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*Retraction*

# Retracted: A Personalized Recommendation Algorithm for Political and Ideological Courses in Colleges Using Multiple Interests of Users

**Mobile Information Systems**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## References

[1] L. Luo, "A Personalized Recommendation Algorithm for Political and Ideological Courses in Colleges Using Multiple Interests of Users," *Mobile Information Systems*, vol. 2022, Article ID 1990037, 11 pages, 2022.

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*Research Article*

# A Personalized Recommendation Algorithm for Political and Ideological Courses in Colleges Using Multiple Interests of Users

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Due to the development of social economy and the continuous growth of science and technology, the historical progress of the information age has opened up. With its mass audience, vast range, and powerful guiding technology, streaming media technology has significantly reduced the time and gap among people in various parts of the world, particularly in the field of education. However, political and ideological education classes in colleges are not sufficiently focused, and as a result, personalized recommendations and analysis of users' various interests are not possible because of low precision, low user coverage, excessive recommendation time, and poor optimal solution capability. To fill these issues, this study provides a personalized recommendation system for political and ideological courses in colleges based on the interests of multiple users. This paper developed a framework for mining knowledge points in political and ideological course, mined knowledge points in a course using association rules, and calculated the weight of knowledge points using hierarchical tree theory. Apart from these, this paper established the user interest model to obtain the learning characteristics of learners. The experimental results show that the proposed algorithm has higher recommendation accuracy, higher user coverage, short recommendation time, and good optimization ability, which proved that it has a high application value. Based on this study, it can be argued that in modern era of education, the proposed recommendation system of political and ideological education has significant comparative importance for promoting political and ideological education in colleges.



## 1. Introduction

The concept of political ideologies provides students with a viewfinder through which to examine complicated political concepts. The political and ideological hypothesis curriculum in colleges is responsible for educating students' work outlook, their skills, worldview, and values, as well as the frontier development of associated majors. As a result, it has become the primary objective of ethical education and is an important stage in enhancing the effectiveness of persons' exercise to fully improve the political and ideological construction in vocational courses. The deployment of ideological political awareness in professional course teaching effectively takes benefit of this situation in expert syllabus teaching, fully mining political and ideological substances from learning and teaching methodology, which conscientiously performs the education throughout the whole importance of organizational curriculum teaching [1].

Apart from the foregoing, political and ideological syllabus is a crucial way to practice the educational mechanisms in colleges and universities. In addition, theoretical and political education classes are provided during the process of teaching in higher education and are an important scheme for institutions to develop high-quality students. Theoretical and political education in colleges is currently primarily focused on huge classes and open classes for combined teaching. Loneliness, poor compatibility, a lack of coherence effects, and a failure to form an educational approach with personal support are the main issues that need to be resolved. As a consequence, personalized suggestions of political and ideological courses of education are critical when combined with student characteristics. As an outcome, personalized recommendation techniques for college political and ideological courses constructed on multiple user interests are the primary research focus of many researchers. Furthermore, as networks and information technology emerge rapidly, the quantity of network information data used in theoretical education courses also grows fast. When challenged with a variety of theoretical learning courses, it is necessary to study systematically how to make specific suggestions. By analyzing users' behavioral preferences such as through various referring methodologies, personalized suggestions can effectively filter out unnecessary information [2].

At the moment, personalized recommendations are extensively utilized in a range of social networking [3] applications such as media, entertainment, books, films [4], and fog music [5]. Correspondingly, the authors of [6] suggested a modified recommendation procedure created on feature mining of user activity. It builds a user behavior information feature data mining technique that employs an important data block detection approach to merge user behavior information, and extracts semantic data attributes reflecting user interests. So under limitation regulation of association procedures, the proposed hybrid design of user interest characteristics is created to realize the mining of user interest characteristics, and personalized information suggestion is realized based on the conceptual dispersion and user behavior interests. The modeling results demonstrate that the proposed has a huge feature settlement and enhances the efficiency of suggestion system output. In contrast, in [7] the researchers proposed time trust least mean fourth (TTLMF), a personalized recommendation algorithm that incorporates relationship of trust, time constraints, and tag information. Based on an established tag-based personalized recommender system, this method fully utilizes the relationship of trust between clients. Furthermore, the existing context's period information makes the adding appropriate extra relevant to the needs of the users. Researchers of [8] proposed an algorithm that combines matrix error and XGBoost algorithm, storing user's item with SVD ++ algorithm to prevent the effect of many incomplete data on algorithm accuracy. Their model then gets a monitored model for predicting user ratings using the XGBoost features. The algorithm is employed in the MovieLens data set for experimental examination, and the results indicate that the algorithm's implementation impact is improved.

