1
p_2	1	1	0	1
p_3	0	1	1	1
p_4	1	0	1	1

(4) Items that the target user has rated are found out for score prediction:

$$P_{A,i} = \overline{R_i} + \frac{\sum_{j \in I_k} \mathrm{sim}(i, j)(R_{A,j} - \overline{R_j})}{\sum_{j \in I_k} sim(i, j)}$$

where $\overline{R_i}$ and $\overline{R_j}$ represent the average scores of items i and j and $sim(i, j)$ refers to the similarity between items i and j.

Data sparsity is the main drawback of CFRA (Jiang et al., 2021). In the actual data, users have actually rated few items (Zheng et al., 2020), which gives the user-item scoring matrix a large sparsity; it is generally filled by using the mean or mode, but it is easy to decrease the accuracy. Therefore, the matrix filling method is improved based on the item attributes and is combined with UCFRA to obtain an improved UCFRA.

In addition to the scoring system, the recommendation system includes user attributes, item attributes, etc. Table 1 shows an example.

In Table 1, I_1, I_2, I_3, and I_4 are items, U_1, U_2, U_3, and U_4 are users, p_1, p_2, p_3, and p_4 are item attributes, $U - I$ refers to the user's rating of the item, and $p - I$ refers to the presence or absence of an attribute in the item, 1 for yes and 0 for no.

The calculation formula of average score $r'_{A,P}$ given by user A to attribute p is:

$$r'_{A,P} = \frac{\sum_{i \in I_{A,p}} R_{A,i}}{|I_{A,p}|},$$

where $I_{A,p}$ refers to the set of items that have been scored by user A and contain attribute p and $|I_{A,p}|$ refers to the number of items in the set.

At the same time, attributes that users prefer are assigned weights. The calculation formula of user A's preference weight $W_{A,p}$ for attribute p is:

$$W_{A,p} = \frac{N_{A,p}}{N_{A,all}},$$

where $N_{A,p}$ refers to the number of items that have been scored by user A and contain attribute p, $N_{A,all}$ refers to the total number of items that have been scored by user A. Finally, the preference of user A for attribute p is expressed as:

$$f_{A,p} = r'_{A,P} \times W_{A,p}.$$

When filling the matrix based on the item attribute:

1. if there are items in the set of items already rated by the user that have the same attributes as the missing items, the filling formula is:

$$R'_{A,i} = \frac{\sum_{j \in I_{A,j}} R_{A,j}}{|I_{A,j}|},$$

where $I_{A,j}$ refers to the set of items that have exactly the same attribute as the items to be filled;

2. if there is no item in the set of items already rated by the user that has exactly the same attributes as the missing item, but all attributes of the missing item exist in the set, then the filling formula is:

$$R'_{A,i} = \frac{\sum_{p \in i} r'_{A,P} \times f_{A,p}}{\sum_{p \in i} f_{A,p}}.$$

Based on this, the calculation of user similarity is improved:

$$sim(X, Y) = \frac{\sum_{p \in P_{X,Y}} (f_{X,p} - \overline{f_X})(f_{Y,p} - \overline{f_Y})}{\sqrt{\sum_{p \in P_{X,Y}} (f_{X,p} - \overline{f_X})^2} \sqrt{\sum_{p \in P_{X,Y}} (f_{Y,p} - \overline{f_Y})^2}},$$

where $P_{X,Y}$ refers to the set of attributes of the items rated by both users X and Y, $f_{X,p}$ refers to the preference of user X to attribute p, and $\overline{f_X}$ is the attribute mean of user A.

Ultimately, the steps of the improved UCFRA are as follows. After establishing the item-attribute and user-score matrices, the attribute scores and preferences are calculated to obtain the user's attribute preferences. Then, the scoring matrix is filled. The user similarity is calculated based on the item attributes to obtain the set of top K nearest neighbors. A recommendation list is obtained by score prediction to obtain the online learning course recommendations.

