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Article

Artificial Intelligence Enabling Civic Education in Colleges and Universities: Synergistic Operation Strategies of Red Culture Dissemination and Enterprises

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Abstract: Under the background of education informatization, the needs of learners are becoming more and more diversified, and how to efficiently allocate educational resources according to the personalized characteristics of learners has become a core issue in the research of college education. In this paper, taking the Civic and Political Education in colleges and universities as the research object, we explored the collaborative operation strategy of red culture dissemination and enterprise based on artificial intelligence. The FKCM algorithm is improved by the algorithm of Approximate Neighborhood Propagation (AP) for the construction of a dynamic portrait of the student population, and a matrix decomposition recommendation algorithm combining reliability and influence propagation is proposed to realize the accurate recommendation of learning resources for Civic and Political Education in colleges and universities. Compared with the standard FCM algorithm and the FKCM algorithm, the AP-FKCM algorithm proposed in this paper both obtain the optimal ACC value. The proposed recommendation model has similar performance with the social recommendation model CUNE, which is better than other comparative models, and has high development value, with RMSE and MAE values of 0.9259 and 0.6315 on 70% training set, respectively.This paper provides a modeling tool for the accurate recommendation of the learning resources of Civic and Political Education in colleges and universities, as well as for the collaborative operation of red culture dissemination and enterprises.

Keywords: student portrait; FKCM algorithm; nearest neighbor propagation algorithm; matrix decomposition recommendation; Civic and political education in colleges and universities

1. Introduction

The year 2013 marked the beginning of the big data era, 2016 saw the rapid development of artificial intelligence, and 2019 ushered in the era of “smart+” and VR industries. This demonstrates that the wave of technological innovation in intelligence continues to surge [1]. Technologies such as artificial intelligence, virtual reality, and big data are closely interconnected and constantly achieving new breakthroughs, deeply influencing all aspects of social life [2]. Under the empowerment of intelligent technologies, higher education ideological and political education has been able to optimize its educational models, mechanisms, and structures [3]. Driven by technology, the need for educational paradigm reconstruction has become increasingly urgent [4]. The education sector has increasingly focused on the integration and application of intelligent technologies, with society and schools also initiating various effective experiments, sparking a revolutionary wave of integrating education with intelligent technologies.

Researchers have proposed the concept of educational artificial intelligence, whose core technologies include knowledge representation, machine learning and deep learning, natural language processing, intelligent agents, and affective computing [5]. The application and development trends of these technologies generally focus on intelligent teachers and assistants, intelligent testing, teaching partners, information discovery, and educational research [6-7]. Researchers have pointed out that intelligent education is an educational approach that uses artificial intelligence technology to help learners develop their intelligence. It aims to achieve a perfect integration of human intelligence and machine intelligence, thereby constructing a human-machine collaborative intelligence system [8-10]. This teaching method not only helps learners better understand and master knowledge points but also enables them to better realize their potential.

Currently, scholars believe that the application of artificial intelligence technology in education primarily focuses on six areas: learner models, learning behavior analysis, at-risk warning systems, academic support and assessment, and educational resource selection. For example, Literature [11] integrates artificial intelligence into the educational process to provide personalized learning experiences for each learner, tailoring learner models to individual needs. Literature [12] utilizes big data processing technology and artificial intelligence to develop an online learning behavior analysis model, which is applied to an empirical analysis of an online learning platform to explore learning behavior clustering, course recommendations, and learning outcomes. Literature [13] employs SMOTE and ensemble methods to address class imbalance issues, thereby improving the student dropout warning system, and finds that the enhanced decision tree model performs most effectively in dropout risk warning.

Ideological and political education is a highly challenging task that not only requires students to master basic general knowledge and professional skills but also demands they possess innovative thinking and the ability to utilize new technologies to deeply understand and grasp human thought, thereby better serving students [14]. With the widespread adoption of online education tools such as "Two Weibos and One App," MOOCs, and Yu Classroom, online education has long been an integral part of ideological and political education. With the unprecedented development of artificial intelligence technology, scholars are actively exploring how to closely integrate next-generation artificial intelligence with ideological and political education to enhance teaching effectiveness [15]. For example, Literature [16] explores how artificial intelligence technology can innovate ideological and political education through a "human-machine collaboration" model, aiming to utilize artificial intelligence technology to improve teaching effectiveness and students' critical thinking abilities. Literature [17] integrates data mining and artificial intelligence technology to optimize the course environment for ideological and political education in higher education institutions and proposes a "three-stage comprehensive" network architecture for evaluating the effectiveness of ideological and political education in higher education institutions. The above studies indicate that the application of artificial intelligence in ideological and political education in higher education institutions is still in its exploratory phase, covering multiple areas such as student ideological and political education. However, systematic research has not yet been established, and discussions remain limited to theoretical and value-oriented aspects, lacking practical research.

This paper explores the methodological path of AI-enabled ideological education in colleges and universities, and provides a basis for the development of synergistic operation strategies for red culture dissemination and enterprises. First, student portrait modeling is carried out, and AP-FKCM, a student group portrait clustering method combining the nearest neighbor propagation algorithm and the kernel fuzzy hierarchical clustering algorithm, is proposed. Then, a matrix decomposition recommendation model integrating reliability and influence propagation is constructed, so as to realize the intelligent recommendation of the Civic and Political Education in colleges and universities. Meanwhile, in order to verify the effectiveness of the model, it is compared with other models, and the construction of student portraits is experimentally analyzed.

2. Construction of a Dynamic Portrait of the Student Body of Higher Education Civic Education

This chapter proposes a dynamic portrait construction method for the student group of ideological education in colleges and universities, which divides the group and constructs the portrait according to the multidimensional characteristics of students, and lays the foundation for the accurate recommendation of ideological education resources.

2.1. Modeling of Student Profiles

Student portrait is a feature that describes the behavioral aspects of students, which is a prerequisite for realizing the recommendation of college Civics education resources based on user portrait technology. The group dynamic student portrait model constructed in this paper is mainly divided into three dimensions of features, namely, student behavioral features, basic student features, and features of knowledge in the field of college civic education, and the three dimensions of features form the student portrait labeling system. In this paper, a ternary group is defined to characterize the student portrait model, then the student portrait model is defined as shown below:

$$User = \langle Base, Behaviour, Knowledge \rangle \tag{1}$$

Mining the student registration information and online behavior data on the learning platform of college civic education, and based on the intersection of knowledge graph and student behavior in the field of college civic education, the analyzed features are mapped for student portrait labeling. The modeling of student portraits mines the historical behaviors of students on the learning platform and performs student basic attribute labeling based on the basic attribute information left by each student. Students may leave readable data in the process of interacting with the learning platform, which is combined with the keywords in the text data as the concept nodes of the knowledge graph, that is to say, combined with the expression of different contexts, to form student behavior labels.

In this paper, the specific mapping of labels is based on the title data of Civic Education generated under the user behavior of a certain learning platform, extracting the keyword information related to Civic Education learning resources from the title, and then searching for the keywords with the same or similar concepts from the Domain Knowledge Graph, and then finding the parent nodes and subclass nodes in the keywords about the keywords, and finally deleting the factors that are irrelevant to the keywords and retaining the similar keywords of parent and child nodes, which constitutes the knowledge sub-portrait of college civic education. This kind of label expansion combined with specific behavioral contexts produces more grounded associative labels.