According to the results of the foregoing analysis, existing methods can significantly improve the recommendation effect and recommend to users the information and data they require. Traditional methods, on the other hand, have low recommendation accuracy, user coverage, and recommended consumption in practical applications. Because of the above issues, this article proposes a personalized algorithm for college theoretical and political courses in various consumer interests. The key offerings of this research article are listed as under:

(1) First, this paper examines the mining of knowledge points in ideological and political courses and calculates their respective weights.
(2) Second, it designs and explains a personalized recommendation algorithm for college political and ideological courses.
(3) Finally, the precision results, course recommendation time results, and optimization ability test results of various courses are compared.

The rest of this paper is distributed into five units: Section 2 explains knowledge mining, Section 3 explains the planned personalized recommendation algorithm for college political and ideological courses, Section 4 explains the experimental work, simulations, and results, and Section 5 concludes this paper.

## 2. Mining of Knowledge Points in Political and Ideological Courses and Calculation of Their Weights

*2.1. The Framework for Mining Knowledge Points of Political and Ideological Courses.* The knowledge point mining construction of political and ideological courses mainly extracts data from databases. Data warehouses [9] or other data sources through mining engines identify appreciated data from a large amount of data for a recommendation. The visual user interface is the system and user interface. A communication platform is provided between the mining systems, and the mining system provides relevant knowledge through the knowledge base when searching for mining requirements and tasks submitted by users. At the same time, the mining results are displayed or explained to users through a visual interface. The knowledge recommendation service's course selection decision-making provides multiple course selection tactics based on the characteristics of individual students. It replaces the traditional course selection method with a focus on timely data production. Furthermore, the variety of data gathering channels improves the real-time presentation of recommendations and the correctness of the findings. Figure 1 shows the structure of knowledge point mining in political and ideological courses.

Under the knowledge point mining structure of political and ideological courses revealed in Figure 1, association rules [10] are used to mine knowledge points in political and ideological courses. The specific process is as follows:

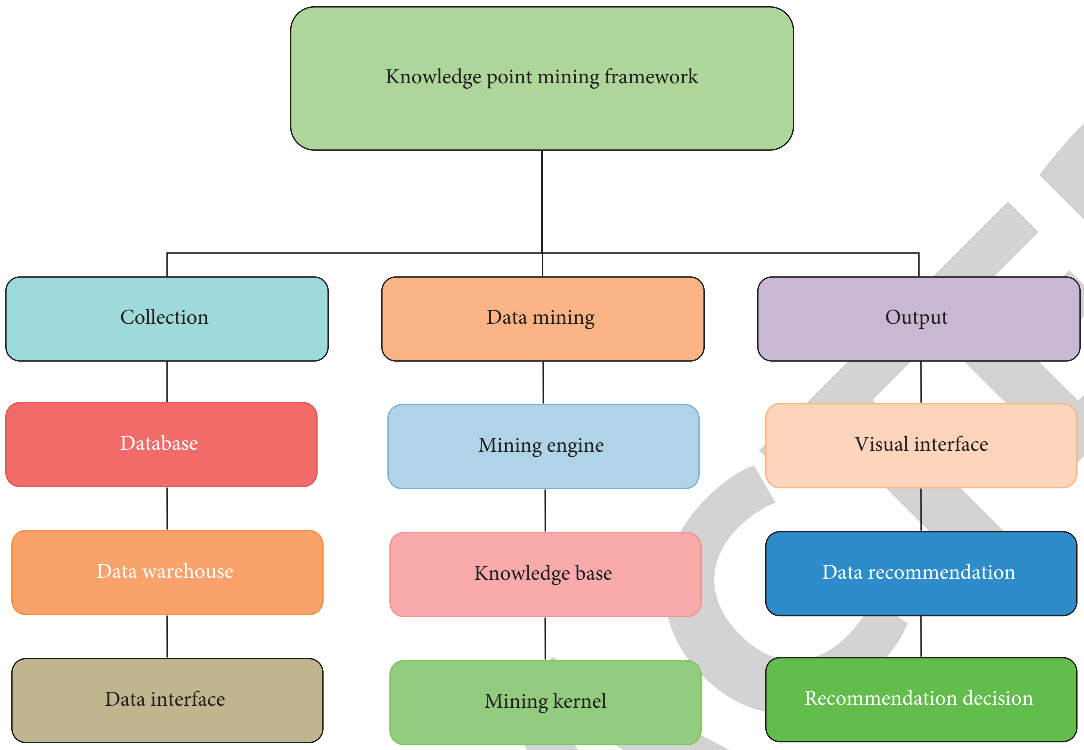


Figure 1: Knowledge point mining framework for political and ideological courses.



