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Exploring the Intelligent Development Path of Civic and Political Education Theory System in the New Era Facing Big Data Environment

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Abstract Ideological and political education has developed into the era of informationization and technologization, and should consciously follow the changes in the social environment to make corresponding adjustments. Based on big data technology, this paper shifts the development of ideological and political education activities to a targeted and fine implementation. Combined with the actual situation of student management in colleges and universities as well as college students' civic education, a quantifiable student information model is constructed and a personalized learning resource recommendation system is established through data collection, cleaning and normalization. The system adopts user-based collaborative filtering recommendation algorithm to recommend personalized learning resources, and then adopts content filtering recommendation algorithm to optimize the recommendation system for the problems of sparse scoring and “cold start”. After testing, the similarity of collaborative filtering and content-based similarity have the same weight, and the error value is minimized when the number of recommendation lists is 10. The algorithm of this paper is applied to the personalized learning resources recommendation system for teaching practice, compared with the effect of other algorithms, the students' performance under the method of this paper is significantly improved, and the students are satisfied with the effect of using the system.

Index Terms Big Data, Collaborative Filtering Recommendation, Content Filtering Recommendation, Civic Education

I. Introduction

At present, artificial intelligence has been integrated into all aspects of social life, and its practice and application in the fields of smart cities, smart factories, smart homes and other areas have opened up a new mode of economic and social development and improved the convenience of people's lives [1]. In view of this, the Chinese government has emphasized that the innovation and application of AI should start from the need to safeguard and improve people's livelihood and create a better life for the people, and promote the in-depth application of AI in people's daily work, study, and life, and create a smarter way of working and living [2]. And the promulgation of the “new generation of artificial intelligence development plan”, “higher education artificial intelligence innovation action plan” and other documents, but also a strategic plan for the development of artificial intelligence in a number of areas of the strategy [3]. Under the influence of this strategic and revolutionary change of the times, the trend of ideological and political education and the integration and development of artificial intelligence has been unstoppable, and the ideological and political education in the new era has gradually shown the development trend of precision, intelligence, and personalization [4], [5].

The application of artificial intelligence in ideological and political education makes it present new opportunities and challenges in educational theory, teaching methods, teaching technology application and other operational mechanisms, and puts forward new requirements for the innovative development of ideological and political education [6]. Under the background of weak artificial intelligence, artificial intelligence in the field of cognitive intelligence is still in the primary stage, especially in the external knowledge intervention, logical reasoning or domain migration, the performance is poor, the application of technology is relatively narrow and single, the combination of ideological and political education and artificial intelligence in ideological and political education is still stuck in the process of teaching and the use of artificial intelligence at the superficial level [7]-[9]. At the same time, as the “Internet aborigines” of the student population and the increasingly close connection with the intelligent society, ideological and political education how to adapt to the development of the intelligent society, how to adapt to the needs of college students in the era of artificial intelligence on ideological and political education, ideological and political education has become an important issue that needs to be resolved in the field of ideological and political education [10]-[12]. Therefore, examining artificial intelligence from the perspective of ideological and political education, starting from the teaching link, attempting to find the point of convergence between the two and amplify it, in order to enhance the scientific and advanced nature of the research on the integration and development of artificial intelligence and ideological and political education, enrich the content of the basic theoretical research on ideological and political education, and then improve the theoretical system of the research on the integration and development of artificial intelligence and ideological and political education [13]-[15].

In this paper, we applied big data technology and artificial intelligence technology to study the application of “Precision Civics”, and designed a personalized learning resource recommendation system based on collaborative filtering recommendation algorithm. In view of the problems of sparse scoring and “cold start” that may occur in the algorithm, the system optimizes the way of obtaining user information, and adopts implicit scoring to score learning resources. For newly registered users, the system adopts content filtering algorithm to recommend learning resources. The experiments used accuracy, recall and F1 value as evaluation indexes to verify the performance of the system. Different algorithms were respectively applied to the system for teaching practice to analyze the effect of the improved recommendation algorithm on the role of Civic and Political Education.

II. Intelligent Development Design of Civic Education Theory System

II. A.“Precision Civics” Based on Big Data Modeling

The essence of “Precision Civic Education” is to meet the students' needs for Civic Education with the excellent Civic Education resources of the school, taking the Civic Education work as the supply side and the audience of Civic Education as the demand side, and focusing on how to accurately match the demand side and the supply side. Since the audience of Civic and Political Education is college students, it is necessary to pay attention to the differences and individualization between the objects of Civic and Political Education. Only by continuously paying attention to the changes in demand and carrying out in-depth supply-side reform, can we reach a dynamic balance between supply and demand.

Fully investigate the existing student service platforms and businesses, business processes, constraints, etc., use big data analysis technology to sort out the business processes of student work itself, choose the technical routes and framework structure, and carry out in-depth excavation and correlation analysis of these originally isolated core data to obtain valuable information from them, so as to obtain the best solution for accurate civic politics.

Adopting big data analysis method, the data of online behavior and values of college students on campus are sampled. Using observation and quantitative analysis, we cleaned and transformed the data from various business systems and the “Smart Campus” data, and trained the data analysis model with the test set data. Accurately recognize students. How to recognize students accurately and quickly is an important part of carrying out ideological education activities. The data distributed in different service platforms and systems are used to solve the problem of campus information silos through big data processing technology to realize data sharing. Based on deep learning algorithms to analyze the massive behavioral data, “portrait” of the data subject, the use of big data analysis combined with deep learning models to assess the students' learning situation and learning ability, to provide data and technical support for the subsequent educational practice [16].

