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A Study of Online Educational Resource Recommendation for College Chinese Courses Based on Personalized Learning

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This paper analyzed the application of recommendation technology to online educational resources for college Chinese courses based on personalized learning. Traditional collaborative filtering algorithms, i.e., user-based collaborative filtering (CF-U) and item-based collaborative filtering (CF-I) algorithms, were analyzed and a recommendation algorithm was designed by combining the above two algorithms for recommending online educational resources. An analysis was conducted on data from the open online course (MOOC) platform of Chinese colleges. The results show that the highest precision and coverage rate of the combined algorithm was 80.2% and 59.4%, respectively, which were superior to the traditional CF algorithms, and it also had a high training efficiency. When training 100% of the data, the training time of the combined algorithm was 209 s. The experiment results demonstrate the combined algorithm is effective in resource recommendation and can be promoted and applied in practice.

Keywords: personalized learning, educational resources, online education, recommendation technology

1. INTRODUCTION

With the development of Internet technology, education delivery modes have also changed greatly. Online education has developed rapidly and various large-scale online education platforms have emerged. However, due to the massive amount of complex educational resources on these platforms, it has become difficult for learners to find resources that meet their individual needs so they can achieve personalized learning (Dora et al., 2016), hence recommendation technology has been applied in online education to make personalized recommendations for educational resources. Recommendation technology can help people find items of interest more efficiently and quickly (U et al., 2017), but it has not been applied widely in the field of education. Zuo et al. (2015) proposed a multi-objective recommendation model that provides multiple recommendations for multiple users in a single run. They found that the method is able to make more diverse and accurate recommendations. Alhamid et al. (2017) designed a contextual recommendation-aware approach that combined relevant tags and rating information to personalize recommendations. They found through experiments on the last.fm data set that the method had a high recommendation quality. Ma et al. (2016) introduced an object associated with history records or has been purchased by similar users to the specified user and proposed a recommendation method based on heat bidirectional transfer. By conducting experiments on two data sets, they found that their method had better performance in terms of accuracy, diversity, etc. Verma et al. (2016) proposed a new recommendation system incorporating active feature-based model selection to help knowledge workers

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Table 1 Examples of resources for college Chinese courses.

Course name	Course details
College Chinese	Analyze the value and connotation of classical literature in past Chinese dynasties.
Chinese around us	Improve abilities to use and understand Chinese through analyzing literature and teaching general literary knowledge.
Design of Chinese reading instruction	Construct new teaching models using classic texts in different genres and language styles as examples.
Study of Chinese written language	Teach the basics and development history of Chinese character study and the transition and evolution of Chinese characters.
Language pedagogy	Learn to master the characteristics and rules of teaching reading, writing and oral communication related to the Chinese course and understand different teaching methods and their characteristics.
Chinese poetic art	Discuss the concepts, elements, general knowledge, and attitudes of poetry in light of the characteristics of Chinese poetry.
Literary creative writing	Summarize the characteristics and techniques of writing, study the ways of disseminating the results of writing, and conduct effective practical teaching.

discover useful new content and found through experiments that the method reduced the document classification time per file by as much as 23 times without sacrificing accuracy. Zhang et al. (2020) designed a sparse bilinear convolution-based collaborative filtering recommendation algorithm and combined it with association rule mining to mine the label information of personalized dynamic web pages. They found through simulation experiments that the method performed well in recognizing and classifying attributes and improved the ability of intelligent recommendation for personalized dynamic web pages. This paper focuses on personalized learning for learners and applies recommendation technology to the selection of online educational resources for college Chinese courses. A combined algorithm was designed to recommend educational resources. An analysis was conducted with data from the massive open online course (MOOC) platform of Chinese colleges to verify the feasibility of the method in practice.