3. EXPERIMENT AND ANALYSIS

Experiments were conducted on the Windows 10 operating system. Intel(R) Core(TM) i910900X CPU@3.70GHz was used. The memory was 64 GB. The program was written by Python. First, the performance of the recommendation algorithm was analyzed using the MovieLens 100K dataset (Bahraini Saputra and Danar Sunindyo, 2019). The set contains 100,000 scores given by 943 users for 1,682 movies of 19 categories. The evaluation indexes were:

(1) precision rate: $Precision = \frac{\sum_{u \in U} |R_u \cap T_u|}{\sum_{u \in U} |R_u|}$,

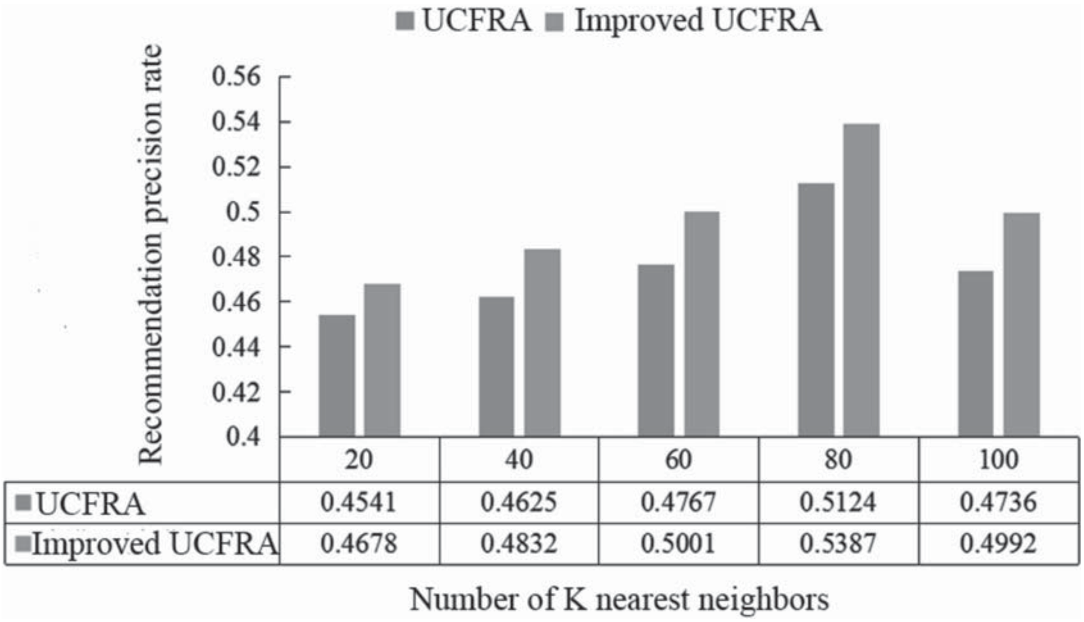


Figure 3 Comparison of recommendation precision rate.

Table 2 Examples of social science courses.

Course name	Number of users	Number of scores
Situation and Policy	57,660	22,496
Outline of Modern Chinese History	51,760	732
Basic Principles of Marxism	24,432	4,615
Ideology and Morality and Rule of Law	23,373	5,112
Introduction to Labor Education	10,533	855

(2) coverage rate: $Coverage = \frac{U_{u \in U} R(u)}{|I|}$,
where R_u is the recommendation list of the algorithm, T_u is the set of items that users have scored, and I and U are the set of items and users.

The recommendation precision rates of the UCFRA and improved UCFRA were compared by ten-fold cross-validation. The comparison of recommendation precision rates for different K nearest neighbors is shown in Figure 3.

Figure 3 shows that the recommendation precision rate increases first and then decreases as the value of K increases. When the number of K nearest neighbors is 20, the precision rate of the improved UCFRA is 3.02% higher than that of the UCFRA (0.4678 vs. 0.4541). When the number of K nearest neighbors is small, the recommendation precision rate is not high because there are fewer items to recommend. When the number of K nearest neighbors reaches 80, the precision rates of both algorithms are the highest at 0.5124 and 0.5387, respectively, and the precision rate of the improved UCFRA is 5.13% higher than the UCFRA, which verifies the reliability of the improved recommendation algorithm. When the number of K nearest neighbors increases further, the precision rate of the algorithm decreases instead, which might be due to the similarity between users decreasing when the number of nearest neighbors is high.