II. B.Information modeling

II. B. 1) Data collection and cleansing

In the actual use of the scenario, students' information data are often scattered in different information systems and databases, before the establishment of the model, it is necessary to sort out, summarize and clean the information used, the data and information flow is shown in Figure 1.

In the big data environment, data sources are diverse and complex, and data quality varies. Data cleansing is a key part of data preprocessing, which makes data more accurate, complete, usable, consistent and standardized through operations such as deleting, modifying or filling in missing values, dealing with outliers and duplicates, and adjusting data formats, so as to improve the accuracy and reliability of data analysis and mining. After the data collection of student information, the data need to be further cleaned and processed, specifically including filtering non-student data, checking whether the logical relationship between data fields is reasonable, data de-weighting, and processing of missing values.

II. B. 2) Establishment of the information model of student civic politics

Students' ideological and political information can be expressed through a unified multi-layer information model, which consists of multiple levels, and each level is divided according to the size of information gain (IG). Information gain is the difference of information entropy, and the larger the information gain value of a feature item, the higher its importance. In the Student Civic and Political Information Model, the information gain of each level is equal within a certain range. A level is subdivided into multiple elements, and the information elements describe the information of that level in multiple ways. The student information model consists of a key layer, a sub-critical layer, and a basic information index layer, and the student civic and political information model is shown in Figure 2.

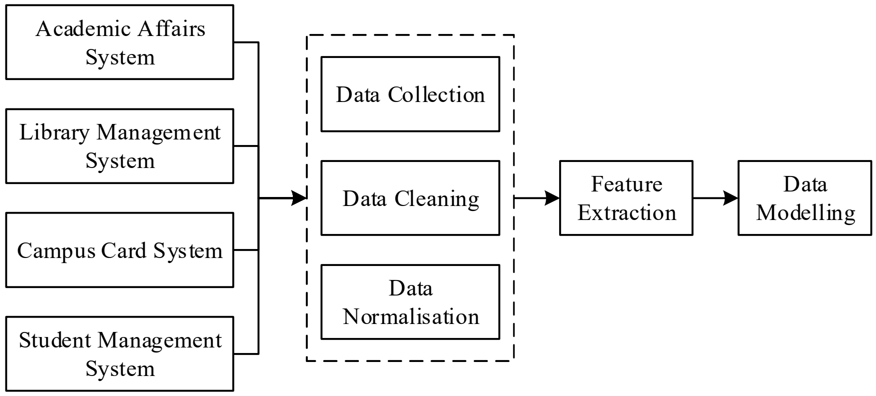

Figure 1: Student information processing process

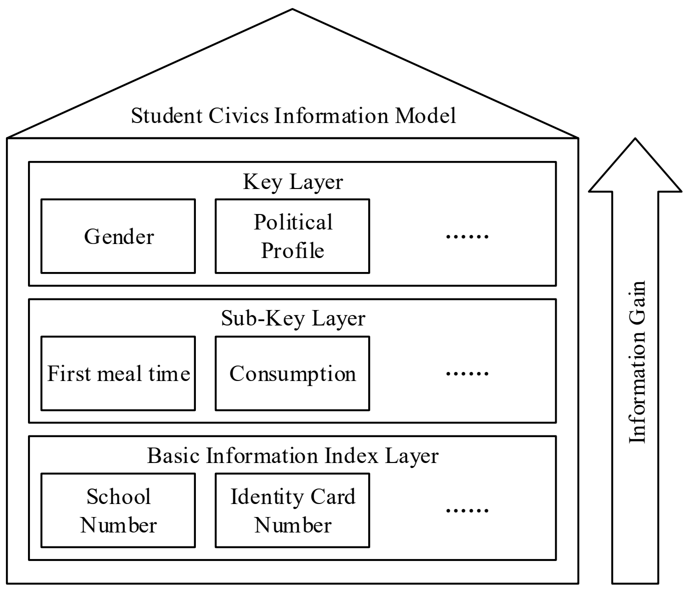

Figure 2: Student thinking information model

(1) Key Layer

Basic evaluation of students' ideological and political qualities, this layer of information has the greatest information gain, including gender, political appearance, psychological assessment results, physical test results, academic performance and other information elements.

(2) Sub-critical layer

Side-by-side comprehensive evaluation of students' ideological and political qualities, including information elements such as first meal time, on-campus consumption, and time spent on the Internet. The information in this layer has certain data mining value. For example, the first meal time can be obtained from the students' first consumption time in the cafeteria, which can judge whether the students get up early and whether the three meals are regular, and then deduce the students' life and psychological state; the Internet time can judge whether the students are too indulged in online entertainment, and can remind the students who are on-line for more than a certain threshold to have a conversation, and restrict the students' Internet time by charging the Internet fee in steps, and so on.

(3) Basic Information Indexing Layer

It is essentially for identifying students, including basic identifying information such as student number, ID number, etc. It is not involved in subsequent processing, but only for the purpose of being able to quickly retrieve the required students. For different levels of information elements, different weights are set according to the size of the information gain, for the key layer of information, the weight is set to 0.7, and the sub-critical layer is 0.3. The weights will be used in the subsequent similarity comparison.