(a) Generation of item sets: To generate all frequent item sets, the occurrence frequency of item sets is not less than min-sup.

(b) Association rules generated from frequent item sets: The association rules search for all sets of items with more support than the minimum support and then use larger item sets to create the required rules with more trust than the minimum trust. The rules must meet minimum support and minimum configuration at the same time. The common method of relationship rules is the Apriori algorithm. Its basic principle is to first mine the user's history to generate an aggregation tree to obtain the most common item set of user behavior, then define the recommendation factor as the confidence of association rules multiplied by distance, and finally determine the recommendation item by the size of the recommendation factor. Figure 2 shows the process of knowledge point mining in political and ideological courses.

Association rules can be modeled offline, which can guarantee the real-time necessities of personalized recommendations. However, the obvious disadvantage of association rules is the choice of support and confidence thresholds. If the selection is inappropriate, it will increase time cost and reduce recommendation quality. In addition, with the further expansion of the data scale, the results obtained based on the association rules are often too complicated, which disturbs the quality of recommendations. Therefore, the association rules will be improved by calculating the weight of knowledge points in order to optimize the preprocessing effect of knowledge points in political and ideological courses and provide a theoretical basis for the personalized recommendation of courses.

*2.2. Calculation of Knowledge Point Weight.* According to the hierarchical relationship of knowledge points, each node represents a knowledge point, and there is an upper and lower relationship between nodes, that is, parent-child relationship, which is connected by arrows. The upper level of each pair of nodes connected by arrows is the parent node, and the lower level pointed by the arrow is the child node. The information points denoted by the parent node include the information points denoted by the child node. The first parent node is the root node of all knowledge points.

In this hierarchical tree expressed by the parent-child relationship, it can be concluded that the nearer to the root node, the broader the variety of information points denoted by the node, and the farther away from the root node, the knowledge points denoted by the node are in the expert domain. The more subdivided the knowledge division, the better the granularity of the information points, and the

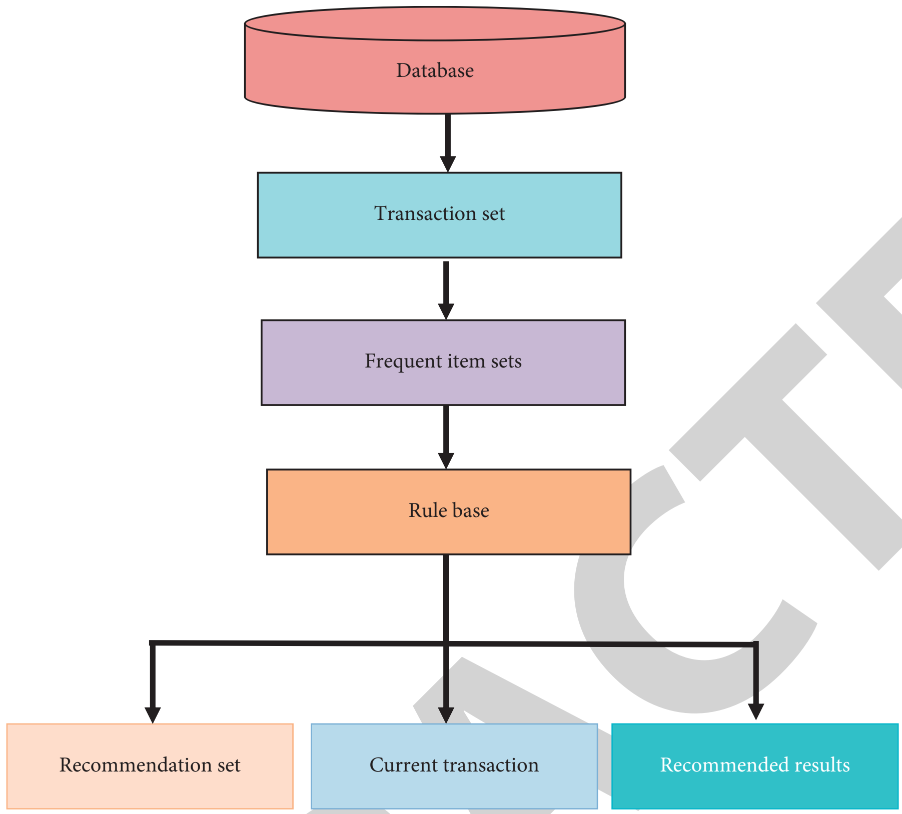


Figure 2: Mining process of knowledge points in political and ideological courses.



