International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 3024-3034

https://doi.org/10.70517/ijhsa463253

Optimization of online resource recommendation method for ideological and political theory courses based on collaborative filtering algorithm

Fei Huang[1,*]
[1] Pingdingshan Polytechnic College, Pingdingshan, Henan, 467000, China
Corresponding authors: (e-mail: hf2011230001@163.com).

Abstract The increasing number of online resources makes effective matching of students' individualized learning needs become the focus of the teaching reform of ideological and political theory courses. In this paper, we construct students' user profiles in two directions: dynamic and static, and utilize Jaccard and cosine similarity to calculate the similarity of user profile features. The Louvain algorithm is introduced to divide the community of "user characteristics-user-item-item characteristics" association network to improve the efficiency of resource recommendation. We design an improved collaborative filtering model based on a multi-layer resource recommendation matrix, and generate a dynamic resource list by combining the time decay function to correct students' interests. The results show that the model improves the recommendation performance by 10.03%-73.47% compared with other benchmark methods. Practical teaching applications improve students' self-initiated motivation and learning efficiency at the 0.01 significance level. The number of students with high scores (≥90 points) increased from 16.3% to 26.2%. The resource recommendation model based on the improved collaborative filtering algorithm can realize the effective recommendation of resources and assist students to improve the level of Civics Theory course.

Index Terms collaborative filtering algorithm, similarity calculation, Louvain's algorithm, resource recommendation matrix, Civics education

I. Introduction

With the ever-changing development of Internet technology, smart education is in the ascendant. Online education platforms and Civic and political resource libraries represented by Learning Power are emerging, which promote the development of the Civic and political curriculum at a certain level [1]. Teachers and students can search for Civic and Political knowledge resources to support and enhance the construction of Civic and Political courses through online learning platforms anytime and anywhere, in order to better articulate the relevant knowledge and connotations in the teaching of Civic and Political education [2]-[4]. On the other hand, it also makes online learning resources grow explosively, and teachers and students are unable to sift out the Civics course resources that meet their interests and needs from a large amount of complex data [5]-[7]. In the process of searching for resources, they are easily affected by some weakly related and poor content resources, and in the long run, not only the work and learning efficiency of teachers and students will be greatly reduced, but also easily fall into the psychological anxiety of being surrounded by a large amount of information [8]-[10]. In order to make real-time and personalized recommendation of the Civics and Political Science course resources that are of interest to teachers and students and have educational significance, it is necessary to combine the recommendation algorithm technology with the online learning system, so that teachers and students can more conveniently obtain the online resources that are helpful to them in the system [11]-[14]. Therefore, the design and development of a learning recommendation system for Civics and Political Theory courses is of great significance for students' learning and teachers' lectures.

In this paper, we construct user profiles by labeling multidimensional student user data. Using cosine similarity and other methods, we calculate the comprehensive similarity of the user's basic information characteristics, browsing frequency and browsing time. The Louvain algorithm is used to classify "user characteristics-user-item-item characteristics" associated network communities to explore potential information of different types of users. We design a multilevel resource recommendation matrix, incorporate content and improve collaborative filtering algorithms to improve the accuracy of the model's resource recommendation. Compare the model with the baseline method in multiple dimensions to determine the advantages of the model in terms of basic performance and convergence. Compare the changes in students' learning attitudes and academic performance before and after using the model-recommended resources to verify the model's resource recommendation effect.

II. Collaborative Filtering Based Recommendation of Online Resources for Civics and Political Science

This chapter systematically analyzes the construction principle and construction process of collaborative filtering-based online resource recommendation model for Civics and Politics to provide technical support for the subsequent assisted learning of Civics and Politics theory courses.

II. A. Collaborative filtering model based on user profiles

II. A. 1) Labeling of user data

User data labeling that is, the user's relevant information is labeled, the premise of building user profiles is to label user data. It is generally divided into static information labels and dynamic information labels.

In the recommendation of online resources for Civic and Political Theory courses, static information labels are fixed and unchanging information describing the basic characteristics and attributes of students in the user portrait. Such labels mainly include basic demographic information, learning interests, social relationships and psychological characteristics of users. This information is relatively stable and does not change over time, providing a comprehensive understanding of the student's static attributes. Dynamic information labels, on the other hand, are real-time or time-series information in the user profile that reflects students' learning behaviors and activities. Such labels include users' search behavior, clicking behavior, application usage behavior, and learning sentiment analysis. Unlike static information, dynamic information is updated over time, providing more information about students' real-time learning behaviors and trends.