2.2. Updating of Student Profiles

Dynamic student portrait will be changed over time, so that the set of student interest labels are constantly updated and expanded, the only way we can well meet the changing interests of the target student user needs.

In this paper, we obtain the interest labels from the text data of the titles of the students' civic and political education resources, and combine the same labels with the time series to predict the interest value of the labels in the next moment, so as to achieve the purpose of updating the student portrait, and the specific formula for the calculation of the weights is as follows:

$$F_{t+1} = \frac{1}{T}(Y_t - Y_{t-T}) + F_t \tag{2}$$

The F_{t+1} represents the predicted value, which is an estimate of the moment Y_{t-T} relative to F_t, when it is necessary to bring F_t into the formula to derive it:

$$\begin{aligned} F_{t+1} &= \frac{Y_t}{T} + \frac{F_t}{T} + F_t \\ F_{t+1} &= \frac{1}{T}Y_t + \left(1 - \frac{1}{T}F_t\right) \end{aligned} \tag{3}$$

Let $\alpha = \frac{1}{T}$, the smoothing constant, be brought into the above equation to obtain:

$$F_{t+1} = \alpha Y_t + (1-\alpha)F_t \tag{4}$$

From the above equation we conclude that prediction can be done as long as there are observed and predicted values from the previous period, without the need for all the previous data, by smoothing the exponential prediction model for the prediction of the next moment of the label weight, so as to get the predicted value represents the updated weight label, the following gives the steps of the student portrait updating model:

Input: a collection of student interest labels at different time moments, e.g., T_1 moment vector labels $Y_{T_1} = \left(X_{1_{T_1}}, X_{2_{T_1}}, X_{3_{T_1}}\right)$.

Output: predict the value of label weights at the next moment.

Steps:

(1) Integrate the same interest labels according to the time series to form

$timeSeries(X_n) = \left(X_{n_{T_0}}, X_{n_{T_1}}, X_{n_{T_2}}\right)$ set.

(2) Input $timeSeries(X_n)$ into the smoothed exponential prediction model as the initial value of the observed series.

(3) Compute the resulting predicted value F_{t+1}.

2.3. Construction of Cluster Student Profiles

In order to reduce the consumption of system storage space by the labels generated from the student user portraits of online learning platforms, this paper adopts a division-based clustering method to divide the student user portraits into clusters, so as to form a group of people with similar interests. It can be seen that the clustering algorithm directly affects the advantages and disadvantages of group division, so this paper proposes an optimized kernel fuzzy C-mean clustering algorithm to improve the accuracy of student portraits in groups.

2.3.1. Student Portrait Clustering Based on FKCM Algorithm

The final clustering results in the default sample space in the fuzzy C-mean clustering (FCM) algorithm [18] are the same, however, the distribution of the samples and the selection of the features are different in practice, and the differences in the influence of the samples on the clustering results of the user portraits must be considered. Therefore, this paper adopts the kernel-based fuzzy C-mean (FKCM) clustering algorithm to make some upgrades to the FCM algorithm in order to better adapt to the user portrait data.

FKCM belongs to the division clustering, its basic design idea is to put the input samples in the high-dimensional feature space through the mapping of Mercer kernel function, which increases the variation of the classification difference between the samples, so as to overcome some of the problems of the above fuzzy clustering, for example, the FCM clustering algorithm can't solve some of the problems such as the classification difference between the various categories, the intersection of the data, and the asymmetric form of the data. There are three main types of common Mercer Gaussian kernel functions, which are linear Gaussian kernel function, polynomial function and Gaussian kernel function. The Gaussian kernel function provides the corresponding feature function space in infinite dimensions, so the given finite sample space is linearly divisible, and when the Euclidean distance is used in the high-dimensional feature space, then the fuzzy clustering objective function in the high-dimensional feature space is defined as:

$$
\begin{aligned}
J_{Km}(X;U,V) &= \sum_{j=1}^{C}\sum_{i=1}^{N} u_{ji}^{m} \left|\phi(x_i) - \phi(v_j)\right|_E^2 \\
&= \sum_{j=1}^{C}\sum_{i=1}^{N} u_{ji}^{m} \left[K(x_i, x_i) - 2K(x_i, x_j) + K(v_j, v_j)\right] \\
&= \sum_{j=1}^{C}\sum_{i=1}^{N} u_{ji}^{m} d_{Kji}^{2}(x_i, v_j), 2 \le C \le N
\end{aligned}
\tag{5}
$$

Then the affiliation function of the feature space should be satisfied:

$$
u_{ji} = \left(1/d_{Kji}^{2}(x_i, v_j)\right)^{1/(m-1)} \Big/ \sum_{j=1}^{C} \left(1/d_{Kji}^{2}(x_i, v_j)\right)^{1/(m-1)} \tag{6}
$$

Clustering centers for:

$$
\phi(\hat{v}_j) = \sum_{i=1}^{N} (u_{ji})^m \phi(x_i) \Big/ \sum_{i=1}^{N} (u_{ji})^m, j = 1, 2, \ldots, C \tag{7}
$$

can be calculated:

$$
K(x_i, \hat{v}_j) = \phi(x_i) \circ \phi(\hat{v}_j) = \sum_{k=1}^{N} (u_{jk})^m K(x_k, x_i) \Big/ \sum_{k=1}^{N} (u_{jk})^m \tag{8}
$$

$$K\left(\hat{v}_j,\hat{v}_j\right)=\phi\left(\hat{v}_j\right)\circ\phi\left(\hat{v}_j\right)=\sum_{k=1}^{N}\sum_{l=1}^{N}\left(u_{jk}\right)^m\left(u_{jl}\right)^m K\left(x_i,x_l\right)\Big/\left[\sum_{k=1}^{N}\left(u_{jk}\right)^m\right]^2 \tag{9}$$

So the new affiliation function under the feature space is updated as:

$$\begin{aligned}\hat{u}_{ji}&=\frac{\left(1/d_{Kji}^2\left(x_i,\hat{v}_j\right)\right)^{1/(m-1)}}{\sum_{j=1}^{C}\left(1/d_{Kji}^2\left(x_i,\hat{v}_j\right)\right)^{1/(m-1)}}\\&=\frac{\left(1/\left(K\left(x_i,x_i\right)-2K\left(x_i,\hat{v}_j\right)+K\left(\hat{v}_j,\hat{v}_j\right)\right)\right)^{1/(m-1)}}{\sum_{j=1}^{C}\left(1/\left(K\left(x_i,x_i\right)-2K\left(x_i,\hat{v}_j\right)+K\left(\hat{v}_j,\hat{v}_j\right)\right)\right)^{1/(m-1)}}\end{aligned} \tag{10}$$

The process of clustering using the FKCM algorithm is shown below:

Input: set of user portrait samples, number of clusters c.

Output: affiliation matrix, clustering center.

Step1: Initialize the affiliation matrix.

Step2: Calculate the distance from the samples to the clustering center based on the similarity.

Step3: Recalculate the affiliation degree of each sample according to the new affiliation function formula.