more the knowledge points can reflect the characteristics of the course, which can better assist students in clarifying which specific knowledge points have not been fully grasped. Therefore, based on this idea, this article puts forward the weight index of the knowledge point relationship to reflect the weight of the knowledge point in the curriculum. The weights of nodes $p_i$ and $p_j$ are defined as follows:

$$W\left(p_i, p_j\right) = \frac{L\left[P\left(p_i, p_j\right)\right]}{D\left(p_i, p_j\right)}. \tag{1}$$

Among them, $P(p_i, p_j)$ denotes the adjacent mutual parent node of nodes $p_i$ and $p_j$; $L$ represents the path length from the nearest common parent node to the root of the tree; $D(p_i, p_j)$ represents the average space from nodes $p_i$ and $p_j$ to the root node of the tree, and its expression is

$$D\left(p_i, p_j\right) = \frac{L(p_i) \times L\left(p_j\right)}{2}. \tag{2}$$

Among them, $L(p_i)$ represents the reference weight when selecting knowledge points; $L(p_j)$ represents the density of knowledge points. Combining equations (1) and (2) to obtain the calculation, equation of knowledge point weight is

$$W' = \frac{L\left[P\left(p_i, p_j\right)\right]}{D^2} \times W\left(p_i, p_j\right). \tag{3}$$

A simple knowledge point weight diagram is shown in Figure 3. This figure demonstrates that knowledge points have a weight value. The stronger the association between the two knowledge items, the higher the weight value. Otherwise, the more closely the two knowledge pieces are linked better.

According to the above analysis, the knowledge point weight of the political and ideological courses is obtained. The results of calculation can be referred to in the course recommendation to mention appropriate courses for students so that students can understand the course situation and obtain more accurate recommendation results.

## 3. Personalized Recommendation Algorithm for College Political and Ideological Courses

*3.1. Multi-Source and Multi-Task Interest Reasoning Algorithm.* The personalized recommendation has become an important way for students to choose courses. Cooperative filtering algorithm is presently the most extensively used personalized recommendation skill, but the conventional cooperative filtering recommendation algorithm is not suitable for personalized recommendation in the case of users with multiple interests. Taking into account this factor, this article takes user interest as the research foundation and is based on fully considering the requirements of pupils for

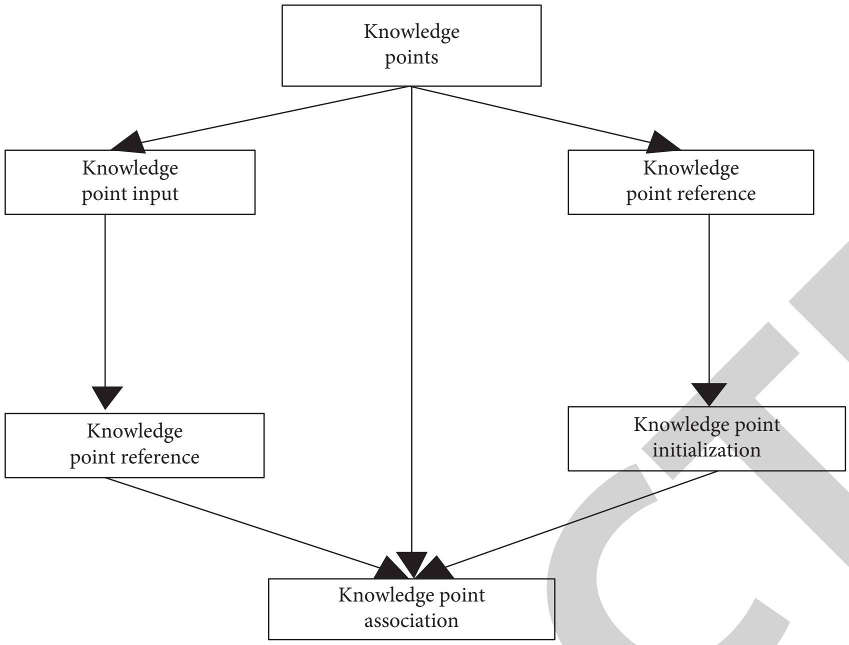


Figure 3: Weights of knowledge points.



the course, combined with the weight of knowledge points to bring out the course recommendation design. Associated with conventional algorithms, the superiority of the algorithm in this paper is that it can handle personalized recommendations under multiple interests of users. When the items in the data set are quite different in content and user interests are scattered, the advantages of this algorithm will be more obvious.

*3.1.1. Solutions for Multi-Interest Recommendation.* The improvement idea of the traditional cooperative filtering algorithm is as follows: for the same user, if the prediction item is different, the neighbor users used to predict are also different; that is, the neighbor user is related to the item to be predicted, to ensure that the neighbor user used for prediction is the same as the current user. Having similar interests and hobbies in the project to be predicted is the key to ensuring the accuracy of the algorithm [11]. This improved method requires a certain level of content similarity between the item used to predict and the item to be predicted. This is used to predict the interest preference of another knowledge point based on the student's preference information for a knowledge point, and its accuracy rate will greatly improve. The multi-source and multi-task interest reasoning algorithm specifically includes the input, output, and calculation process of the algorithm:

(a) Input

(i) $M$ user's rating of $N$ knowledge points.