II. B. 3) Comparison of similarities in student information models

In order to facilitate the comparison of similarity between students and the analysis of clustering and discrete points at a later stage, each of the above information must be quantified into measurable values, which can be classified into categorical (qualitative) and numerical (quantitative) from the perspective of the attributes of the information elements.

Classified attributes are symbols or names of things, and do not have the nature of numbers. For classified attributes, in order to facilitate the algorithm to discover the association between data, a classified attribute can be transformed into multiple binary attributes, i.e., binaryization.

(1) Similarity Comparison of Categorical Attributes

For the similarity between binaryized categorical attributes, the Jaccard coefficient J can be used to measure:

$$\operatorname{sim}(F_1, F_2) = J = \frac{f_{11}}{f_{01} + f_{10} + f_{11}} \tag{1}$$

where F_1, F_2 are the values of the two binary attributes to be compared, and f_{11}, f_{01}, f_{10}, f_{11} denote the number of binary attributes when both a and b take 0, a takes 0 and b takes 1, a takes 1 and b takes 0, and both a and b take 1, respectively.

(2) Similarity comparison of numerical attributes

For numerical attributes, the attribute values are sequentially transformed into vectors and the cosine similarity measure is used to measure the difference between two vectors α and β:

$$\operatorname{sim}(F_1, f_2) = \frac{1}{d(\alpha, \beta)} = \frac{\|\alpha\|\|\beta\|}{\alpha \cdot \beta} \tag{2}$$

where F_1 and F_2 are the values of the two numerical attributes to be compared, "·" denotes the vector dot product, $\alpha \cdot \beta = \sum_{k=1}^{n} \alpha_k \beta_k$, and $\|\alpha\|$ is the length of the vector, $\|\alpha\| = \sqrt{\sum_{k=1}^{n} \alpha_k^2}$.

Combining the student information model with multiple information elements, the similarity between two students' information models M_i as well as M_j is:

$$\operatorname{sim}(M_i, M_j) = \sum_{k \in E} \omega_k \operatorname{sim}(M_{ik}, M_{jk}) \tag{3}$$

where E is the set of all information elements, k is a single information element, and ω_k is the weight of a single information element in the similarity comparison.

For the comparison results, a set of thresholds can be set to constitute the interval (ω_m, ω_n), which is categorized into the following cases based on the similarity comparison results:

(1) $\operatorname{sim}(M_i, M_j) \geq \omega_n$, it can be assumed that the two students have a high degree of similarity, and can be grouped into one category in the work of student civic education and unified management.

(2) $\omega_m < \operatorname{sim}(M_i, M_j) < \omega_n$, it can be assumed that there is a certain degree of similarity between the two students, which can be analyzed in the context of the specific situation.

(3) $\operatorname{sim}(M_i, M_j) \leq \omega_m$, it can be assumed that there is a low degree of similarity between the two students, and that different teaching and management approaches should be used in student management.

II. C.Personalized Learning Resources Recommendation System Design

The personalized learning resource recommendation system is developed using Java language and adopts a 4-tier architecture, which are client layer, network layer, application layer, persistence layer, and also includes a database. The structure of the personalized learning resource recommendation system is shown in Figure 3.

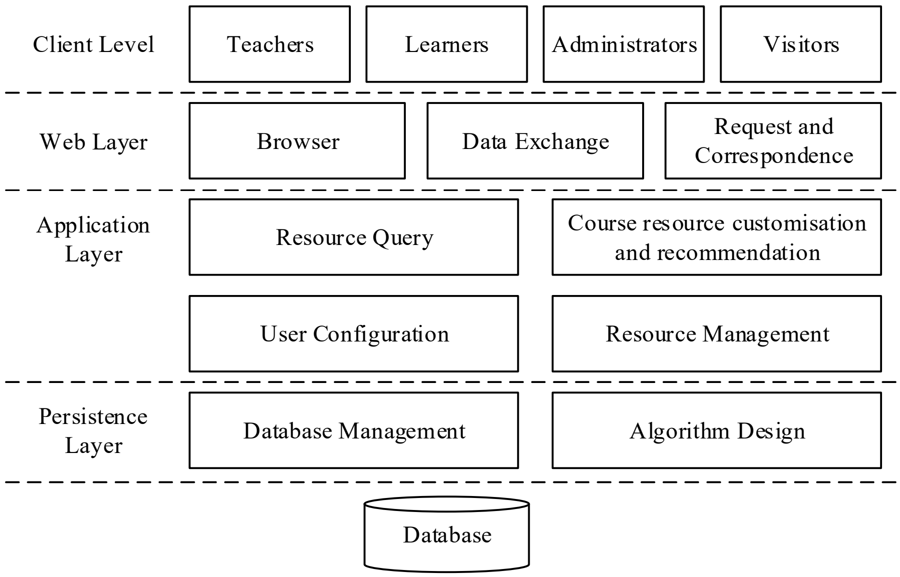

Figure 3: Personalized learning resource recommendation system structure

II. C. 1) Recommendation system algorithm design

The design and implementation of the recommendation algorithm is the core part of the recommendation system that can recommend personalized learning resources. Through the use of recommendation algorithms can be presumed that the learner's preferences, learning priorities, etc., so as to provide learners with relevant personalized Civics learning resources.