Step4: If $\left|J_H\left(t\right)-J_H\left(t-1\right)\right|>\varepsilon,t\leftarrow t+1$, go to Step3, otherwise, the algorithm stops, and output the affiliation matrix.

2.3.2. Improved Optimized Clustering Algorithm

The improvement of FKCM clustering algorithm focuses on the problem of input parameters, and in this paper, we use the algorithm of Approximate Neighborhood Propagation (AP) [19] to improve the input parameters.

The basic idea of the AP algorithm is mainly to analyze and calculate the data similarity between multiple potential sample points, and regard all multiple sample points in each potential data set as data cores that can be used as potential data aggregation and classification, in order to quickly screen and find out the appropriate clustering centers, the algorithm searches continuously, so as to obtain two different clustering information, which are the attractiveness information and the degree of belonging information respectively Attractiveness information is the degree of suitability of a point j to be the clustering center of a data point i, denoted as $r\left(i,j\right)$. The attribution information is the degree of suitability of the point i to be the clustering center of j, denoted as $a\left(i,j\right)$.

The process of updating the two information alternately above is actually the iterative updating process of the nearest neighbor propagation algorithm, which sets both $r\left(i,j\right)$ and $a\left(i,j\right)$ to 0 at the initialization stage, and the process of updating these two information alternately is as follows:

$$r\left(i,j\right)\leftarrow s\left(i,j\right)-\max_{j'\neq j}\left[a\left(i,j'\right)+s\left(i,j'\right)\right] \tag{11}$$

$$a\left(i,j\right)\leftarrow\begin{cases}\max\limits_{i\neq j}\left\{0,r\left(j,j\right)+\sum\limits_{i'\neq i,j'\neq j}\max\left[0,r\left(i',j\right)\right]\right\},i\neq j\\ \sum\limits_{i'\neq j}\max\left[0,r\left(i',j\right)\right],i=j\end{cases} \tag{12}$$

The bias parameter P is introduced in the AP algorithm, and the value of the P parameter will be related to the number of final clustering results, when the value of the bias parameter is larger, it indicates that the number of clusters in the final output is larger. Conversely, if the value of the bias parameter is smaller, the number of clusters in the final output is smaller. Therefore, the algorithm needs to find the optimal number of classes by varying the bias parameter P, and if P also finds the optimal range, then the bias clustering results in an optimal outcome. In each loop iteration, the updated result consists of two parts, one part is the value after the current iteration, and the other part is the result of the previous iteration, and the values of these two parts are weighted and calculated to get the updated result now, and the formula of the weighted update method is as follows:

$$r^{(t)}(i,j) \leftarrow \lambda r^{(t)}(i,j) + (1-\lambda)\left\{s(i,j) - \max_{j'\neq j}\left[a^{(t-1)}(i,j') + s(i,j')\right]\right\} \tag{13}$$

$$\begin{aligned} &\text{If } i \neq j, a^{(t)}(i,j) \leftarrow \lambda a^{(t-1)}(i,j) + \\ &(1-\lambda)\min_{i\neq j}\left\{0, r^{(t-1)}(j,j) + \sum_{i'\neq i, j'\neq j} \max\left[0, r^{(t-1)}(i',j)\right]\right\} \end{aligned} \tag{14}$$

$$a^{(t)}(j,j) \leftarrow \lambda a^{(t-1)}(i,j) + (1-\lambda)\left\{\sum_{i'\neq i, j'\neq j}\left[0, r^{(t-1)}(i',j)\right]\right\} \tag{15}$$

2.4. Experimental results and analysis

2.4.1. Validation of the Effectiveness of the Improved FKCM Clustering Algorithm

The experimental data in this section comes from the Iris, Wine dataset of the UCI Machine Learning Library, and its specific attribute information is shown in Table 1.

Table 1. Dataset attribute information.

Data set	The number of instances and	Data dimension	Number of clusters
Iris	160	5	3
Wine	186	14	3

In order to verify the clustering performance of the improved algorithm, the FKCM algorithm optimized using the AP algorithm is noted as AP-FKCM, and the improved algorithm is compared with the standard FCM algorithm and the FKCM algorithm, and the three algorithms adopt the same parameter configurations in experiments, which are specifically set as follows: the population size N is set to be 40, and the number of trials for each algorithm to run independently is 40, and the maximum number of iteration is preset as 200. The upper limit of the number of trials is 200, and the results achieved by the three different algorithms after clustering optimization on different datasets are shown in Table 2, using the accuracy rate ACC as the evaluation index.

It can be seen that AP-FKCM obtains the optimal ACC value on both datasets. On the Wine dataset, the accuracy of the AP-FKCM algorithm increases by 26.8% and 3.3% compared to the standard FCM algorithm and the FKCM algorithm, respectively, indicating that the algorithm's performance is greatly improved on high-dimensional data. On the Iris dataset, the accuracy of the AP-FKCM algorithm increases by 12.1% compared to the standard FCM algorithm, which is not as effective as on the high-dimensional dataset, but it is still improved.

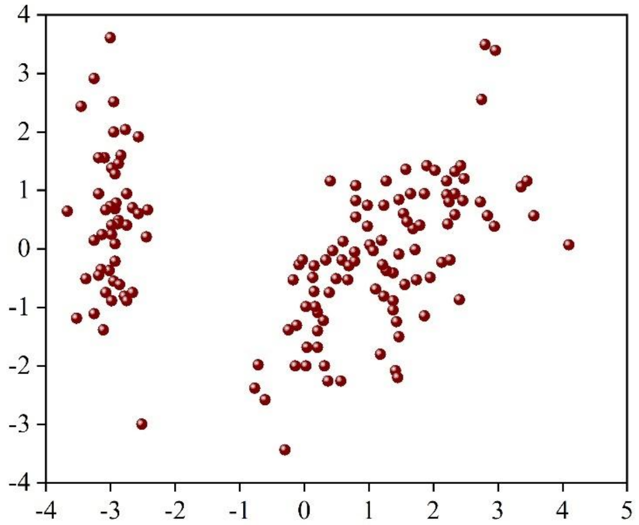
Table 2. Comparison of results of FCM clustering optimization.

Algorithm	Data set	
	Wine	Iris
FCM	0.684	0.796
FKCM	0.919	0.895
AP-FKCM	0.952	0.917

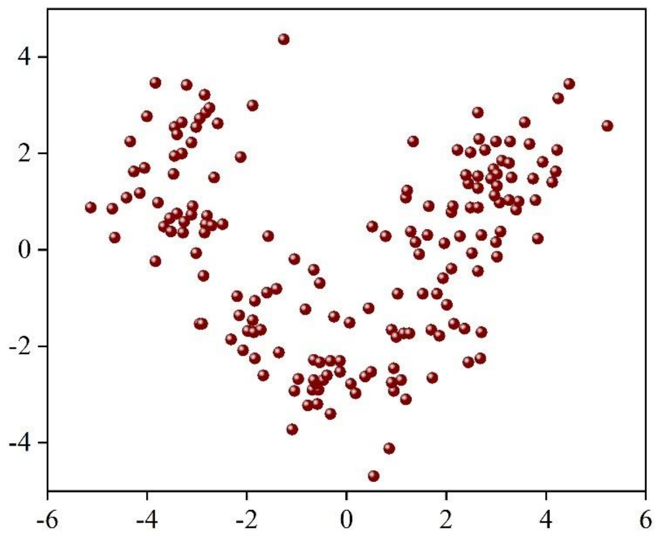
In order to demonstrate the clustering effect of the algorithms, the Iris and Wine datasets are selected for clustering and graphing in the experiments, and the original distributions of the datasets as well as the clustering results of the FKCM algorithm and the AP-FKCM algorithm are shown in Fig. 1. Where (a) and (b) represent the original distribution of Iris and Wine datasets, (c) and (d) represent the clustering results of FKCM algorithm on Iris and Wine datasets, respectively, while the clustering results of

AP-FKCM algorithm on Iris and Wine datasets are (e) and (f), respectively.