2. PERSONALIZED LEARNING THEORY

Personalized learning refers to learning that is flexible in meeting individual needs and takes into account the personality characteristics of different learners (Hyslop & Mead, 2015; Yovanoff et al., 2017). Most traditional education methods are teacher-oriented for teaching tasks (Kinshuk, 2015) and do not pay sufficient attention to students' initiative and motivation. However, with the development of Internet technology, methods of knowledge dissemination and acquisition have changed (Li et al., 2018) and online education has developed rapidly (El-Bishouty et al., 2015). Due to the characteristics of online education, students can obtain richer and better teaching resources and can access all kinds of information to help them better understand the various learning paths, their learning preferences, etc.

Compared to traditional learning methods, personalized learning is characterized by:

(1) a differentiation of learning content: the learning objectives and learning content are developed by the teacher in consideration of the students' individual differences or needs;

(2) active learning: learners no longer learn passively but actively learn and acquire knowledge at any time and any place.

In the current online education environment, the vast array of resources makes it difficult for learners to find the most suitable to achieve personalized learning. This paper analyzes the online education resources for college Chinese courses. There are many resources on the MOOC platform to support Chinese courses , with some examples listed in Table 1.

To realize personalized learning, learners need to find the most appropriate resources to support their learning from the huge number of educational resources available; therefore, the application of recommendation technology is studied in this paper.

3. PERSONALIZED RECOMMENDATION ALGORITHM

Recommendation algorithms can provide users with personalized services (Song & Nie, 2020) and they are often used effectively on video sites, social networking sites (He & Tan, 2015), e-commerce sites (Jing et al., 2018), etc. Two types of collaborative filtering (CF) algorithms are commonly used (Ha & Lee, 2017), namely the user-based collaborative filtering (CF-U) algorithm (Koohi & Kiani, 2016) and the

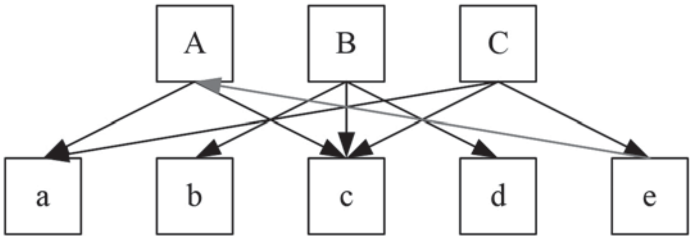

Figure 1 The principle of the CF-U algorithm.

Table 2 User-item matrix.

	Item_1	Item_2	……	Item_n
User_1	$R_{1,1}$	$R_{1,2}$	……	$R_{1,n}$
User_2	$R_{2,1}$	$R_{2,2}$	……	$R_{2,n}$
……	……	……	……	
User_m	$R_{m,1}$	$R_{m,2}$	……	$R_{m,n}$

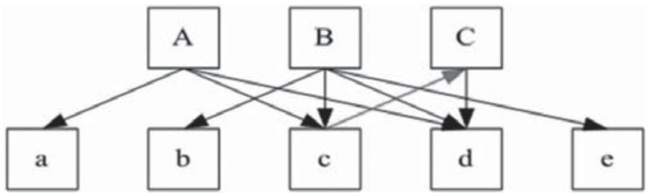

Figure 2 The principle of the CF-I algorithm

item-based collaborative filtering (CF-I) algorithm (Zou & Fekri, 2015).

The principle of the CF-U algorithm is as follows. Similar people will choose similar things, so when making recommendations to a user, recommendations can be made based on the hobbies of people who are similar to the user. Learners and learning resources are taken as an example. As shown in Figure 1, user A chooses resources a and c, user B chooses resources b, c, and d, and user C chooses resources a, c, and e. Since both users A and C choose resources a and c, it can be assumed that they have similar preferences, so resource e can be recommended to user A.

In the CF-U algorithm, the user-item matrix is the used source data, as shown in Table 2. The data at the i-th row and j-th column represent the rating of user i on resource j. In the MOOC, the rating values range from 0 to 5.