At present, commonly used recommendation algorithms for personalized content include association rule recommendation, content filtering recommendation and collaborative filtering recommendation. Among them, the recommendation algorithm of association rules is to make relevant rules by the administrator, so as to recommend learners according to the rules [17], and the accuracy of this recommendation algorithm cannot meet the requirements of learners. The content filtering recommendation algorithm mainly filters and recommends text-based resources, while the categories of learning resources include audio and video, etc. [18], this recommendation algorithm cannot be applied. Collaborative filtering recommendation algorithms recommend to learners based on the matching degree of learning resources and according to the size of the similarity [19]. This algorithm has the advantages of adaptability, high accuracy and potential interest mining. Therefore, it can be designed using collaborative filtering recommendation algorithm.

When using collaborative filtering recommendation algorithm, it can be designed based on the user or the project, in order to ensure the real-time and accuracy of online learning, the final design will be based on the user. The process of user-based collaborative filtering recommendation algorithm is as follows:

Step 1: Relevant information such as the user's personal information, learning history and behavioral information is acquired, and this information is transformed into a rating of the learning information using a weighted approach. The relationship matrix between user information and ratings is shown in Table 1. The M_{ij} in the table represents the rating result of user i on resource j.

Table 1: User information and scoring relationships

	User 1	......	User i	User n
Resources 1	$M1_1$	......	Mi_1	......
......	......	......	......	......
Resources j	$M1_j$	......	$M1_j$	Mn_j
Resources n	$M1_n$	......	Mi_n	Mn_n

Step 2: Search for users with similar interests. When performing the search, the learning resources rated by both users p and q at the same time are summarized in a set denoted as $Res_{p,q}$, and the similarity is computed using cosine similarity or correlation similarity methods. Where the cosine similarity $S(p,q)$ is calculated as in equation (4):

$$S(q,p)=\cos(\vec{p},\vec{q})=\frac{\vec{p}\cdot\vec{q}}{\|\vec{p}\|\times\|\vec{q}\|}=\frac{\sum_{s\in Res_{p,q}}M_{p,s}M_{q,s}}{\sqrt{\sum_{s\in Res_{p,q}}M_{p,s}^2\sum_{s\in Res_{p,q}}M_{q,s}^2}} \tag{4}$$

The correlation similarity $S(p,q)$ is calculated as in equation (5):

$$S(q,p)=\frac{\sum_{s\in Res_{p,q}}(M_{p,s}-\bar{M}_p)(M_{q,s}-\bar{M}_q)}{\sqrt{\sum_{s\in Res_{p,q}}(M_{p,s}-\bar{M}_p)^2}\sqrt{\sum_{s\in Res_{p,q}}(M_{q,s}-\bar{M}_q)^2}} \tag{5}$$

where: $M_{p,s}$ and $M_{q,s}$ are the results of user p and q's ratings on the used s resources, respectively. $\bar{M}_p$ and $\bar{M}_q$ are the results of the average ratings of users p and q on all the used s resources, respectively.

Step 3: Aggregate the most similar users. That is, based on the computed similarity results, the users are sorted according to the results from high to low, and the set X formed by the top N users is the most exhaustive set of users, as in equation (6):

$$X=\{User_1,User_2,User_3,\cdots,User_N\} \tag{6}$$

Step 4: Correction of similarity calculation results. Due to the different situations of different users, their ratings of learning resources are still subjective and there is no uniform evaluation standard. In order to reduce the users' subjective ideas about learning resources, the cosine similarity is corrected, i.e., the users' average rating results of learning resources can be subtracted from the rating, which is calculated as in equation (7):

$$S(q,p)=\frac{\sum_{s\in Res_{p,q}}(M_{p,s}-\bar{M}_p)(M_{q,s}-\bar{M}_q)}{\sqrt{\sum_{s\in Res_{p,q}}(M_{p,s}-\bar{M}_p)^2}\sqrt{\sum_{s\in Res_{p,q}}(M_{q,s}-\bar{M}_q)^2}} \tag{7}$$

Step 5: Using the ratings of similar users of the learning resource, predict the results of the target users' ratings of the learning resource. In making rating predictions, equations (8)-(10) are generally used:

$$M_{p,s}=\frac{1}{N}\sum_{q\in X}S(q,X)\cdot M_{q,s} \tag{8}$$

$$M_{p,s}=\frac{1}{\left|\sum_{q\in X}S(q,X)\right|}\sum_{q\in X}S(p,X)\cdot M_{q,s} \tag{9}$$

$$M_{p,s}=\bar{M}_p+\frac{1}{\left|\sum_{q\in X}S(q,X)\right|}\sum_{q\in X}S(p,X)\cdot(M_{q,s}-\bar{M}_q) \tag{10}$$

For the three calculation methods of Eqs. (8)~(10), the 2nd calculation method is more concise and the accuracy meets the requirements of the system, so the 2nd method is adopted for the calculation of the rating prediction. After the calculation is completed, the rating prediction results of each learning resource are arranged in ascending order, and are recommended to users in order according to their needs.

II. C. 2) Recommendation system algorithm optimization

In order to avoid the problems of sparse ratings and “cold start” of recommender systems, content filtering recommendation algorithms can be used to avoid these problems.