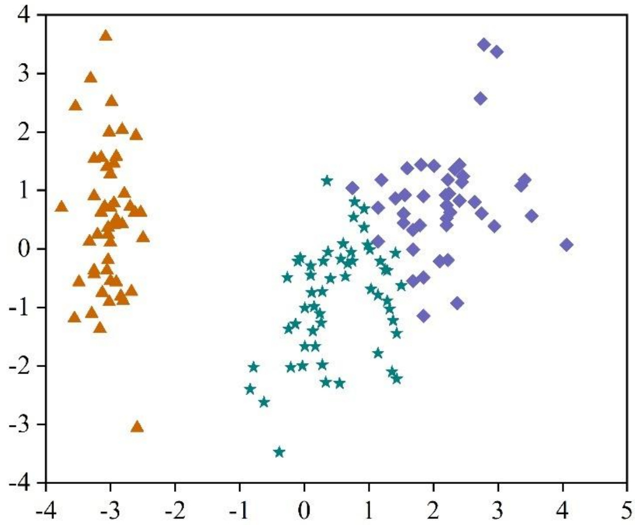
It can be seen that the boundaries between the clusters are not very clear given that the FCM algorithm defines the clustering relationships through the degree of affiliation. This affiliation-based fuzzy clustering method makes the division between clusters more flexible, which helps to reflect the intrinsic structure of the data more accurately. Meanwhile, the improvement of the algorithm accuracy also verifies the effectiveness of the method.The FCM algorithm is mapped by the Mercer kernel function, which improves the stability of the algorithm and reduces the algorithm error. The comprehensive clustering optimization results show that the AP-FKCM proposed in this paper is effective and achieves better results in the optimization of high-dimensional datasets, and the AP-FKCM can effectively deal with clustering optimization problems.



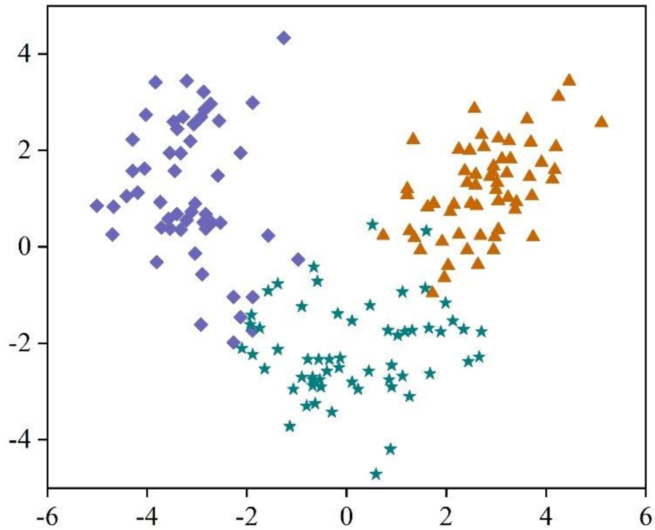
(a) Distribution of the Iris dataset



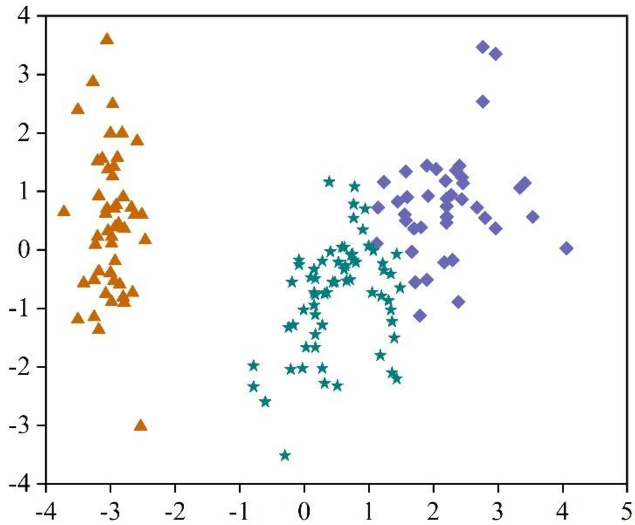
(b) Distribution of the Wine dataset



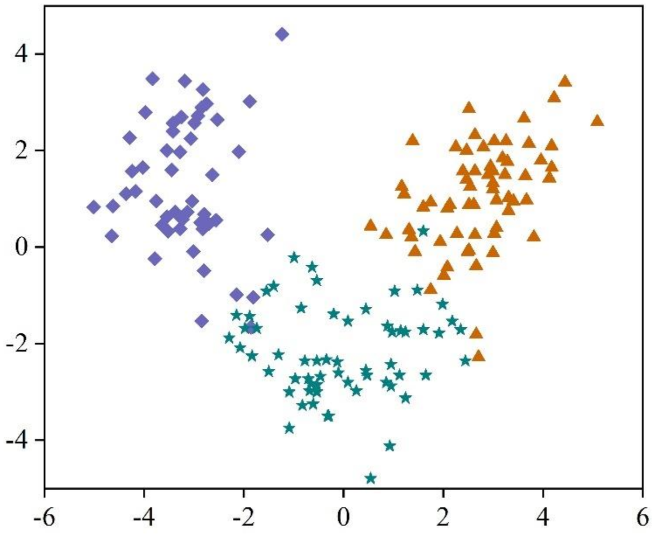
(c) Clustering results of FKCM on Iris



(d) The clustering results of FKCM on Wine



(e) Clustering results of AP-FKCM on Iris



(f) Clustering results of AP-FKCM on Wine

Figure 1. Clustering effect.

2.4.2. Construction and analysis of student portraits

(1) Identification of Learner Groups in Civic Education in Colleges and Universities

In order to differentiate between groups of learners, the study clusters students according to their process data, which can not only discover the learning characteristics of the group of learners but also the collection of behavioral attributes within the learners, thus helping teachers of Civics in colleges and universities to find out the learning patterns of the groups of students and to tailor their teaching to the needs of the students. At the same time, according to the clustering results, we can also push personalized learning resources for different groups of Civics education, and give timely learning warnings and teaching interventions. Cluster analysis for learner group identification includes three steps: first, appropriate indicators should be selected as input variables. Secondly, the appropriate clustering algorithm should be selected according to the needs. Finally the results of the categories are analyzed and interpreted.

In the selection of clustering indicators, the results of the classification of feature indicators of MOOC learner clustering research are referred to, in which interaction indicators, learning performance indicators, and in this study, participation indicators and achievement indicators are extracted. On this basis, evaluation indicators are introduced, namely, teachers' evaluation of students, and the selection of variables corresponding to the indicators is shown in Table 3.