(ii) Knowledge point similarity threshold $\varphi_s$, neighbor user similarity threshold $N_s$, and user evaluation score threshold $G$ for the item.

(iii) The preference of user for a certain knowledge point; the calculation equation is

$$F_{ij} = E_{ij}\left[\lambda_{ij} + \left(1 - W'\right)\right] \times U_{ij}. \quad (4)$$

Among them, $E_{ij}$ represents the evaluation of the $j^{\text{th}}$ knowledge point by the $i^{\text{th}}$ user. $\lambda_{ij}$ represents the evaluation of the $j^{\text{th}}$ knowledge point by the $i^{\text{th}}$ user yet. $U_{ij}$ represents the set of items for which the $i^{\text{th}}$ user has not made an evaluation.

(b) Output

For any user $i$'s most preferred item in the content of the political and ideological course, the current user to be predicted is called the current user $A_i$.

(c) Calculation process

(i) Calculate the neighbor knowledge points of knowledge point $j$, that is, the knowledge points most similar to knowledge point $j$, denoted as $s_j$.

(ii) For any user $i$ and knowledge point $j$, predict user $i$'s evaluation of the $j^{\text{th}}$ knowledge point, and record the predicted value as $P_{ij}$.

(iii) According to the order of size of $P_{ij}$, determine user $i$'s most preferred knowledge points, and realize multi-interest recommendation according to the preference results.

*3.1.2. Text Representation Method of Interest.* To express each interest in a text document, how to extract the tag vocabulary related to the interest is a crucial issue. Based on prior knowledge, when people enter an interest as a keyword into a search engine for a query, many web pages related to this interest will be returned, and these web pages will be sorted according to the degree of relevance to the interest. Since these web pages describe this interest to varying degrees, these tag words can be extracted from these web pages.

Therefore, this article extracts multiple interest tags from web pages. The specific steps for extracting interest tags based on web pages are as follows:

(i) Use a search engine to search with interest as the keyword to be queried, and then select $X$ web page from the returned web pages.

(ii) Analyze the obtained $X$ web page, extract the main content of the web page, and merge it into the text.

(iii) Use the bag-of-words model to simplify the natural language processing of the text.

(iv) Process the simplified text and calculate the importance of each word to the document.

(v) Extract the content with the weight value of the knowledge point at the TOP position, and label the weight information to form a set. The form of the definition set is as follows:

$$Y_x^t = \left\{\left(y_{x_1}, t_1\right), \left(y_{x_2}, t_2\right), \ldots, \left(y_{x_n}, t_n\right)\right\}. \tag{5}$$

Equation (5) represents a set containing multiple elements, where each element is a binary array, and the members of the binary array are tags and weights related to interests. Among them, the text information expressing interest can be expressed by equation as follows:

$$Y = \left\{y_{x_1}, y_{x_2}, \ldots, y_{x_n}\right\}. \tag{6}$$

Each interest can be represented by a text, and a one-to-one correspondence is established between interest and text. When there are many tags, or the tags that appear have a higher weight, then the user's interest can be related to the content to a certain degree. This is the theoretical basis of the multi-source and multi-task interest reasoning research proposed in this section.

*3.1.3. User Interest Modeling.* According to the above-mentioned analysis of the multi-interest recommendation ideas and text representation of interests, in the design of multi-source and multi-task interest inference algorithm, the user's interest represents a very wide range, covering the basic learning characteristics of students, including knowledge system, education factors such as degree, learning ability, learning style, knowledge content mastered, learning environment, gender, and age. The specific learning characteristics of learners are described in Table 1.

By collecting static and dynamic user information, a more standard user interest model can be established. The user interest model $Q_i$ in this paper can be expressed as follows:

$$Q_i = \{(q_1, v_1), (q_2, v_2), \ldots, (q_n, v_n)\}. \tag{7}$$

Among them, $v_i$ represents the user's interest keywords, which are usually related to the model of the teaching resource that needs to be matched; $q_i$ represents the weight of the keyword. User interest modeling is an abstract expression of user interest, which expresses user characteristics using spatial vector values by extracting keywords. This is

Table 1: Description of learner characteristics.

| Feature | Feature description |
|---|---|
| Learning method | Classroom learning, autonomous learning |
| Learning background | School, home, on-the-job |
| Age stage | 18–22 years old |
| Learning motivation | Quality training, skills |
| Knowledge system | Literature, science and engineering, engineering, medicine |
| Geographical division | Local, foreign, and other provinces |

more conducive to the quantification of the teaching resource recommendation process, so that the value of the teaching resource can be realized, and it has a greater value in the practice process.