Based on the recommendation scenario in this paper, the static information labels include students' gender, age, and interests. The dynamic information label is divided into two parts: browsing habits and preferred knowledge point information. Preferred knowledge point information is based on the user's operating behavior including history browsing record, history forwarding record, comment and like record; browsing habit includes the frequency of browsing and browsing stay time. Figure 1 shows the specific user data labeling system.

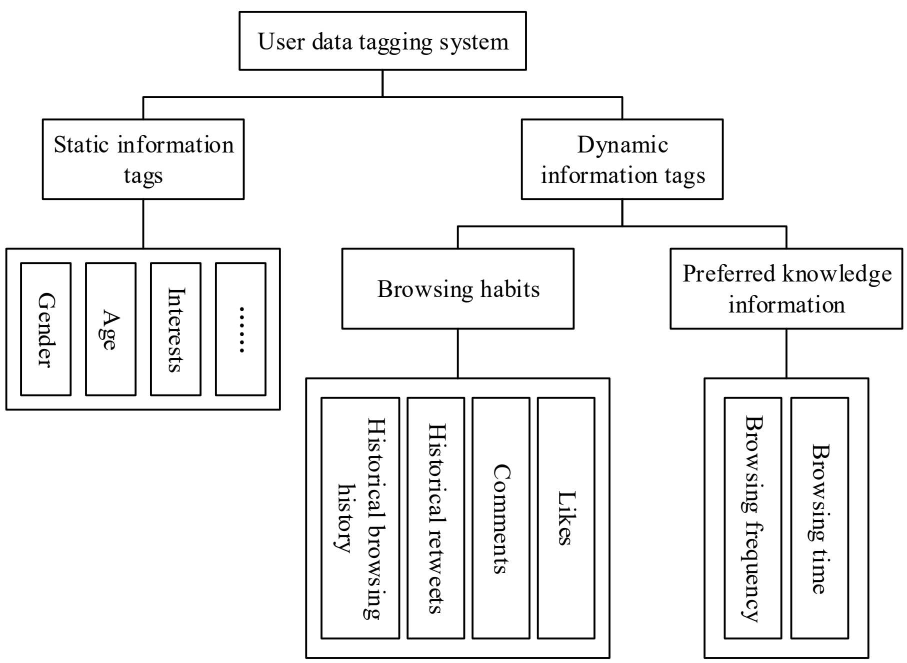

Figure 1: User Data Tag System

II. A. 2) Establishment of user profiles and similarity calculation

In order to more accurately characterize the user's features and interests, the text constructs a user profile that incorporates multiple features. Specifically, the model can be represented by $P = \{C, BF, BT\}$, covering three parts, each with its unique features. In the first part $C = \{G, A, M, I\}$, it includes the basic information characteristics of the user, which are gender (G), age (A), learning status (M) and interests (I). The second part BF indicates the browsing frequency of the user. The third part BT indicates the browsing time of the user in a day.

In order to facilitate the calculation of the similarity of the user's basic information labels, this paper chooses to use the Jaccard similarity calculation method, so it is necessary to represent all the features in binary. In the gender feature, the user selects male as 1, and selects female as 0. Other features are binaryized in a similar way to get the binary result of the user's basic information label c, and then the similarity calculation is performed on c, and the specific formula is shown below:

$$CSim\left(U_i,U_j\right)=\frac{\sum_{i=1}^{L}\left(C_i\wedge C_j\right)}{\sum_{i=1}^{L}\left(C_i\vee C_j\right)} \tag{1}$$

where L denotes the length of the binary sequence c, C_i is the binary representation of the basic information label of user U_i, and C_j is the binary representation of the basic information label of user U_j. The similarity between the basic information labels of each two users is calculated sequentially to obtain the similarity result CS in the first part.