To find similar users, user similarity needs to be calculated. In this paper, the person similarity algorithm is used to find the top K users with the greatest similarity as neighboring users, calculated as follows:

$$sim\,(i,j) = \frac{\sum_{k\in I_{ij}}\left(R_{i,k}-\overline{R_I}\right)\left(R_{j,k}-\overline{R_j}\right)}{\sqrt{\sum_{k\in I_{ij}}\left(R_{i,k}-\overline{R_I}\right)^2}\sqrt{\sum_{k\in I_{ij}}\left(R_{j,k}-\overline{R_\mathrm{j}}\right)^2}},$$

where I_{ij} refers to the union set of the resources rated by user i and the resources rated by user j, $I_{ij} = I_i \cap I_j$, and $\overline{R_j}$ refers to the average score of the scores given by user i.

Based on the similarity, the top K users are selected as neighboring users, and the set of similar users obtained is written as S_U. Then, the scores of the items that the users have not rated are calculated as follows:

$$R_{u,i} = \overline{R_U} + \frac{\sum_{n\in s_U} sim\,(u,n)\left(R_{n,i}-\overline{R_n}\right)}{\sum_{n\in s_U} sim\,(u,n)},$$

where $R_{u,i}$ refers to the score of resource i given by user u, $\overline{R_U}$ refers to the average scores of resources given by user u, $sim\,(u,n)$ refers to the similarity of user u and user n, $R_{n,i}$ refers to the score of resource i given by user n, and $\overline{R_n}$ refers to the average score of resources given by user n.

Based on the calculated scores, the top N resources are selected and recommended for the current user and a top-N recommendation set is obtained.

The principle of the CF-I algorithm is as follows. Learners and learning resources are taken as an example. As shown in Figure 2, user A likes resources a, c, and d, user B likes resources b, c, d, and e, and user C likes resource d. It is assumed from the fact that both user A and user B like resources c and d that the two resources are similar; therefore, resource c can be recommended to user C as well.

The calculation method of the CF-I algorithm is roughly similar to the CF-U algorithm. In the calculation process of the CF-I algorithm, the similarities between different resources i.e., the items, are calculated instead of the similarities of users. This paper uses cosine similarity for the calculation as follows:

$$sim(i,j) = cos(\vec{i},\vec{j}) = \frac{\vec{i}\cdot\vec{j}}{\|\vec{i}\|\cdot\|\vec{j}\|},$$

where sim (i, j) refers to the similarity of resource i and j. The larger the value of $sim(i,j)$, the more similar the two resources. After calculation, the top-N resources are used as the set of neighboring resources of the current resource. Then, this set is used to calculate the score of the current resource

Table 3 Experiment data.

	$Item_1$	$Item_2$	$Item_3$	$Item_4$	$Item_5$	……	$Item_{500}$
$User_1$	5.0	3.6	4.5	3.6	4.2	……	3.6
$User_2$	4.6	4.8	4.1	3.8	4.3	……	3.5
$User_3$	4.7	4.1	4.9	4.1	4.8	……	1.9
$User_4$	2.1	4.5	3.6	5.0	2.8	……	5.0
……	……	……	……	……	……	……	……
$User_{160}$	4.8	5.0	4.8	3.6	4.6	……	2.7

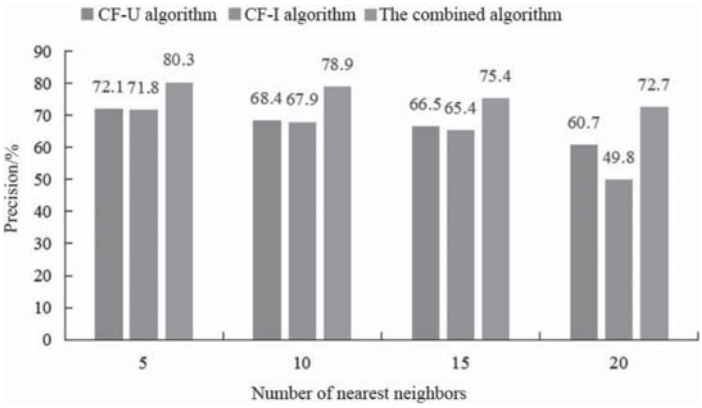

Figure 3 Comparison of accuracy between the three algorithms.

given by the users to determine whether to recommend the item or not, which is the same as the CF-U algorithm.