### *3.2. Realization of Personalized Recommendation for Political and Ideological Courses in Colleges*

*3.2.1. Recommendation Model.* The knowledge points mining and weight calculation results of political and ideological courses, and the knowledge features involved in user interest modeling are used as input to establish a university political and ideological course recommendation model. As per the function, the model is divided into input part, processing part, and output part. The recommendation model of political and ideological courses in colleges mainly relies on the LSTM network [12] to construct, and the detailed explanation of every link is as below:

(i) The input part converts the user's original learning record into the data form required by the LSTM network calculation, that is, the vector representation of the courses each user has learned.

(ii) The processing part is to process the input data through the LSTM network to obtain the output result. The structure of the LSTM network needs to be determined, including the number of network layers, time steps, and connection settings between layers. This article takes the number of courses as the number of feature values and accordingly defines the input data dimensions and output data, that is, the number of neurons in the input and output layers. The length of the user's course learning sequence determines the time step for each calculation. The maximum time phase is defined as the maximum value of the user's course sequence. At the same time, when reading each user's learning sequence, the corresponding sequence length needs to be specified. In this way, the construction of the entire LSTM network model is determined.

(iii) The softmax layer maps the value of the output vector of the LSTM processing layer to the (0, 1) interval.

(iv) The output part takes the last dimension of the processing result of the softmax layer to get the final recommended course vector.

*3.2.2. Mixed Recommendation of Political and Ideological Courses Based on BP-RNN.* In view of the conventional recommendation method ignoring the user behavior sequence and the user's multiple interests, this paper designs a BP and RNN hybrid recommendation model. The behavior order comprises information nearly the interest of user transfer. The input of the system is the real performance of the user, and the output is the subject of the following short-term event. In the input layer, the length of the input vector is equal to the amount of items, only the organized corresponding to the active item is 1, and the others are 0.

RNN and BP neural network share the same output layer. The central of the network is to merge the output layers to yield a single result, which is calculated as follows:

$$Z = \sum_{i=1}^{N} \left( f_1 \left( \sum_{i=1}^{N} z_i w_{ki} - \theta_i \right) - Y_k \right)^2. \tag{8}$$

Among them, $f_1$ denotes the sample size; $z_i$ represents the input value; $w_{ki}$ represents the weight update speed; $\theta_i$ represents the actual value corresponding to the input value; $Y_k$ represents the output value.

For the $l^{\text{th}}$ output layer in the RNN, the calculation equation of the activation function of the $h^{\text{th}}$ unit is

$$R(n) = f_i \sum_{i=1}^{N} (Y_k \times Y_{nk}) f_2(z_k) w_{ki}. \tag{9}$$

Here, $f_2$ denotes the amount of components of the RNN layer. Therefore, the probability $P_U$ that the user may choose item $u$ can be calculated by equation

$$Z_{ij} = \frac{\sum_{i=1}^{N} v_i x_i \times \theta_i}{\sum_{j=1}^{N} v_j x_j \times \theta_j}. \tag{10}$$

Among them, $x_i$ and $x_j$ both represent the weight parameter; $\theta_i$ and $\theta_j$ both represent the probability of the user learning the course; $v_i$ and $v_j$ both represent the learning rate. The hybrid recommendation model of political and ideological courses based on BP-RNN not only considers users' interests, but also considers users' favorite topics and popular topics, obtains the most popular topics through analysis, and recommends the topics to users.

*3.2.3. Implementation of College Political and Ideological Course Recommendation Based on Improved Collaborative Filtering Algorithm.* The conventional collaborative filtering algorithm describes the partiality by matching the association degree of measurable form and uses the object collaboration in the nearest interest point set to produce and predict recommendation objects. The traditional collaborative filtering algorithm uses the cold start data set collected in the early stage and can achieve better recommendation effect through fixed strategies. However, in the early stage of introduction, it is unable to effectively find the nearest set of interest points for the target user due to a lack of a large number of reliable data and severe data sparsity, resulting in poor real-time performance of the algorithm. When data sparsity reaches an extreme, it is easy for new users to experience a cold start, resulting in poor scalability. Considering that the audience of college political and ideological course recommendation is relatively fixed and the level is regular, the article-based collaborative filtering algorithm is used to establish the college political and ideological course recommendation model [13]. The modeling process is as follows:

The vector-based method is used for the quantitative calculation of similarity. Based on the Euclidean distance theory of calculation, let assume that $a$ and $b$ are any 2 points in the $C$-dimensional space, and the Euclidean space among them is revealed in the equation

$$d(a,b) = \sum_{i,j=1}^{N} (a_i - b_i)^2. \tag{11}$$

To utilize the Euclidean space for the measurable calculation of similarity, the form of equation (11) is transformed, such as

$$\text{Sim}(a,b) = \frac{1}{1 + d(a,b)}. \tag{12}$$

Here, the distance between $a$ and $b$ can denote pupils' quantitative favorite for a certain political and ideological course. We have obtained the students' quantitative preference for an ideological and political course, overcome the shortcomings of the traditional collaborative filtering algorithm, enhanced the real-time nature of the recommendation of Ideological and political courses in Colleges and universities, and expanded the application scope of the recommendation mode of Ideological and political courses in Colleges and universities. Propose and implement a university course recommendation model based on an improved collaborative filtering algorithm. The improved collaborative filtering algorithm based on hybrid is adopted based on the actual needs of political and ideological course recommendation in colleges. The disadvantages of the traditional collaborative filtering algorithm's low efficiency and weak adaptability are better solved by introducing the gradual forgetting curve based on the timeliness change of user interest [14]. The model optimization process is as follows:

The historical preference fusion mechanism is introduced to group and fuse all students' historical preference information. The historical preference fusion similarity set is formed based on the similarity of content-based interest points in the students' evaluation matrix of political and ideological courses, and the similarity between political and ideological courses is calculated. The specific equation is

$$V_C = \frac{\sum_{i=1}^{N} f_i \times U_i}{C_s(a_s, b_s)} \pm p_k. \tag{13}$$

Among them, $U_i$ represents the collection of all students; $a_s$ and $b_s$, respectively, represent the historical preference data of student $i$ for political and ideological courses in a certain period; $p_k$ represents the average value of the historical preference data of political and ideological courses in a certain period [15].

Introducing the time attenuation factor $\delta(t)$, and integrating the influence of time on the recommended rules, the time attenuation factor is expressed as equation

$$\delta(t) = \int_{-\infty}^{\infty} x_i(t) h(t,\theta) \mathrm{d}\theta + e^{\Omega t} t_{\min}. \tag{14}$$

Among them, $x_i(t)$ denotes the time when pupil $i$ has a preference and score for political and ideological courses; $h(t,\theta)$ represents the time difference between different students' preference for political and ideological courses; $\Omega t$ denotes the largest moment when political and ideological courses are preferred; $t_{\min}$ denotes the smallest moment when political and ideological courses are preferred; $e$ denotes the rate of decay of the time decay factor. Utilized on the aforementioned examination, equation (14) can be enhanced as below:

$$\delta(t) = \sum_{i=1}^{N} h_i(t,\theta) = \sum_{i=1}^{N} \left[ e \times h_i(t,\theta)_i \right]. \tag{15}$$

To calculate the similarity of political and ideological curriculum preferences among students, an overlooking curve founded on the timeliness of student interest is introduced:

$$Sf = e^{t/h}. \tag{16}$$

Clarifying the constraints of time change on recommendation rules shows that the longer the interval of the time among students' preferences for political and ideological courses, the smaller the impact of the addition of time attenuation factor between students, so as to realize the design of recommendation algorithm for political and ideological courses in colleges [16].

## 4. Simulation and Experimental Work

In order to check the efficiency of the proposed algorithm for college political and ideological courses under the multiple interests of users, an experimental analysis is carried out. Compare it with common recommendation algorithms such as personalized recommendation algorithms based on user behavior feature mining and personalized recommendation algorithms that integrate trust relationships, time factors, and label information.

*4.1. Experimental Software and Hardware Environment and Data Set.* The hardware/software of experimental environment is listed in Table 2. The number of users is 13,680, and the total number of courses is 737, mainly computer, English, and political and ideological related courses. The data include the user's learning records and scoring records. The time span is from May 2016 to July 2020. The total number of records is 148,170. Among them, the training set accounted for 80%, with about 118,000 records, and the test set accounted for 20%, with about 30,000 records.

With the help of web crawler tools, the political and ideological courses and users in the data set are taken as the target, and the course resource information, user information, and behavior information are collected. Among them, the course resource information uses the website navigation classification bar as the entrance, and the course resource information under each category is crawled in turn. To obtain user information, refer to the platform user ID code form, randomly select multiple class ID codes as the starting account, set the ID increase step to 1, sequentially crawl the user information in the data set, and perform validity screening and confirmation at the same time. On the basis of the user's information, visit the user's homepage one by one and obtain their course participation information. Through 2 rounds of data collection (respectively on October 1, 2017, and June 30, 2020), the details of the data obtained are shown in Table 3.