(1) Optimization of user information acquisition

After the user enters the system, it is necessary to determine the user's learning style. If it is the first-time user, the user's style is mainly determined according to the self-selected interests. If the user has logged in several times, the Felder-Silverman scale can be used to data mine the user's learning history.

Assuming that the actions that can affect the user's learning style mainly include M_1, M_2, $\cdots$, and M_n kinds, if the threshold of an action in a certain category belongs to $A \leftrightarrow B$ and $B \leftrightarrow C$, respectively, then the action will be determined by $Mi \in \{A\}$ and $Mi \in \{C\}$, or $Mi \in \{B\}$ if not in the above range. For subsequent computation, the result Mi_s of the random action Mi of user s is computed in the manner of equation (11):

$$Mi_s = 1\left(ifMi_s \in \{C\}\right), 0\left(ifMi_s \in \{B\}\right), -1\left(ifMi_s \in \{A\}\right) \tag{11}$$

The learning style V_s of the user s is calculated based on the above as in equation (12):

$$V_s = \frac{\sum_{i=1}^{n} Mi_s}{n} \tag{12}$$

where: n denotes the number of actions for all learning styles. In this way the learning styles of various types of users can be determined.

(2) Algorithm optimization for scoring sparseness

Many users do not rate the learning resources accordingly after using them, which leads to the problem of sparse rating in the system. On the other hand, users' ratings may be subjective, and even if they are rated, they cannot truly reflect whether they are interested in the learning resources. Therefore, implicit scoring can be used to score the learning resources, i.e., the relevant parameters of the user's learning process are scored according to the relevant standards, such as learning time, downloading, forwarding, favoriting, etc. After evaluating the learning resources according to 1-5 points, the total sum is the implicit scoring result of the user's scoring of the learning resources.

(3) Algorithm Optimization for “Cold Launch

The problem of “cold start” mainly exists in the newly registered users, and the algorithm of content filtering can be used to solve this problem.

The first step is to form a vector model of learning resources and users, which can be represented as a vector space model.

Step 2: Update the vector model of the user in real time according to the change of the user's interest. The updating method can be manual or automatic. Manual updating is to re-select the interest of the user when logging in. Automatic updating is a real-time modification of the initially selected interests based on the user's learning process of the learning resource.

Step 3: Content filtering is performed on the model to calculate the similarity between the learning resources and the user vector model. This can be calculated using the cosine formula as in equation (13):

$$S(\vec{m},\vec{n}) = \cos(\vec{m},\vec{n}) = \frac{\vec{m}\cdot\vec{n}}{\|\vec{m}\|\times\|\vec{n}\|} \tag{13}$$

where: $\vec{m}$ and $\vec{n}$ are vector models of learning resources and users respectively.

Step 4: Sort the resources in descending order and recommend them to users from front to back according to their needs. After the user learns the learning resource, the system can obtain the rating of the learning resource, and then the collaborative filtering recommendation algorithm can be used to recommend it.

III. Testing and analysis of recommendation algorithms

III. A. Experimental data set

In order to test the effectiveness of the improved recommendation algorithm, it needs to be verified on the corresponding dataset, and the public dataset related to the recommendation of Civics and Political Science education courses is relatively sparse, so we use Python crawling technology to collect the data on the website. In accordance with the data resource requirements of this paper, the courses on the MOOC of Chinese universities are selected as the experimental data, and the corresponding courses are searched for with the keywords of database course and course Civic and Political Science, respectively, and the data are crawled using the Scrapy crawler framework, which is commonly used to quickly obtain data from websites and is also the mainstream solution in current crawling technology. For the crawling of website data, a hierarchical collection method is used. Firstly, we start from the start page of all courses in the website and return all the course lists composed of various types of tags, then we customize Xpath expression to get the detail URL of each course from the course list, and then we access the URL recursively using Xpath expression to get the data such as the course id, description of Civic and Political Elements, the time of launching the course, course instructors, number of students and so on, and then we analyze the comments of the users. Then we analyze the URL of the comment page to get the user id, course id, rating time, evaluation content and other user comment information, and finally we convert the collected XML file data into CSV format and save it in the database to prepare for the subsequent data preprocessing.

After the data preprocessing work finally selected 500 database related courses Civics, 3200 users and 72,630 rating information. The next step is the testing and analyzing phase of the algorithm, before the experiment, it is firstly divided into two parts: the training dataset and the testing dataset, 80% of which is selected as the training set and 20% as the testing set, and the results of the recommendation algorithm are evaluated by the evaluation indexes introduced below.

III. B. Evaluation indicators

(1) Prediction accuracy. The indicator of Mean Absolute Error (MAE) is used for evaluation.The calculation of MAE is shown in equation (14):

$$MAE = \frac{\sum_{i=1}^{N_u} \left| p_{ui} - r_{ui} \right|}{N_u} \tag{14}$$

where N_u denotes the number of resources to be predicted to be rated, p_{ui} denotes the predicted rating of resource i by user u, and r_{ui} denotes the actual rating of resource i by user u.