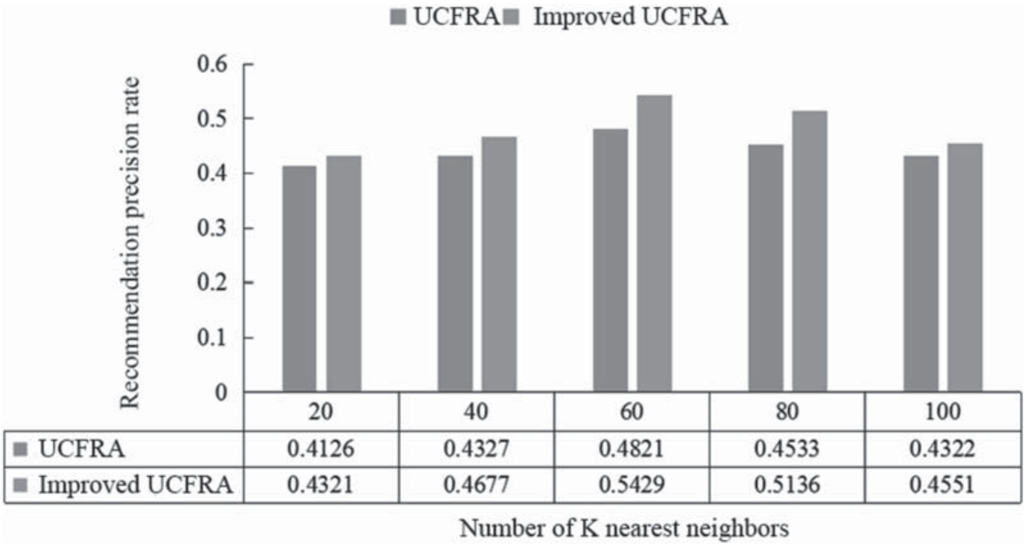
Then, the improved UCFRA was applied in the recommendation of social science courses. Taking Chinese University Massive Open Online Courses (MOOC) as an example, several social science courses are shown in Table 2.

The data related to users and social science courses were collected from China University MOOC to establish a dataset of social science courses, including 45,218 scores given by 97,864 users to 172 courses. Among the scores, 70% of them were used for algorithm training, and 30% were used for testing. The recommendation precision rate of the two algorithms was compared. The results are shown in Figure 4.

Figure 4 shows that when the number of K nearest neighbors is 60, both algorithms have the highest recommendation precision rate. The precision rate of the improved UCFRA is 12.61% higher than that of the UCFRA (0.5429 vs. 0.4821), and the precision rate of the improved UCFRA is always higher than that of the UCFRA.

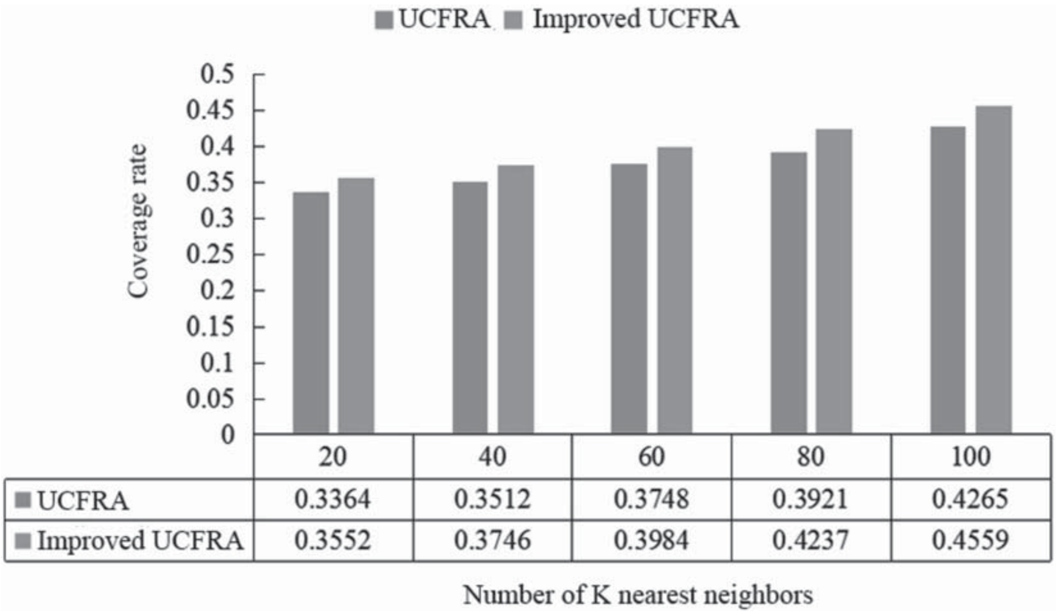
Then, the coverage rates of the two algorithms were compared. The results are shown in Figure 5.