***Table* 3.** Clustering indicators and variables.

Serial Number	Indicator name	Variable name
1	Participation indicator	The total amount of test questions
2		PAD usage duration
3		Reading duration
4		Total number of interactions
5	Process evaluation indicators	The number of times it is rated as excellent
6		The number of times it is rated as good
7	Performance indicator	Average score
8		Accuracy rate
9		Overall average score

For the selection of clustering algorithm, this study used the improved AP-FKCM clustering algorithm to analyze the student data, and the tool used was SPSS software.

1) Categorization of students

In this study, the total number of students' test questions, the length of IPAD use, the length of reading, the total number of interactions, the number of times evaluated as excellent or good, the average score, the correctness rate, and the total grade point average data were standardized. Participation indicators, evaluation indicators, and achievement indicators were selected for cluster analysis using SPSS software to classify them into three categories, and the final cluster centers are shown in Table 4, the number of cases in each cluster is shown in Table 5, and the results of cluster analysis for some students are shown in Table 6.

Table 4. Final clustering centers.

	Clustering		
	1	2	3
Participation	-0.684	0.864	-0.127
Process evaluation	-1.475	-0.469	1.165
Achievements	-1.418	-0.158	0.938

***Table* 5.** The number of cases in each cluster.

Clustering	1	12
	2	10
	3	17
Effective	32	
Missing	0	

***Table* 6.** Results of student cluster analysis (Part).

Student number	Participation indicator	Process evaluation indicators	Performance indicator	Clustering result
1	-0.218	1.164	0.597	3
2	0.884	-1.559	-2.472	1
3	0.422	-0.695	-0.027	2
4	-0.443	1.167	0.462	3
5	1.704	0.146	-1.453	2

The results of clustering the student data are visualized in a RadViz radar chart, and the clustering result RadViz radar chart is shown in Figure 2, where different colored dots represent different categories.

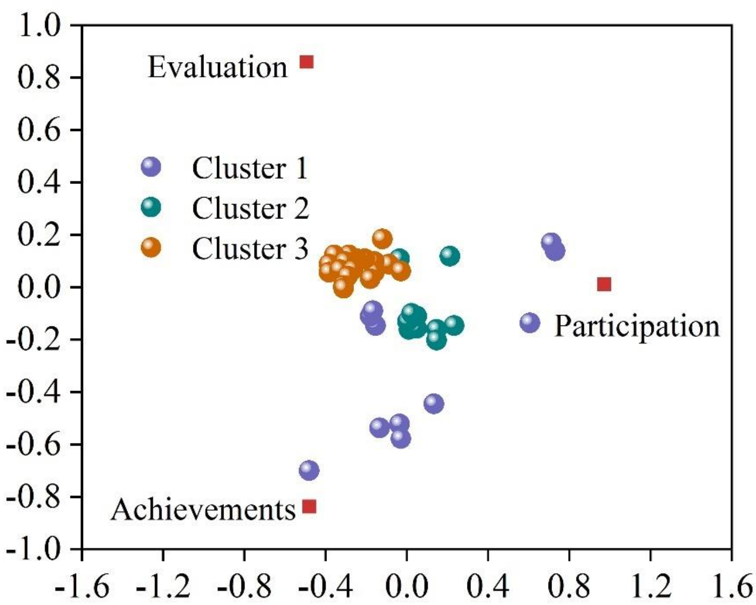


Figure 2. RadViz radar map.

2) Group category portrait

Through the results shown above, the participation index, process evaluation index, and achievement index can be clustered into three categories of learners. In order to differentiate between the three groups of learners, this study named the groups of learners in different categories based on the findings of previous scholars. The naming and portrait characteristics of each category of learners are as follows:

Cluster 1: The first category of students' online learning is not outstanding in terms of participation, process evaluation, and achievement performance. Students in this category have low immersion in online learning and do not fully complete the online learning tasks assigned by the instructor nor do they utilize mobile tools for fragmented learning. They did not perform well on online engagement indicators such as the number of exercises practiced and the number of hands raised in class, and they did not achieve good grades. Not only do they not adapt to online learning methods, but they are also unable to be highly engaged in offline learning, dislike paper-based exercises, and have low adherence to the Internet. Teachers' evaluation of their classroom performance is poor, communication and interaction with teachers are low, and students' information processing is inclined to be contemplative, which is named "potential" learners in the study.

Cluster 2: The second group of students is not outstanding in the process evaluation index and achievement index of online learning, but has better performance in the participation index. This group of students has a high level of online participation, is better adapted to the new learning mode of online learning, and is more active. The length of use of mobile learning tools performs well, but the percentage of time invested in learning is not in good condition. The information processing style favors active learners who like to raise their hands actively in class and are happy to practice online exercises, but the final performance indicators are not good. The reason may be that although students are interested in online learning, they want to improve their learning through online learning, but they have not mastered the method of utilizing the resources for learning, and the study named this type of students as "aggressive" learners.

Cluster 3: The third group of students does not have outstanding performance in the indicators of online learning participation, but has better performance in the indicators of process evaluation and achievement. Students in this category are not active in online learning as a learning mode, and their adhesion to and immersion in mobile devices and online learning platforms are low. Students are good at facilitating their own learning through traditional paper-based learning and communication with their teachers, and their information processing style favors active learners, who are better evaluated by their teachers. Students with good grades and strong independent learning ability are able to make and implement their own study plans and adapt to traditional offline learning methods, and the study names these students as "independent" learners.

3. Recommendations for the decomposition of the matrix of ideological resources integrating reliability and influence dissemination

In order to realize the accurate recommendation of the ideological and political education resources in colleges and universities, and then promote the synergistic operation of red culture dissemination and enterprises, this chapter proposes a matrix decomposition recommendation algorithm that integrates reliability and influence dissemination on the basis of the constructed dynamic portrait of the student user group.

3.1. Description of the problem

For a given recommender system, the matrix $P = [P_{ij}]_{m\times n}$ is used to represent the users' predicted ratings of the items, and the elements P_{ij} represent real numbers in the interval $[1,5]$. The adjacency matrix $S = [S_{ik}]_{m\times m}$ represents the reliability relationship between users, and S_{ik} represents a real number in the interval $[0,1]$, and a value of "0" means that the user u_i is unreliable for the user u_k and a value of "1" means that user u_i is very reliable to user u_k and the matrix S is asymmetric. In social networks, the matrix $T = [T_{ik}]_{m\times m}$ is the transfer matrix for influence propagation, and the element t_{ij} refers to the probability of propagation from user u_i to user u_j, and if there are edges in the social network from user u_i to user u_j, that is, user u_j trusts user u_i, then $t_{ij} > 0$, otherwise $t_{ij} = 0$. f_i denotes the influence propagation vector of user u_i and $f_{i\to j}$ denotes the influence of user u_i on user u_j.

3.1.1. User Reliability

User reliability is the degree of accuracy with which a user can recommend items to other users.