(2) Recommendation precision. The main metrics are accuracy rate, recall rate, and the reconciled mean (F-Score) of the two. The accuracy rate and recall rate are shown in Eq. (15) and Eq. (16), respectively:

$$Precision = \frac{R_u \cap T_u}{R_u} \tag{15}$$

$$Recall = \frac{R_u \cap T_u}{T_u} \tag{16}$$

where R_u and T_u denote the actual and predicted recommendation results, respectively.

The F-Score is used to weigh the accuracy and recall and reconcile the gap between the two values. If the F-Score value is low, it means that at least one of the resulting accuracy and recall has a large fluctuation. If the F-Score value is high, then the results of accuracy and recall are stable and the recommendations are more accurate.The calculation of F-Score is shown in equation (17):

$$F - Score = \frac{(\alpha^2 + 1) \times Precision \times Recall}{\alpha^2 \times (Precision + Recall)} \tag{17}$$

where α is the weighted reconciliation coefficient of the two.

The actual calculation generally sets α to 1, i.e., the F1 value is shown in equation (18):

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{18}$$

The range of values is (0-1).

III. C. Testing and analysis

In order to compare the recommendation results derived from the original recommendation algorithm and the improved recommendation algorithm. Here three sets of experiments are designed, Experiment I compares the effect of the values of similarity calculation weights a of the two algorithms Collaborative Filtering and Content Based Recommendation in the improved recommendation algorithms on the recommendation results. Experiment II compares the MAE values of the four algorithms in terms of prediction accuracy for different number of recommendation lists, i.e., K values. Experiment III compares the accuracy, recall and F1 values of the four algorithms in terms of recommendation accuracy, so as to analyze the recommendation effect of the recommendation algorithms.

Experiment 1 takes the improved recommendation algorithm as an example, and takes the MAE value of the improved recommendation derived from the ratio a of the similarity of the collaborative filtering algorithm to the similarity weight based on the content recommendation in the four cases that the number of K values of the recommended list is 15, 20, 25, and 30, respectively, which is used to determine the minimum error of the improved recommendation algorithm under which the error of the improved recommendation algorithm is minimized, and to provide an optimal solution for subsequent comparisons of results of the different algorithms. The results of MAE comparison for different similarity weights are shown in Fig. 4. The MAE value is minimized when a is 0.5. From this we can conclude that, with a fixed number of recommendation lists, the error value is minimized when the similarity of collaborative filtering and content-based similarity in the similarity calculation session of the recommendation algorithm have the same weight.

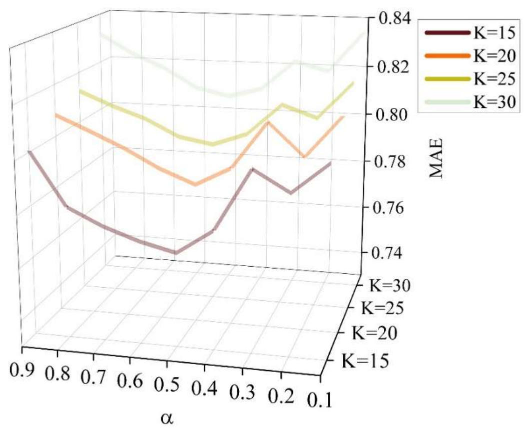

Figure 4: MAE comparison of different similarity weights

Experiment 2 is based on experiment 1, and the similarity weight a is set to 0.5, comparing the prediction accuracy effect of user-based collaborative filtering (User-CF), item-based collaborative filtering (Item-CF), content-based recommendation (Content-Base) and the improved recommendation algorithm (Ours), and the final MAE value comparison results are shown in Fig. 5. As the number of recommendation lists K increases, the MAE value decreases, and when K=10, the MAE value decreases to the lowest, and then the MAE value increases with the increase of K. From this, it can be found that, when the number of recommendation lists is around 10, the prediction scoring error is the smallest, so in the similarity computation and generation of recommendation lists, the length of the recommendation list can be set to 10, which will make the recommendation effect is optimized. It can also be found that when the value of K is 10, the MAE of the improved recommendation algorithm is reduced by 8.13%, 6.32% and 4.92% compared with the user-based collaborative filtering algorithm, the item-based collaborative filtering algorithm and the content-based recommendation algorithm, respectively. It shows that when the K value is fixed, the recommendation effect of the improved recommendation algorithm is higher than other algorithms.

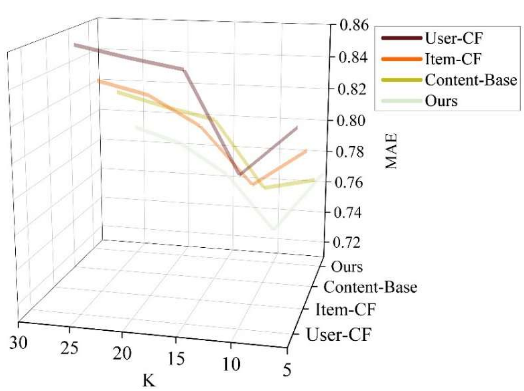

Figure 5: MAE of different recommendation algorithms

Through the analysis of Experiment 1 and Experiment 2, in Experiment 3, the number of recommended lists K value is set to 10, the similarity weight a is set to 0.5, and under the condition of the lowest MAE value, the accuracy, recall and F1 value size of the four algorithms are calculated to analyze the effect of recommendation accuracy of the different recommendation algorithms, and the resulting results of the comparison of the accuracy, recall and F1 value are shown in Figure 6. From the comparison results, it can be seen that the accuracy rate of the improved recommendation algorithm compared with the other three algorithms increased by 25.2%, 18.1%, 10.4%, the recall rate increased by 20.7%, 17.3%, 8.5%, and the F1 value increased by 22.6%, 17.8%, and 9.5%, respectively. It can be seen that the algorithm optimizes the problems of cold start and resource matrix data sparsity, and is higher than the other three algorithms in the three indexes of recommendation accuracy, and the combined prediction accuracy indexes of Experiment 1 and Experiment 2 can be concluded that the improved recommendation algorithms have improved the recommendation effect to a certain extent.