Both algorithms have their advantages and disadvantages (Wu & Chen, 2015). The advantage of the CF-U algorithm is its ability to make highly accurate recommendations but it is limited by the number of users as the complexity of the calculation increases with an increase in the number of users. The CF-I algorithm, however, can calculate the similarity of items well in the case of sparse data, but it tends to recommend items which are familiar to users.

Therefore, to achieve better recommendation results in the study of online educational resources, this paper combines the CF-U algorithm with the CF-I algorithm to develop a combined algorithm. Firstly, a set of similar items is generated by calculating the degree of user interest in new resources using the CF-I algorithm. Then, the CF-U algorithm finds the nearest neighbors within the range of similar items to obtain the final value to generate recommendation results. This method can complete a large number of similarity calculations, thus reducing the amount of calculation needed and improving the recommendation effect.

4. ANALYSIS

Experiments were carried out on user data on the Chinese college MOOC platform. The user information and the scores given by the users for different resources were collected. One hundred and sixty users provided 1600 scores on 500 teaching resources which were used as the experiment data set, 70% of which were used for training the algorithm and 30% for testing the algorithm. The experiment data are detailed in Table 3.

The performance of the algorithm was compared using two indicators, precision and coverage rate. For resource p, the resource set recommended by the algorithm was represented as $R(P)$, and the resource set visited by the users was represented as $T(P)$. Then,

$$\text{precision} = \frac{T(P) \cap R(P)}{R(P)},$$

$$\text{coverage} = \frac{T(P) \cap R(P)}{T(P)}.$$

Experiments were carried out by setting the number of the nearest neighbors as 5, 10, 15 and 20. The precision of the different algorithms is compared in Figure 3.

As shown in Figure 3, the precision of the algorithms decreased as the number of selected nearest neighbors increased. When the number of nearest neighbors was five, the precision of all the algorithms was highest, 72.1%, 71.8% and 80.3% for the CF-U algorithm, the CF-I algorithm and the combined algorithm, respectively, i.e., the precision of the combined algorithm was 8.2% higher than that of the CF-U algorithm and 8.5% higher than the CF-I algorithm. When the number of nearest neighbors increased to ten, the precision of the combined algorithm decreased by 1.4%, and when it increased to 15, precision decreased again by 3.5%. When the number of nearest neighbors selected was 20, the precision of the combined algorithm decreased by 7.9% compared with precision when the number of nearest neighbors was five. Overall, the precision of the combined algorithm was higher than that of the CF-U algorithm and the CF-I algorithm, which indicates that the combined algorithm is able to obtain more accurate results and make better recommendations in relation to learning resources.

The coverage rates of the different algorithms are shown in Figure 4.

Figure 4 shows that with an increase of the number of selected nearest neighbors, the coverage rates of the different

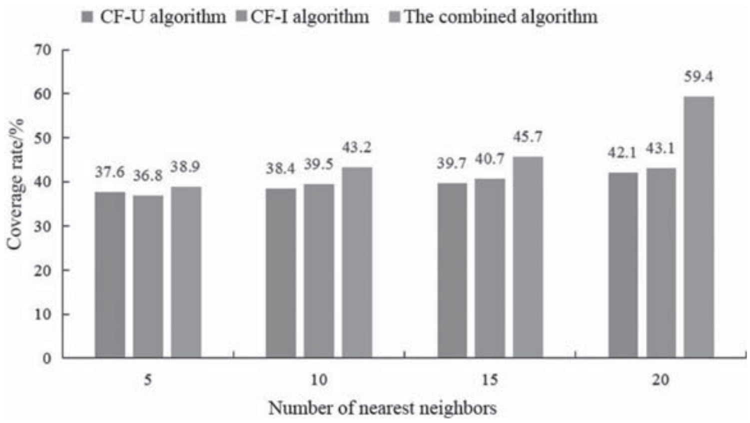

Figure 4 Comparison of coverage rates between the three algorithms.