Definition 1: User Reliability

User $u_j \in U$ is the only recommending user for user u_i, and for $h \in CI_{ij}$, the target user u_i has the following prediction score for item h:

$$P_{ih} = \overline{R}_i + \frac{(R_{jh} - \overline{R}_j) \times sim(u_i, u_j)}{|sim(u_i, u_j)|} \tag{16}$$

Where CI_{ij} is the set of items rated by user u_i and user u_j at the same time, $sim(u_i, u_j)$ is the similarity of ratings between user u_i and user u_j, and $\overline{R}_j$ is the average ratings of the items by user u_j. The recommendation ability of user u_i to user u_j is calculated as follows:

$$pr_{ij}^h = 1 - \frac{|P_{ih} - R_{ih}|}{P_{\max}} \tag{17}$$

Where pr_{ij}^h denotes the estimated value of recommendation ability of target user u_i to recommended user u_j on item h, and $P_{\max}$ denotes the maximum difference value between predicted and actual ratings. The recommendation accuracy of target user u_i to recommended user u_j is calculated as follows:

$$PR(u_i, u_j) = \frac{\sum_{h=1}^{|CI_{ij}|} pr_{ij}^h}{|CI_{ij}|} \times \frac{1}{1 + e^{-\frac{|R(j)|}{2}}} \tag{18}$$

where $|R(j)|$ denotes the number of items rated by user u_j. When the value of $|R(j)|$ is large enough, the value of the right term of Eq. (18) tends to 1. For a very small $|R(j)|$, the value of this term is about 0.6. When $|R(j)| > 5$, the value of this term is greater than 0.9. When the number of ratings of user u_j is small, the reliability of user u_j for user u_i should be reduced accordingly. The reliability of a user is evaluated based on its recommendation accuracy, and from this, a user reliability matrix S of size $m \times m$ can be obtained.

3.1.2. Influence Dissemination by Users

Definition 2: Propagation of a user's influence

Denote by $f_{i \to j}$ the influence of user u_i on user u_j:

$$f_{i \to j} = \frac{1}{1+\lambda}\left(\sum_{k \in N_j} t_{kj} f_{i \to k} + v_{i \to j}\right)$$
$$s.t., f_{i \to i} = \alpha_i, \quad j = i, \alpha_i > 0 \tag{19}$$

where $N_j = \{j_1, j_2, \ldots, j_m\}$ is the set of neighbors of user u_j, and since the learning of non-zero values of t_{kj} is outside the scope of the present chapter, it is assumed that they are known and usually satisfy $\sum_{k=1}^{m} t_{kj} \le 1$. Each user u_i is assigned a confidence value α_i that can be learned from a priori domain knowledge. In particular, this value should be maximized if a user u_i shows complete confidence in the information, and will be 0 if the user u_i is not interested in the information.The parameter λ denotes the damping coefficient during the propagation of the user's influence, and takes a value in the range of $(0,+\infty)$, with the smaller the value of λ the smaller the blocking of the influence propagation.

The influence propagation vector $f_i = \left[f_{i\to 1}, f_{i\to 2}, \ldots, f_{i\to m}\right]^T$ of the user u_i can be expressed by equation (20):

$$f_i = Av_i \tag{20}$$

where A is equal to $(I+\lambda I-T)^{-1}$, the vector $v_i = [0,0,\ldots,v_{i,i},\ldots,0]^T$, only the i th term $v_{i,i}$ is not zero, and $v_{i,i}$ is computed as in equation (21):

$$v_{i,i} = \frac{\alpha_i}{a_{ii}} \tag{21}$$

This results in an inter-user influence propagation matrix f.

3.2. Matrix Decomposition of Convergence Reliability and Impact Propagation

In this section, a matrix decomposition model is proposed to integrate the user's ratings, inter-user reliability, and social relationship data.

3.2.1. Matrix Decomposition of User Reliability Relationships

Each user u_i is mapped into two different potential feature vectors described by a specific feature vector Q_i for influencing and a specific feature vector U_i for being influenced. The vector Q_i and the vector U_i represent the behaviors of "influencing others" and "being influenced by others", respectively. The vector Q_i can be interpreted as "what types of items were recommended by user u_i", and the vector U_i as "what types of items were preferred by user u_i with respect to the same d -dimensional latent characteristics". prefers what type of items". Given such vectors, the reliability value S_{ik} can be modeled as the inner product form of the vectors Q_i and U_k.

3.2.2. User-Influenced Communication Relationships

In order to take into account the impact of influence propagation among users in social networks on recommendation generation during the matrix decomposition process, the following regularization term is added to the objective function:

$$\sum_{(i,j)\in\Phi} \left\| U_i - \frac{1}{\left\| f_{\cdot i} \right\|_0} \sum_{t\in f_{\cdot i}} f_{ti} U_t \right\|_F^2 \tag{22}$$

The regularization term means that the feature vector of user u_i depends on the feature vectors of the users that affect it, and this solution is reasonable and can effectively alleviate the cold-start problem in recommender systems.

3.2.3. Matrix Decomposition Model for Convergence Reliability and Impact Propagation

This section proposes the AFFECT model to describe how a specific user can influence other users' ratings of an item by recommending it.

The rating matrix R is identical to the m users in the reliability matrix S, so the matrix R and the matrix S are related to a matrix decomposition process by sharing the user-specific potential space. In the affect model, the affect-specific feature matrix Q is chosen as the potential feature space shared by the matrix R and the matrix S. The vector Q_i represents both: how the user u_i influences others and how u_i evaluates the project, and the project-specific potential feature vector V_j describes how the user evaluates the project j, which, taken together, $Q_i^T V_j$ represents how user u_i influences other users' ratings of item j, which is an approximation of the actual score R_{ij}. Thus, the feature matrices Q, V and U can be learned simultaneously by minimizing the following objective function:

$$\begin{aligned} L = & \sum_{(i,j)\in\Omega} \left(g(Q_i^T V_j) - R_{ij} \right)^2 + \sum_{(i,k)\in\Psi} \left(g(Q_i^T U_k) - S_{ik} \right)^2 \\ & + \alpha_u \left(\sum_{(k,i)\in\Phi} \left\| U_k - \frac{1}{\|f_{\cdot k}\|_0} \sum_{t\in f_{\cdot k}} f_{tk} U_t \right\|_F^2 \right) \\ & + \alpha_r \left(\sum_i (m_{q_i} + n_{q_i}) \|Q_i\|_F^2 + \sum_j n_{v_j} \|V_j\|_F^2 + \sum_k n_{u_k} \|U_k\|_F^2 \right) \end{aligned} \tag{23}$$