(1) Users' browsing frequency

The browsing frequency in the user's dynamic information label can visualize the user's browsing habits, which can effectively improve the accuracy of the recommendation algorithm, so this label information is incorporated into a part of constructing the user profile. This helps to provide a more comprehensive understanding of the user's behavioral characteristics, which supports the provision of personalized services and the improvement of the accuracy of the recommendation system. Specifically, the browsing frequency BF is calculated as shown in Equation (2) below.

$$BF=\frac{1}{D}\sum_{d=1}^{D}BF_d \tag{2}$$

where D denotes the number of days in the data that the statistical user has been browsing, and BF_d denotes the number of items browsed by the user on the dth day.

(2) User's browsing time

Digging deeper into the user's behavioral information is an important part of building a comprehensive user profile, and the user's browsing time, as one of the key indicators, is able to effectively reflect the user's browsing habits. Users with similar browsing habits tend to have more similar identity characteristics, or show higher attention to the same category of information. This phenomenon provides an opportunity to learn more about users, as their choice to browse certain types of content at certain times of day often reflects their interests. This correlation of browsing times also provides rich clues for socialized recommendations. Users with similar browsing times may have more common topics. To facilitate the calculation of similarity, this paper segments the time: early morning, early evening, morning, noon, afternoon, evening and late night.

In order to calculate the vector representation of browsing time, firstly, we need to organize the data to get the set of all items $C_u=\left\{c_{u,1},c_{u,2},\cdots,c_{u,n}\right\}$ for which the user exists browsing behavior, and after that, it is calculated according to the time division. The specific calculation method is shown in equation (3) below:

$$BT=\frac{BN}{\sum_{d=1}^{D}BT_d} \tag{3}$$

where BN denotes the total number of user views for each time period.

(3) Multi-dimensional similarity calculation

Since the obtained user portrait contains three parts, and the first part of the user's basic information label has been obtained similarity matrix CS, it is necessary to use cosine similarity for the remaining two parts $PT=\{BF,BT\}$ to carry out joint similarity calculation. The specific calculation method is shown in Equation (4):

$$PTSim\left(PT_i,PT_j\right)=\frac{PT_i\cdot PT_j}{\left\|PT_i\right\|\cdot\left\|PT_j\right\|} \tag{4}$$

where PT_i and PT_j are the second and third part of the user portrait vector representations of user U_i and user U_j, respectively. The final user portrait similarity matrix US can be obtained by adding the similarity matrix CS and the similarity matrix PTS, which is calculated as shown in Equation (5).

$$US = CS + PTS \tag{5}$$

II. B.Community segmentation in a network of associations

The "user feature-user-item-item feature" association network contains local clustering between users and items, i.e., the community structure of users and items. Combining the community structure in complex networks with collaborative filtering recommendation algorithms can further explore the potential information in the network.

Louvain's algorithm is efficient and accurate with good performance in dividing communities, two key parameters in Louvain's algorithm, modularity and modularity increment, are derived and explained in this section. The concept of modularity Q was proposed in 2004 to measure whether the nodes within the delineated community are closely related, as in equation (6). Where m is the total number of edges in the network; A_{ij} denotes the weight of the connected edges between node i and node j; k_i and k_j denote the sum of the weights of the connected edges pointing to node i and node j; and $\sigma(c_i, c_j)$ is used to determine whether the community c_i is the same as the community c_j.

$$Q = \frac{1}{2m}\sum_{i,j}\left[A_{i,j} - \frac{k_i k_j}{2m}\right] \times \sigma(c_i, c_j) \tag{6}$$

The simplified modularity is calculated as in Equation (7), where $\sum in$ denotes the sum of the internal connected edge weights of community c, and $\sum tot$ denotes the sum of the connected edge weights connected to nodes of community c.

$$\begin{aligned} Q &= \frac{1}{2m}\sum_{i,j}\left[A_{i,j} - \frac{k_i k_j}{2m}\right] \times \sigma\left(c_i, c_j\right) \\ &= \frac{1}{2m}\left[\sum_{i,j} A_{i,j} - \frac{\sum_i k_i \sum_j k_j}{2m}\right] \times \sigma\left(c_i, c_j\right) \\ &= \frac{1}{2m}\sum_c\left[\sum in - \frac{\left(\sum tot\right)^2}{2m}\right] \end{aligned} \tag{7}$$