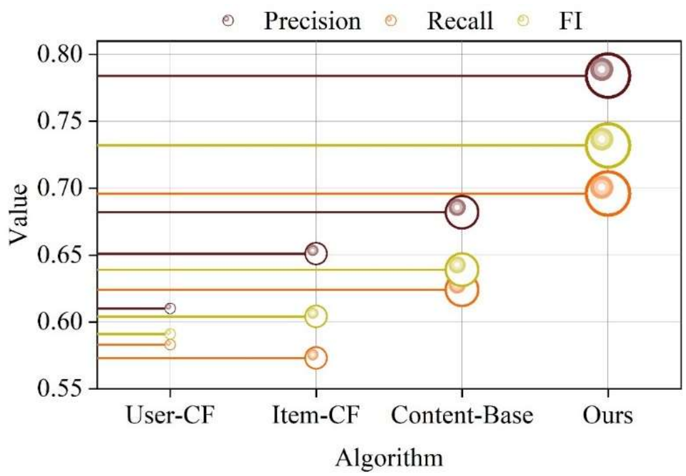

Figure 6: Comparison of recommendation accuracy indicators of four algorithms

IV. Personalized Learning Resources Recommendation Experiment

IV. A. Experimental design

A total of 80 second-year undergraduate students who have completed their studies in Civic and Political Education in School A were invited to participate in this experiment to compare the changes in the learners' knowledge mastery ability after learning the resources recommended by the recommendation algorithm. The learners were divided into four groups according to their pre-test scores, and each group consisted of 20 learners with different cognitive levels.Learners in group A were the experimental group, which recommended student resources according to the improved recommendation algorithm.Groups B, C, and D were the control groups, which were experimented according to the learners' self-directed learning, the knowledge-based recommendation, and the content-based recommendation, respectively.

The experiment is divided into four phases:

(1) Pre-test phase. All learners were required to complete 10 pre-test papers consisting of multiple-choice and fill-in-the-blank exercise resources in any two hours within three days. After the learners completed the pre-test papers, the instructor would mark each learner's paper and the learners could view their answers and the reference answers of the exercises.

(2) Self-diagnosis stage. Learners are required to fill out a self-diagnosis questionnaire, which includes the basic concepts and main theories related to the attributes of Civics knowledge, and learners self-assess their mastery of each knowledge.

(3) Recommendation stage, according to the learners' answers, the corresponding resources are recommended. Learners in different groups study according to the learning resources recommended by the group, and the learning time is two weeks. Learners can get the reference answer of the resource for each answer to an exercise, learn knowledge through the learning resource, and also observe the application of knowledge in the answer to the exercise.

(4) The last stage is the post-test stage, which is similar to the pre-test stage, in which all learners are required to complete the answers to 10 exercise resources in any two hours within three days, and the knowledge involved is the same as that in the pre-test. After completing the test, learners in the experimental group can voluntarily fill out a satisfaction survey about the experiment, including their satisfaction with the recommended resources and system.

IV. B. Comparative experiments and analysis of results

IV. B. 1) Algorithm validation

(1) Comparison of students' performance

The distribution of pre-test and post-test scores of the four groups of learners is shown in Figure 7. It can be seen that in the pre-test stage, the average scores of each group are similar, and there are all learners with different levels of cognitive ability. After the recommended stage of learning, the cognitive abilities of the learners have been improved to different degrees. Among them, when comparing the post-test of group A with the pre-test stage, the average value is improved from 5.2 to 7.7, and the median value is improved from 5.0 to 7.5, which is the most obvious improvement among the four groups, indicating that the improved recommendation algorithm can effectively improve the cognitive ability of the learners in the personalized recommendation. Meanwhile, in the post-test stage, the average score of Group A is 2.2, 2.3 and 2.5 points higher than that of Group B, Group C and Group D respectively. It shows that the effect of improving the overall cognitive ability of learners in the experimental group is most obvious, and the effect of the personalized learning resource recommendation algorithm on the overall cognitive state of learners in this group is most prominent.