Where the parameter α_u controls the proportion of influence between ratings and social relationships in the training model, and α_r represents the parameter that controls the complexity of the model to avoid overfitting. Since the reliable value S_{ik} between users is between 0 and 1, in order to learn the parameters in the model more conveniently, the function $f(x) = x / R_{\max}$ is used to map the rating value R_{ij} in the interval $[0,1]$, where $R_{\max}$ denotes the maximum value of the ratings in the recommender system, and a Logistic function $g(x) = 1/(1+\exp(-x))$ to fix the inner product of potential feature vectors to the interval $[0,1]$. The predicted ratings of user u_i for item j can be obtained by $g(Q_i^T V_j) \cdot R_{\max}$ after training the model. Where n_{u_k}, n_{v_j}, n_{q_i}, and m_{q_i} denote, respectively, the number of items that user k likes, the number of users who consider user u_i reliable, the number of times item j has been rated, and the number of ratings that user u_i has given. The above objective function can be minimized by performing the following gradient descent for all users and items Q_i, V_j, U_k:

$$\begin{aligned} \frac{1}{2}\frac{\partial L}{\partial Q_i} = & \sum_{j\in R(i)} g'(Q_i^T V_j) \left(g(Q_i^T V_j) - R_{ij} \right) V_j \\ & + \sum_{k\in S(i)} g'(Q_i^T U_k) \left(g(Q_i^T U_k) - S_{ik} \right) U_k \\ & + \alpha_r (m_{q_i} + n_{q_i}) Q_i \end{aligned} \tag{24}$$

$$\begin{aligned} \frac{1}{2}\frac{\partial L}{\partial U_k} = & \sum_{i\in S^+(k)} g'(Q_i^T U_k) \left(g(Q_i^T U_k) - S_{ik} \right) Q_i \\ & + \alpha_u \left(U_k - \frac{1}{\|f_{\cdot k}\|_0} \sum_{t\in f_{\cdot k}} f_{tk} U_t \right) + \alpha_r n_{u_k} U_k \end{aligned} \tag{25}$$

$$\frac{1}{2}\frac{\partial L}{\partial V_j} = \sum_{i\in R^+(j)} g'(Q_i^T V_j) \left(g(Q_i^T V_j) - R_{ij} \right) Q_i + \alpha_r n_{v_j} V_j \tag{26}$$

where $R(i)$ is the set of items that user u_i has over rated, $R^*(j)$ denotes the set of users who have over rated item j, $S(i)$ is the set of users who consider user u_i to be reliable, $S^*(k)$ denotes the set of users who are considered to be reliable by user u_k, and $g'(x) = \exp(-x)/(1+\exp(-x))^2$ is the derivative of the logistic function $g(x)$. Since the model in Eq. (23) uses the Affect-specific feature matrix Q as the common user potential space, the learning algorithm is referred to as Affect-MF.

Unlike the Affect model, which uses the feature matrix Q as the potential feature space shared by the matrix R and the matrix S, the model chooses the affected-specific feature matrix U as the matrix R and S shared feature space. The $U_i^T V_j$ represents how user u_i is influenced by other users to rate item j. Similarly, the feature matrices U, V and Q can be learned simultaneously by minimizing the following objective function:

$$\begin{aligned} L = &\sum_{(i,j)\in\Omega}\left(g(U_i^T V_j) - R_{ij}\right)^2 + \sum_{(i,k)\in\Psi}\left(g(Q_i^T U_k) - S_{ik}\right)^2 \\ &+\alpha_u\left(\sum_{(i,j)\in\Phi}\left\|U_i - \frac{1}{\|f_{\cdot i}\|_0}\sum_{t\in f_{\cdot i}} f_{ti}U_t\right\|_F^2\right) \\ &+\alpha_r\left(\sum\nolimits_i (m_{u_i} + n_{u_i})\|U_i\|_F^2 + \sum\nolimits_j n_{v_j}\|V_j\|_F^2 + \sum\nolimits_k m_{q_k}\|Q_k\|_F^2\right) \end{aligned} \tag{27}$$

where n_{v_j}, n_{u_i}, m_{q_k}, and m_{u_i} denote the number of times item j has been rated, the number of ratings given by user u_i, the number of users who consider user u_k to be reliable, and the number of users considered to be reliable by user u_i, respectively.

After independently training the affect and affected models, two sets of feature matrices can be obtained, let Q_i^t and V_j^t be the affect-specific and item-specific vectors learned by the Affect-MF algorithm. Let U_i^d, V_j^d be Affected-specific vectors and item-specific vectors learned by the algorithm Affected-MF. Finally, a synthesis strategy is used to generate an approximation of the actual rating scores:

$$\hat{R}_{ij} = g\left(\left(\beta Q_i^t + (1-\beta)U_i^d\right)^T\left(\beta V_j^t + (1-\beta)V_j^d\right)\right)\cdot R_{\max} \tag{28}$$

3.3. Case Studies

In this chapter, experimental research work is carried out on the S-platform university civic education resource dataset. The effectiveness of the recommendation model in this paper is demonstrated by comparing the matrix decomposition recommendation model, which incorporates reliability and influence propagation, with other recommendation models for experimental analysis, such as SVD, SVD++, Social_MF, etc.

3.3.1. Assessment of Indicators

This paper is concerned with the accuracy of the recommendation results, so the predictive accuracy assessment metric is used as a measure. Predictive accuracy is used to assess the difference between the predicted score and the true score. A smaller degree of deviation indicates a more accurate prediction.

In this chapter, the root mean square error (RMSE) and the mean absolute error (MAE) are used to assess the good and bad model performance. The assessment metrics are shown in equations (29) to (30), respectively:

$$RMSE = \sqrt{\frac{1}{|D_{test}|}\sum_{(u,i)\in D_{test}}\left(r_{ui} - \hat{r}_{ui}\right)^2} \tag{29}$$

$$MAE = \frac{1}{|D_{test}|}\sum_{(u,i)\in D_{test}}\left|r_{ui} - \hat{r}_{ui}\right| \tag{30}$$

where D_{test} denotes the experimental dataset, r_{ui} is the rating of user u on item i, and $\hat{r}_{ui}$ is the predicted rating of user u on item i.

3.3.2. Experimental Comparison Model

In order to verify the effectiveness of the proposed model in the field of accurate recommendation of learning resources for Civic and Political Education, this paper introduces the relevant models researched in the recent years of social recommendation, which will be used as the comparison models for the experiments, specifically including: singular value decomposition model (SVD), the SVD improvement model SVD++, probabilistic matrix decomposition model (PMF) [20], the social recommendation model based on matrix decomposition (Social_MF), and Collaborative User Network-based Social Recommender System (CUNE).

3.3.3. Analysis of Experimental Results

This chapter carries out an experimental research work on the proposed model and some models as comparisons on experimental datasets. Before training the model, the dataset needs to be divided into two data: the training set and the test set. The training set is the data prepared for training the model, while the test set is for verifying whether the trained model is reasonable and preventing the model from overfitting. Among them, the training set can be categorized into 5 types: {30%,40%,50%,60%,70%}. In this chapter, all the models will be analyzed experimentally under different training set proportions, and the experimental results of different recommended models are shown in Table 7. In order to observe the change trend of the models more accurately, the experimental results are visualized in this experiment.The evaluation metrics of all models in different training sets are shown in Fig. 3, and Figs. (a) and (b) show the comparison results of RMSE and MAE values, respectively.