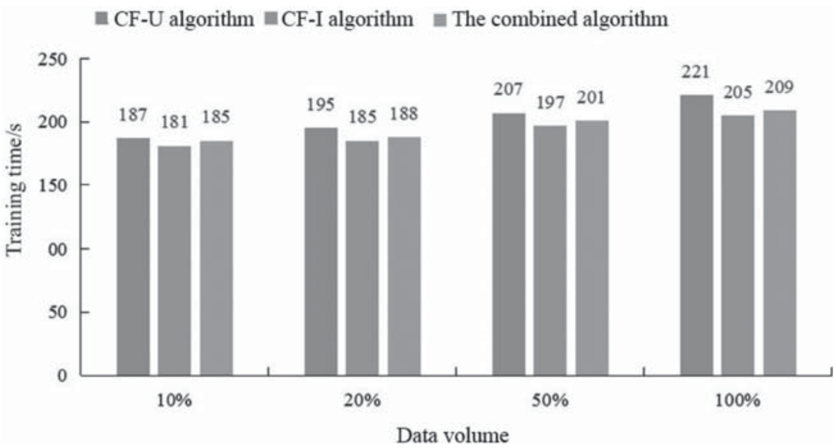

Figure 5 Comparison of training efficiency between the three algorithms.

algorithms improved to some extent. When the number of selected nearest neighbors was five, the coverage rates of the three algorithms were 37.6%, 36.8% and 38.9%, respectively, and the coverage rate of the combined algorithm was 1.3% higher than the CF-U algorithm and 2.1% higher than the CF-I algorithm. When the number of nearest neighbors was ten, the coverage rate of the combined algorithm was 43.2%, which was 4.8% higher than the CF-U algorithm and 3.7% higher than the CF-I algorithm. When the number of nearest neighbors was 15, the coverage rate of the combined algorithm was 45.7%, which was 6% higher than the CF-U algorithm and 5% higher than the CF-I algorithm. When the number of nearest neighbors was 20, the coverage rate of the combined algorithm was 59.4%, which was 17.3% higher than the CF-U algorithm and 17.3% higher than the CF-I algorithm. These results verify that the combined algorithm is effective in recommending online educational resources.

Finally, the training efficiency of the three algorithms was analyzed by training them with 10%, 20%, 50% and 100% of the data, and the time required for the different algorithms is shown in Figure 5.

It shown in Figure 5, with an increase in data volume, the training time required by the different algorithms increases to a certain extent. The training time of the CF-I algorithm was the shortest, followed by the CF-U algorithm and the combined algorithm. Taking 10% of the data as an example, the training time required by the CF-U algorithm was 187 s, the training time required by the CF-I algorithm was 181 s, and the training time required by the combined algorithm was 185 s, which was 1.07% less than the CF-U algorithm. Taking 100% of the data as an example, the training time required by the CF-U algorithm was 221 s, the training time required by the CF-I algorithm was 205 s, and the training time required by the combined algorithm was 209 s, which was 5.85% less than the CF-U algorithm. These results demonstrate that the combined algorithm is able to solve the shortcoming of the large computational volume of the CF-U algorithm and its computational volume was not significantly larger than the CF-I algorithm. In conclusion, the combined algorithm is able to improve the recommendation effect without greatly increasing the complexity, which is more suitable for application in actual online educational resource research.

5. CONCLUSION

This paper analyzed online educational resources for college Chinese courses based on personalized learning and proposed the application of recommendation technology to online education. The author combined the CF-U algorithm with the CF-I algorithm to recommend the most appropriate educational resources for users. It was found through experimentation that the combined algorithm not only had higher accuracy and coverage rate, it also had an obvious advantage in training efficiency. The combined algorithm can be further applied in practice to realize personalized recommendations of online educational resources and promote learners' personalized learning.

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