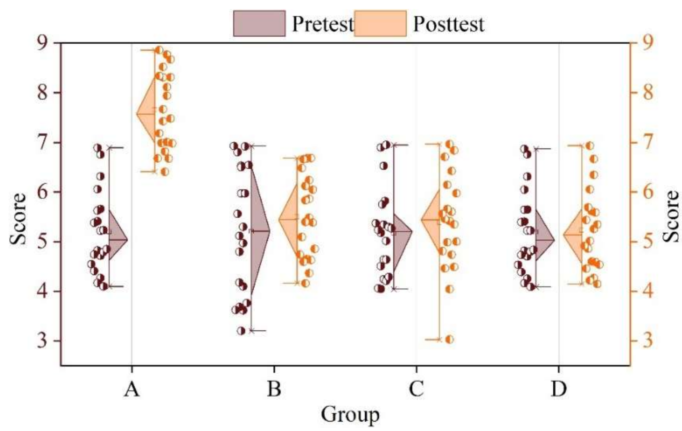

Figure 7: Comparison of the subjects before and after the learner

(2) Independent samples t-test

First of all, W-test was done on the pre and post-test scores of the four groups of learners, and the results are shown in Table 2. From the experimental results, it can be seen that the p-value of the pre and post-test stages of each group in this experiment is greater than 0.05, the original hypothesis is accepted, and the achievement data are all approximately in line with the normal distribution. Therefore, independent samples t-test can be used to verify whether the differences between the scores of different groups in the pre-test stage and post-test stage are significant.

Table 2: W Test

Group	Pretest		Posttest	
	W	P	W	P
A	0.94	0.73	0.919	0.426
B	0.954	0.597	0.939	0.437
C	0.977	0.733	0.881	0.072
D	0.965	0.814	0.933	0.612

The results of the independent samples t-test are shown in Table 3. In the pre-test stage, p>0.05 between the groups, the original hypothesis was accepted and there was no significant difference in scores between each group. It indicates that in the pre-test stage, the experiment controlled for the scoring variables and the distribution of learners' abilities was similar in each group. However, at the posttest stage, p<0.05 between Group A and each control group, the original hypothesis was rejected, indicating that there was a significant difference in scores between Group A and each control group at the posttest stage. In addition, the magnitude of differences, d, all exceeded 0.8, indicating that the personalized learning resource recommendation algorithm adopted by the experimental group could effectively improve learners' cognitive abilities compared to the recommendation algorithm of the control group.

Table 3: Independent sample T test

Group	Pretest				Posttest			
	T	DF	P	D	T	DF	P	D
B-A	0.089	36	0.932	0.04	2.303	36	0.018	0.998
C-A	0.094	36	0.929	0.044	2.271	36	0.006	0.974
D-A	0	36	1	0	2.144	36	0.032	0.897
C-B	0	36	1	0	0.099	36	0.91	0.038
D-B	0.076	36	0.938	0.045	0.169	36	0.864	0.091
D-C	0.07	36	0.93	0.035	0.255	38	0.807	0.103

IV. B. 2) System satisfaction statistics

A total of 20 learners in the experimental group were invited to participate in the satisfaction survey, evaluating each of the following questions:

T1: Very satisfied with the system

T2: Will continue to use the system in the future

T3: Will recommend the system to friends

T4: The system has simple functions and an intuitive interface that is easy to use

T5: The system provides the content that wants to learn

The results of the survey on the intention of the personalized learning resource recommendation system are shown in Figure 8. From the figure, it can be seen that all the learners who participated in the survey think that the system's functions are simple and the interface is intuitive and convenient for learners to use. Most of the learners thought that the system provided the content they wanted to learn, and more than half of the learners said that they would recommend the system to their friends. Learners' satisfaction with the system is high enough to promote the system.

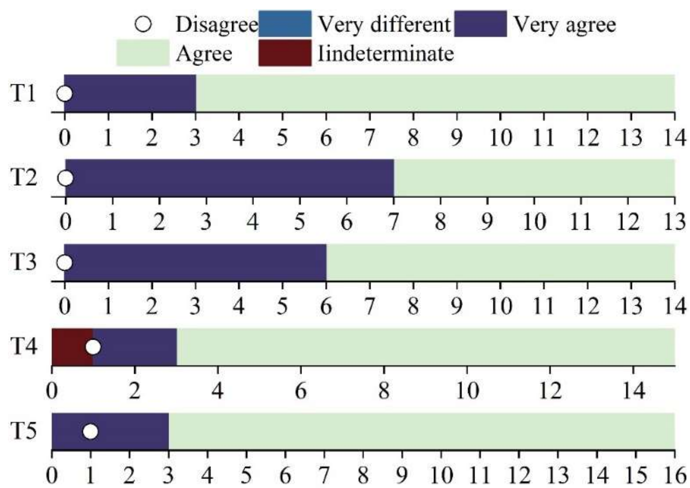

Figure 8: The results of the system use satisfaction survey

V. Conclusion

A personalized learning resource recommendation system is designed to realize “accurate Civics” education. In order to ensure that students can obtain appropriate learning resources efficiently and quickly, a collaborative filtering recommendation algorithm based on user improvement is used to recommend personalized learning resources. In order to ensure that the algorithm does not have the problems of sparse scoring and “cold start”, the content filtering recommendation algorithm is used to optimize the algorithm. Experimental testing of the algorithm and the system resulted in the following conclusions:

(1) Compared with the user-based collaborative filtering, item-based collaborative filtering and content-based recommendation, the improved recommendation algorithm has improved the accuracy rate by 25.2%, 18.1% and 10.4%, the recall rate by 20.7%, 17.3% and 8.5%, and the F1 value by 22.6%, 17.8% and 9.5%, respectively.

(2) After the system applies the improved recommendation algorithm for resource recommendation, the students' performance improves significantly, which indicates that the system in this paper is more effective in recommending personalized learning resources.

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