When Louvain's algorithm assigns any node i in the network to a community c belonging to a neighboring node j, it needs to compute the increment of modularity ΔQ and determine whether or not to move the node based on the value of ΔQ. The module degree increment ΔQ is calculated as in equation (8). Where $k_{i,in}$ denotes the sum of the weights of the connecting edges of node i with the nodes in community c.

$$\begin{aligned} \Delta Q = &\left[\left(\frac{\sum in + k_{i,in}}{2m}\right) - \left(\frac{\sum tot + k_i}{2m}\right)^2\right] \\ &- \left[\frac{\sum in}{2m} - \left(\frac{\sum tot}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right] \end{aligned} \tag{8}$$

ΔQ is simplified as in equation (9), $\sum_{tot} k_i$ denotes the sum of the weights of the edges that are connected to the nodes in community c.

$$\Delta Q = \left[\frac{k_{i,in}}{2m} - \frac{\sum_{tot} k_i}{2m^2} \right] \tag{9}$$

In this paper, the LPA algorithm and Louvain algorithm are used to divide the communities on the "user characteristics-user-item-item characteristics" association network. Compared with LPA algorithm, Louvain algorithm is more accurate in community segmentation, and the community size is relatively small, which can improve the efficiency of calculating similarity within the community. Therefore, this paper chooses Louvain algorithm to divide the community from user characteristics, user ratings, and project characteristics in the association network of "user characteristics-user-item-item characteristics".

II. C. Design of collaborative filtering shortcut methods for online learning resource improvement

II. C. 1) Multi-level resource recommendation matrix design

The construction of a multi-layered resource recommendation matrix is an in-depth understanding of user behavior, resource characteristics, and the complex relationships between them. Each layer of the matrix represents a different recommendation dimension or strategy, such as content-based recommendation, collaborative filtering-based recommendation, and hybrid recommendation. First, a user-resource rating matrix is created to record the user rating information of the accessed resources. Due to the sparsity of user rating data, the effect of directly utilizing this matrix for recommendation is limited, on top of which an improved collaborative filtering algorithm has to be introduced and the execution environment of the matrix has to be designed. Next, the data collected at this point is down-weighted by integrating user ratings, project attributes and other practical situations, and a multi-level resource recommendation matrix is constructed based on the labels set above, as shown in Equation (10).

$$sim(t_{um}, t_{vm}) = \begin{cases} 0\text{-}if \ \ disciplines \ are \ different \\ 0.5\text{-}if \ \ disciplines, \ resources \ are \ different \\ 1\text{-}if \ \ disciplines \ are \ different \end{cases} \tag{10}$$

In Eq. (10), t_{um} and t_{vm} represent the total coverage of resource recommendation, and if is the assumption condition. The base effect of user-resource is corrected by the matrix to get a more accurate representation of user preferences. Based on this, a multi-level recommendation matrix is designed. The first layer is mainly a content-based recommendation strategy, which uses the computed resource feature vectors to recommend resources for users that are similar to their historical learning behaviors. The second layer introduces collaborative filtering algorithms to identify user groups with similar learning preferences within a controlled user similarity range and recommend resources to target users based on their learning behaviors. The third layer is designed as a hybrid recommendation layer, which combines the recommendation results of the first two layers and generates the final recommendation list by weighting or sorting strategies to complete the design and refinement of the resource matrix.

II. C. 2) Constructing an Improved Collaborative Filtering Online Learning Resource Shortcut Recommendation Model

Combining the principle of improved collaborative filtering, we construct a quick recommendation model for online learning resources. The current resource recommendation is based on user-resource interaction data, which is usually expressed as a user-resource rating matrix. However, due to the sparseness of the actual data and the dynamic change of user interest, the direct application of the traditional collaborative filtering algorithm is ineffective, and the model must be modified and improved. First, the historical user ratings are time-decayed to reflect the changes in user interests, as shown in Eq. (11).

$$WeightedScore_{ui} = Score_{ui} \times e^{-s\left(r - d^{a}\right)} \tag{11}$$

In Eq. (11), $Score_{ui}$ represents the user interest, e represents the original score, s represents the scoring time, r represents the decay coefficient, and d^a represents the preset decay coefficient. The current model is based on the actual user interest changes, combined with resource features for collaborative filtering, designing the execution structure of the model, constructing the base expression of the model, and calculating the resource recommendation similarity, as shown in Equation (12).