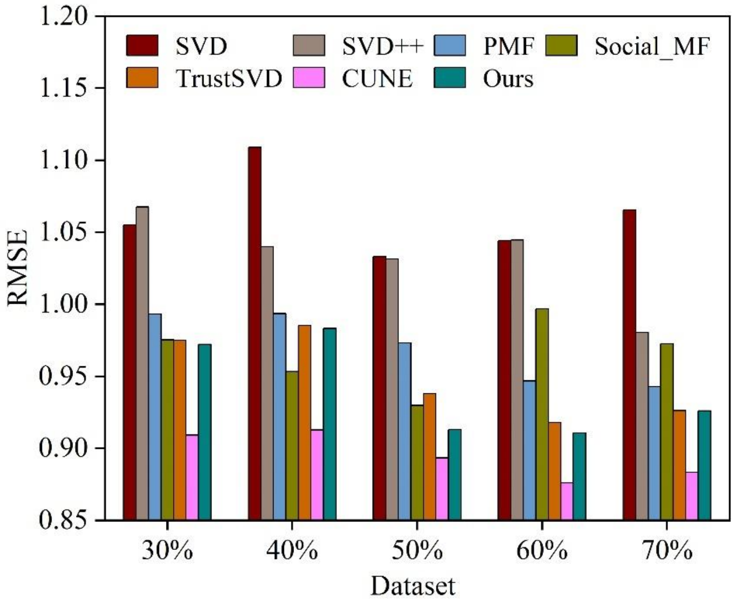
The experimental results show that some basic recommendation models, such as SVDI, SVD++ and PMF, their experimental results under different proportions of training sets are not very satisfactory, and the evaluation metrics, RMSE and MAE, are relatively poor compared to other models. In contrast, the social recommendation models proposed in recent years, such as Social_MF, TrustSVD, and CUNE, have achieved a greater advantage in the results of the evaluation metrics. This indicates that these models have achieved some success in the accurate recommendation of learning resources for Civic Education.

Meanwhile, comparing the Social_MF and TrustSVD models, the RMSE and MAE metrics of the recommendation model proposed in this chapter are improved to a great extent. This demonstrates that this model is able to deeply mine the interest preferences of student users and the personalized characteristics of Civic Education learning resources by integrating the user reliability relationship and the user influence propagation relationship, which improves the accuracy of Civic Education learning resources recommendation. In addition, the RMSE index of the CUNE model is better than that of this paper's model, and the MAE index is slightly worse than that of this paper's model, which reflects that the performance of the CUNE model using the deep learning algorithm is better than that of other models. Even so, the recommendation performance of this paper's model is very similar to that of the CUNE model, indicating the potential development value of the model proposed in this chapter.

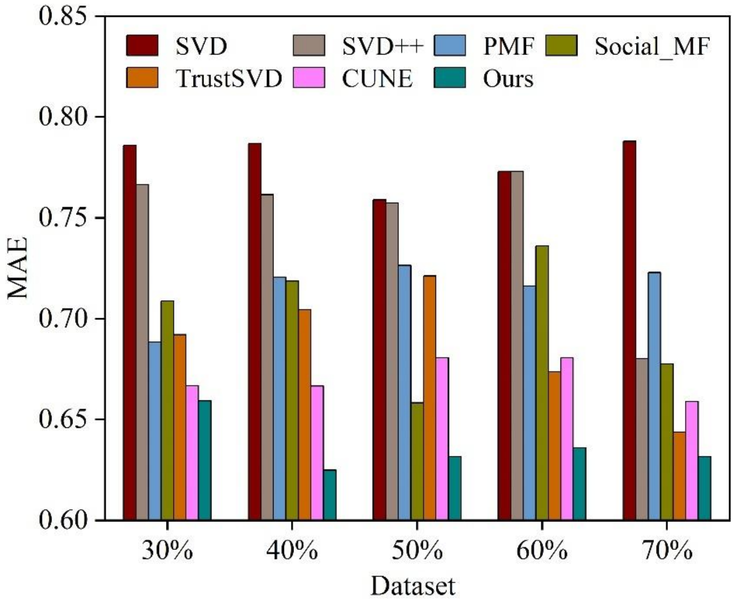
The experimental results for the three recommendation models, Social_MF, TrustSVD64 and the model in this paper, although there are some differences, their patterns of change are extremely similar. The experimental results are all gradually decreasing with the increase of the proportion of the training set, and then tend to stabilize. Taking the model of this paper as an example, when the proportion of the training set is small, such as 30%, this model can not learn the features better during the training process, which leads to a larger error in the model's recommendation results, and the RMSE and MAE values reached 0.9721 and 0.6592, respectively. With the increasing proportion of the training set, the model's evaluation indexes began to decrease continuously, until it reaches a stable experimental results. It indicates that the model in this paper can be trained more efficiently at 60%-70% of the training set, and further learning the feature representation of student users and Civic Education learning resources in the feature space, which makes the prediction results of this model become more accurate.

Table 7. Experimental results of different recommendation models.

Training set	Metrics	SVD	SVD++	PMF	Social_MF	TrustSVD	CUNE	Ours
30%	RMSE	1.0550	1.0676	0.9933	0.9753	0.9750	0.9092	0.9721
	MAE	0.7859	0.7664	0.6884	0.7089	0.6920	0.6667	0.6592
40%	RMSE	1.1089	1.0399	0.9935	0.9532	0.9853	0.9128	0.9831
	MAE	0.7869	0.7614	0.7206	0.7186	0.7044	0.6665	0.6248
50%	RMSE	1.0331	1.0314	0.9731	0.9298	0.9378	0.8933	0.9131
	MAE	0.7589	0.7573	0.7264	0.6582	0.7212	0.6805	0.6316
60%	RMSE	1.0442	1.0446	0.9468	0.9969	0.9178	0.8758	0.9106
	MAE	0.7730	0.7731	0.7160	0.7361	0.6736	0.6806	0.6359
70%	RMSE	1.0655	0.9805	0.9428	0.9725	0.9261	0.8833	0.9259
	MAE	0.7879	0.6801	0.7228	0.6774	0.6438	0.6589	0.6315



(a) RMSE



(b) MAE

Figure 3. RMSE and MAE values of different models.

4. Conclusion

This paper proposes a student group portrait clustering model AP-FKCM and constructs a matrix decomposition recommendation model that integrates reliability and influence propagation, so as to realize the accurate recommendation of college civic education resources empowered by artificial intelligence.

On the Wine dataset, the accuracy of the AP-FKCM algorithm is increased by 26.8% and 3.3% compared with the standard FCM algorithm and FKCM algorithm, respectively. Compared with the standard FCM algorithm, the accuracy of the AP-FKCM algorithm is increased by 12.1% on the Iris dataset, indicating that the performance of the algorithm on high-dimensional data has been greatly improved. At the same time, combined with the indicators of participation, process evaluation and performance, three types of student group portraits were constructed, including "potential" learners, "enterprising" learners and "self-motivated" learners.

Comparing the basic recommendation models SVDI, SVD++ and PMF, as well as the social recommendation models proposed in recent years, Social_MF, TrustSVD and CUNE, the recommendation model proposed in this paper shows a great degree of improvement in both RMSE and MAE metrics. This shows that this model can deeply explore the interest preferences of student users and the personalized characteristics of Civic Education learning resources by integrating the user reliability relationship and the user influence propagation relationship, which improves the accuracy of Civic Education learning resources recommendation. The recommendation performance of the model in this paper is very similar to that of the CUNE model, which indicates that the model in this paper has a large potential for development. In addition, it is found that the model recommendation errors all decrease gradually with the increase of the proportion of the training set, and then tend to stabilize. It indicates that the model in this paper can be trained more efficiently at 70% of the training set, and the prediction accuracy is substantially improved.

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