As seen in Figure 5, the coverage rate of the algorithm increases gradually as the value of K increases. When the number of K nearest neighbors increases from 20 to 100, the coverage rate of the UCFRA increases from 0.3364 to 0.4265, with an increase of 0.0901, while the coverage rate of the improved UCFRA increases from 0.3552 to 0.4559, with an increase of 0.1007. When the number of K nearest neighbors is 100, the coverage rate of the improved UCFRA is 6.89% higher than that of the UCFRA (0.4559 vs. 0.4265). These results indicate the reliability of the improved UCFRA for course recommendation.



	20	40	60	80	100
UCFRA	0.4126	0.4327	0.4821	0.4533	0.4322
Improved UCFRA	0.4321	0.4677	0.5429	0.5136	0.4551

Figure 4 Comparison of the recommendation precision rate of algorithms for the dataset of social science courses.



	20	40	60	80	100
UCFRA	0.3364	0.3512	0.3748	0.3921	0.4265
Improved UCFRA	0.3552	0.3746	0.3984	0.4237	0.4559

Figure 5 Comparison of the recommendation coverage rate of algorithms for the dataset of social science courses.

4. DISCUSSION

With the continuous development of online education (Zhou, 2022), the complex and massive amounts of learning resources make it increasingly difficult for users to find the learning resources they are interested in quickly and accurately, which could discourage online learning. The recommendation algorithm can make personalized recommendations of courses and resources by analyzing user behavior and characteristics. The application of personalized recommendation algorithms in online learning can help to meet users' individual needs and enables users to better utilize the advantages of online learning.

Social science is an important area of study in universities (Cheng et al., 2022) and serves the important task of guiding students to correctly understand the national situation, understand Marxism, and improve their overall academic proficiency. Online learning can help students to undertake social science courses more actively and positively, establish correct political concepts, and achieve all-round development. In order to further improve the efficiency of social science course learning, this paper designed a personalized recommendation algorithm, the improved UCFRA. First, the recommendation performance of the method was verified through experiments conducted on the MovieLens 100K dataset; then, a dataset of social science courses was established for the experiment.

The experimental results showed that the highest recommendation precision rate of the improved UCFRA was 0.5429, which was 12.61% higher than the UCFRA, indicating that the improved UCFRA achieved more accurate recommendation results than the UCFRA and could effectively recommend to users the social science courses of most interest to them. Then, the comparison results of the coverage rate showed that the highest coverage rate of the improved UCFRA was 0.4559, which was 6.89% higher than the UCFRA, further verifying the good performance of the improved algorithm in recommending social science courses.

In the past, social science courses were delivered by traditional teaching methods. However, with the advancement of the Internet, online learning is more capable of motivating students and increasing learner satisfaction, thus improving the effectiveness of social science education (Liu, 2021). The personalized recommendation algorithm designed for social science courses can be further applied in actual online learning, as it has been found to stimulate students' interest in learning and develop their moral consciousness.

5. CONCLUSION

This paper studied the online learning of social science courses based on personalized recommendation algorithms. An improved UCFRA was designed for the personalized recommendation of social science courses. Experiments on different datasets found that the improved UCFRA was superior in terms of precision and coverage rates than the original UCFRA, which can be further promoted and applied in practice to improve the efficiency of online learning.

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