$$X = \sum_{o=1} \aleph o - \sqrt{\gamma} \tag{12}$$

In Eq. (12), X represents the similarity of resource recommendation, $\aleph$ represents the amount of resources in a single cycle, o represents the frequency of resource recommendation, and γ represents the weighting coefficient. Subsequently, the final recommendation list is generated through the weighting or sorting mechanism, which comprehensively utilizes the advantages of a variety of information, improves the accuracy and diversity of recommendations, and realizes the accurate and rapid recommendation of the user's learning needs. However, it should be noted that the current learning resource recommendation criteria and restrictions set by the improved collaborative filtering principle are not fixed, and can be adjusted and revised in real time in accordance with the actual needs, so as to strengthen the efficiency and accuracy of the recommendation, expand the scope of the recommendation, and optimize the real-time effect of the recommendation of online learning resources.

III. Application of resource recommendation models based on improved collaborative filtering

This chapter compares the performance of the constructed resource recommendation model based on improved collaborative filtering with the same type of baseline method. After verifying the validity of the model, it is applied to assist learning in ideological and political theory courses in colleges and universities, and compares the changes in students' learning attitudes and academic performance before and after using the model.

III. A. Model performance comparison and result analysis

III. A. 1) Improved collaborative filtering model vs. baseline approach

In order to evaluate the performance of the proposed improved collaborative filtering model, this paper's method (CF) is compared with a total of four baseline methods, namely BPRMF, NeuMF, LightGCN, and MultiGCCF. Comparison experiments are conducted using four commonly used public datasets, including MovieLens-1M (ML-1M), Yelp, and Amazon-Books.These datasets differ in domain, size, and density. 75% of the dataset was used as training data and 25% as test data. Recall@N (Recall@N) and Normalized Discount Cumulative Gain@N (NDCG@N) were chosen as 2 metrics to evaluate the performance of resource recommendation. Where N= is set to 5, 15, and 30, respectively.

Table 1 shows the performance comparison results. Observing the data in Table 1, it can be found that this paper's method improves the performance by a level of 10.03%-73.47% compared to the other 4 baseline methods in the comparison experiments. In the ML-1M dataset, the performance level of this paper's method is improved by up to 20.03%; in the Yelp dataset, by up to 59.03%; and in the Amazon-Books dataset, by up to 73.47%. Among them, the performance improvement is the highest in the Amazon-Books dataset. According to the comparison results in Table 1, it is verified that the method of this paper has a significant advantage in the performance of online resource recommendation for ideological and political theory courses.

III. A. 2) Model convergence analysis

In order to fully assess the performance stability of the model in this paper, the convergence curves of the model are shown on the ML-1M and Yelp datasets. Figure 2 shows the visualization results. Figure 2 records the loss function value (Loss) for each training round (Epoch) of the model to monitor the stability of the model training process and the convergence speed. Analyzing the convergence in Fig. 2, it is found that the loss function value of this paper's model does not exceed 150 for 120 iterations on the ML-1M dataset and 250 for 150 iterations on the Yelp dataset, and on both datasets, this paper's model stabilizes the loss function value below 50 around the 20th iteration, which shows a good convergence. This also shows that the model in this paper is able to mine and analyze the data related to students' ideological and political theory courses continuously and smoothly.

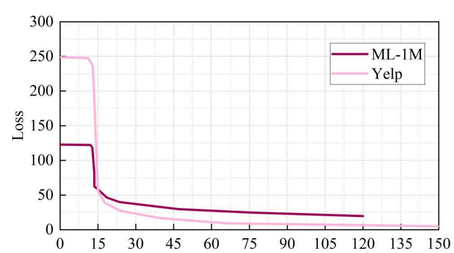

Figure 2: Convergence curve of the model in this paper

Table 1: Performance comparison results

Dataset	Metric	BPRMF	NeuMF	LightGCN	MultiGCCF	CF	Improvement
ML-1M	R@5	0.179	0.165	0.184	0.183	0.212	20.03%
	N@5	0.246	0.229	0.252	0.251	0.285	16.92%
	R@15	0.271	0.251	0.274	0.276	0.307	14.89%
	N@15	0.256	0.240	0.261	0.261	0.288	13.49%
	R@30	0.429	0.412	0.434	0.436	0.471	10.03%
	N@30	0.301	0.285	0.305	0.305	0.329	10.06%
Yelp	R@5	0.063	0.052	0.063	0.065	0.093	53.92%
	N@5	0.046	0.037	0.045	0.045	0.068	59.03%
	R@15	0.104	0.088	0.102	0.105	0.141	42.74%
	N@15	0.057	0.048	0.056	0.057	0.084	55.42%
	R@30	0.186	0.164	0.186	0.188	0.226	25.43%
	N@30	0.079	0.068	0.078	0.079	0.107	41.35%
Amazon-Books	R@5	0.060	0.051	0.061	0.062	0.094	62.74%
	N@5	0.043	0.035	0.042	0.043	0.070	73.47%
	R@15	0.095	0.082	0.097	0.099	0.141	51.56%
	N@15	0.054	0.044	0.053	0.054	0.082	61.63%
	R@30	0.168	0.144	0.116	0.168	0.219	50.40%
	N@30	0.072	0.061	0.072	0.072	0.103	48.46%

III. A. 3) Ablation experiments

In order to validate the effectiveness of the proposed community segmentation method for associative networks, ablation experiments are conducted to deeply analyze its contribution to the overall performance. Figure 3 presents the experimental results. In these ablation experiments, the full CF model is compared with the CF variant (labeled as "w/o") after removing the community segmentation of the associative network in order to observe the performance difference between them. As can be seen from Figure 3, the index value of CF is greater than that of w/o in both the Recall@15 index and the Ndcg@15 index. Among them, the performance of Ndcg@15-CF is up to 0.037 higher than that of Ndcg@15-w/o. Removing the association network community segmentation leads to a significant decrease in the overall performance of the model, which illustrates the importance of association network community segmentation in improving the accuracy and efficiency of resource recommendation. Integrating the associative network community segmentation approach in the model not only enriches the modeling of relationships between students and students, and students and knowledge points, but also plays a key role in handling complex interaction patterns and improving the accuracy of the recommender system.

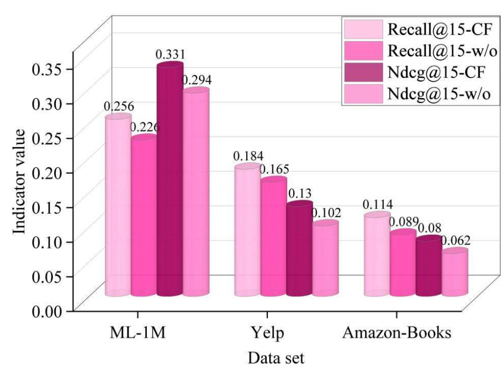

Figure 3: Presentation of experimental results

III. A. 4) Data sparsity test

In order to deeply verify the effectiveness of the proposed CF model in mitigating data sparsity, this section focuses on evaluating the performance of CF1 on student user groups with different sparsity levels. Specifically, all users are categorized into four different groups G1, G2, G3, and G4 based on their interaction frequency. and ensured that the total number of interactions in each group remained consistent. Subsequently, the recommendation effects of CF and LightGCN on these four groups of users were compared.

Figure 4 shows the results of the sparse experiment with CF. In G1, LightGCN has the highest recommendation effect of 0.248, while CF can reach 0.350; in G2, LightGCN has the highest recommendation effect of 0.186, while

CF can reach 0.219; in G3, LightGCN has the highest recommendation effect of 0.144, while CF can reach 0.167; and in G4, LightGCN recommendation The highest recommendation effect is 0.124, while CF can reach 0.133. It is obvious from Fig. 4 that CF outperforms LightGCN in all cases, and it is worth noting that as the number of user interactions decreases (G1<G2<G3<G4), the performance improvement brought by CF is even more significant. This result suggests that CF is able to provide high-quality recommendations despite fewer user interactions, which is largely attributed to its unique approach of association network community segmentation and resource similarity calculation. This approach can effectively capture the learning behaviors of the same type of users related to the target user, and the associations between users and related resources, and thus improve the accuracy and relevance of recommendations in sparse data environments.

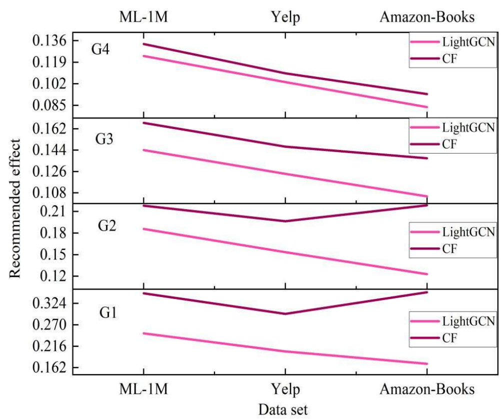

Figure 4: The sparse experimental results of CF

III. B. Comparative analysis of learning attitudes before and after the experiment

After analyzing the performance advantages of this paper's learning resource recommendation model based on the improved collaborative filtering algorithm, the model is applied to 30 students in the sophomore (3) class of Marxism College of a university as an auxiliary teaching tool for teaching. Through the questionnaire of learning attitude in ideological and political theory courses in colleges and universities (11 questions in total), the difference in students' learning attitude before and after learning in the blended teaching mode based on the model resource recommendation is collected, so as to judge the effect of this paper's model in assisting students' learning. Five of the questions are basic information items, which are used to analyze students' learning of ideological and political theory classes.

III. B. 1) KMO and Bartlett's test for learning attitudes

The data cleaning and pairwise processing of the information about students' attitudes in the pre and post-tests were used to test the reliability of the pre and post-tests respectively, and the Alpha values of the clombach on the pre and post side were obtained to be greater than 0.75, and the reliability of the questionnaire was good. The validity of the pre- and post-test questionnaires was further tested by KMO test. Table 2 shows the results of KMO and Bartlett's test for learning attitude. From Table 2, it can be obtained that the KMO values of both pre- and post-tests are equally greater than 0.75, indicating that the variables in the designed questionnaire are valid.

Table 2: KMO and Bartlett Tests of Learning Attitude

KMO and Bartlett tests			
		Pretest	Post-test
KMO sampling appropriateness measurement	-	0.758	0.783
Bartlett's sphericity test	Approximate chi-square	330.504	330.504
	Degree of freedom	30	30
	Significance	0.001	0.001

III. B. 2) Paired Sample Statistics and Correlation Statistics

Second, a paired-sample t-test was performed on the pretest and posttest data, and a multivariate pairwise analysis was performed with A1 representing the first question item of the pretest and B1 representing the first question item of the posterior side. Table 3 shows the results of paired-sample t-statistics and correlation statistics. In Table 3, it can be seen that the mean values of all 11 paired question items are significantly improved, with the mean value of the pre-test question items around 3 and the mean value of the post-test question items close to 4. The standard deviations of the paired question items are no more than 0.1, and the differences are not significant, and there is a strong correlation between the paired items.

Table 3: Results of T-statistics and correlation statistics of paired samples

		Average value	Number of cases	Average standard error	Correlation	Significance
Pairing 1	A1	3.17	30	0.091	0.639	0.001
	B1	3.70	30	0.085		
Pairing 2	A2	2.88	30	0.092	0.816	0.001
	B2	3.11	30	0.096		
Pairing 3	A3	2.66	30	0.095	0.637	0.001
	B3	3.24	30	0.097		
Pairing 4	A4	2.86	30	0.086	0.605	0.001
	B4	3.10	30	0.084		
Pairing 5	A5	2.97	30	0.085	0.623	0.001
	B5	3.45	30	0.097		
Pairing 6	A6	2.70	30	0.092	0.463	0.001
	B6	3.71	30	0.081		
Pairing 7	A7	2.78	30	0.094	0.720	0.001
	B7	3.05	30	0.093		
Pairing 8	A8	2.63	30	0.095	0.572	0.001
	B8	3.31	30	0.093		
Pairing 9	A9	2.96	30	0.094	0.491	0.001
	B9	3.63	30	0.087		
Pairing 10	A10	2.54	30	0.096	0.655	0.001
	B10	3.26	30	0.094		
Pairing 11	A11	3.16	30	0.091	0.572	0.001
	B11	3.70	30	0.084		

III. B. 3) Paired samples t-test for each question item

Table 4 shows the results of the paired samples t-test between the question items. It can be seen that the significance (two-tailed) of all 11 paired question items is 0.001, which is less than 0.01, then the paired variables show differences between them at the 0.01 significance level. After analysis, it can be found that using the blended teaching model based on collaborative filtering learning resource recommendation model can effectively improve students' self internal motivation and learning efficiency in the study of ideological and political theory courses: the difference is presented at the 0.01 significance level.

Table 4: Paired sample t-test for each item

		Average value	Standard deviation	Average standard error of pairing difference	95% confidence interval difference		T	Sig. (Double Tail)
					Lower limit	Upper limit		
Pairing 1	AI-B1	-0.525	0.767	0.073	-0.671	-0.374	-6.957	0.001
Pairing 2	A2-B2	-0.256	0.623	0.060	-0.372	-0.132	-4.124	0.001
Pairing 3	A3-B3	-0.573	0.905	0.086	-0.746	-0.395	-6.436	0.001
Pairing 4	A4-B4	-0.281	0.770	0.075	-0.434	-0.132	-3.701	0.001
Pairing 5	A5-B5	-0.526	0.886	0.084	-0.696	-0.356	-6.023	0.001
Pairing 6	A6-B6	-1.012	0.977	0.095	-1.201	-0.817	-10.503	0.001
Pairing 7	A7-B7	-0.246	0.698	0.067	-0.377	-0.104	-3.556	0.001
Pairing 8	A8-B8	-0.673	0.866	0.084	-0.836	-0.502	-7.835	0.001
Pairing 9	A9-B9	-0.707	0.965	0.092	-0.894	-0.526	-7.442	0.001
Pairing 10	A10-B10	-0.671	0.807	0.082	-0.823	-0.511	-8.401	0.001
Pairing 11	A11-B11	-0.575	0.801	0.085	-0.810	-0.530	-8.402	0.001

III. C. Comparative analysis of performance before and after the experiment

Further compare the students' grades in the class for the end of their freshman year in Ideological and Political Theory without the use of the Resource Recommendation Model and their grades in Ideological and Political Theory for the sophomore year midterm three months after the use of the Resource Recommendation Model. The changes brought to the students by using the resource recommendation model can be visualized through the students' ideological and political theory class grades. Figure 5 shows the comparison of grades before and after the experiment. Comparing the changes in students' grades in Figure 5, it can be seen that after students use the recommendation model for assisted learning, the percentage of the number of people with less than 60 points decreases from 15.3% to 10.2%; the percentage of the number of people with 60-75 points decreases from 37.6% to 25.1%; the percentage of the number of people with 76-89 points increases from 30.8% to 38.5%; and the percentage of the number of people with more than 90 points increases from 16.3% to 26.2%. On the whole, the number of people in the high score band increases significantly, and the number of people in the middle and low score bands decreases accordingly. It indicates that the use of online learning resources recommendation model based on improved collaborative filtering algorithm for assisted learning can significantly help students to improve their interest in ideological and political theory courses and their final knowledge level.

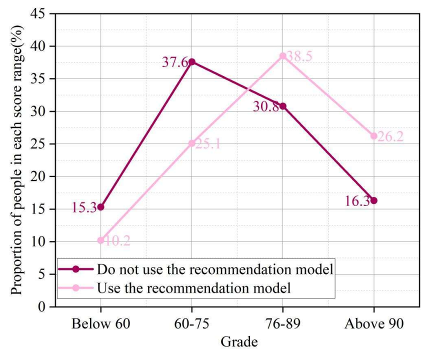

Figure 5: Comparison of grades before and after the experiment

IV. Conclusion

In this paper, we construct an online resource recommendation model based on improved collaborative filtering for Civic and Political Theory courses, and experimentally verify its learning assistance effect. The model improves the recommendation performance by about 10.03%-73.47% compared with four comparison methods in three datasets. After applying the model for resource recommendation to assist Civics learning, students' learning attitudes changed significantly ($p<0.01$). The percentage of students in the high grade band increased from 16.3% to 26.2%, and the percentage of students in the middle and low grade band decreased. The online resource recommendation model for Civics theory class based on improved collaborative filtering has high resource recommendation accuracy and can meet students' personalized learning needs. In the future, we can further explore the introduction of real-time feedback mechanism in the model to improve the timeliness of resource recommendation.

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