### 4.2. Evaluation Index

*4.2.1. Precision.* That is, the accuracy rate of course recommendation refers to the proportion of courses actually studied by users among all courses recommended to users. The calculation equation is as follows:

$$\text{Precision} = \frac{Q(i) \cap Q(j)}{Q(i)}. \tag{17}$$

Among them, $Q(i)$ represents all the courses actually studied by the user; $Q(j)$ represents all the courses recommended to the user. The higher the accuracy rate, the more the recommended courses meet the user's expectations.

*4.2.2. User Coverage.* User coverage refers to the proportion of users who meet the recommendation conditions under a certain condition; that is, if there are 100 users and 50 people recommend related content, then the user coverage rate is 50%.

*4.2.3. Recommendation Time-Consuming.* This indicator mainly reflects the efficiency of the recommendation algorithm and is used to evaluate the real-time performance of the recommendation algorithm.

### 4.3. Analysis of Experimental Results

*4.3.1. Precision.* The personalized recommendation algorithm constructed on user behavior characteristic mining and the personalized recommendation algorithm integrating trust relationship, time factor, and label information are compared with the algorithm in this paper. In the experiment, the recommended list lengths are selected sequentially as 1, 5, 10, 15, 20, 25, 30, and the comparison results of the precision of the three recommendation algorithms under different recommended list lengths are shown in Figure 4.

Table 2: List of hardware and software.

| S No. | Hardware/software | Name/model |
|---|---|---|
| 1. | System | Intel(R) Core(TM) i5-2520M CPU 2.50 GHz |
| 2. | Operating system | Windows 10 |
| 3. | Memory | 8 GB |
| 4. | Experimental software | MATLAB 2012b |
| 5. | Experimental data set | Data set comes from the actual operating data of an online teaching website |

Table 3: Experimental data set.

| Object | The amount of data | Annotation |
|---|---|---|
| User | 5721 people | Number of course options ≥2 |
| Course | 3 | Less than the number of course attribute information |
| Behavioral information | Course selection 259 times | Among them, 5.6% of users only participate in basic courses |

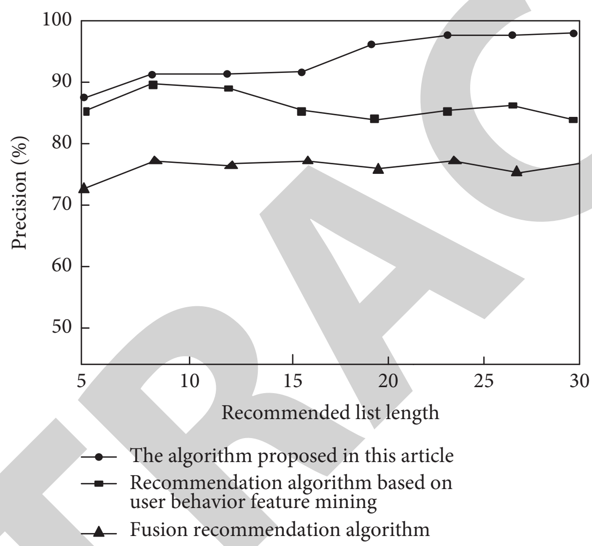


Figure 4: Precision comparison results.

It can be observed from Figure 4 that when the recommended list length is between 5 and 15, the recommendation precision of the algorithm in this paper has no obvious trend of improvement. When the length of the recommendation list is increased, the recommendation precision of the algorithm in this paper will increase significantly, and the maximum precision rate reaches 97%. The recommendation precision rate of the personalized recommendation algorithm based on user behavior feature mining and fusion trust relationship, time factor, and label information has no obvious change characteristics. The experimental results in Figure 5 show that compared with the other two recommendation algorithms, the precision of this algorithm is always the highest, and as the recommendation list increases, the advantages become more obvious. Experiments show that the algorithm in this paper can get better recommendation results.

*4.3.2. User Coverage.* Comparing the user coverage of the three recommendation algorithms under different iteration times and different numbers of users, the comparison result is shown in Figure 5.

By analyzing Figure 5, it can be observed that under different iteration times, the maximum user coverage of the algorithm in this paper reaches 98%. The highest user coverage of personalized recommendation algorithm constructed on user behavior characteristic mining is 78%. The highest user coverage of personalized recommendation algorithm integrating trust relationship, time factor, and label information is 72%. Under different numbers of users, the maximum user coverage of this algorithm is 92%. The highest user coverage of personalized recommendation algorithm constructed on user behavior characteristic mining is 61%. The highest user coverage of personalized recommendation algorithm integrating trust relationship, time

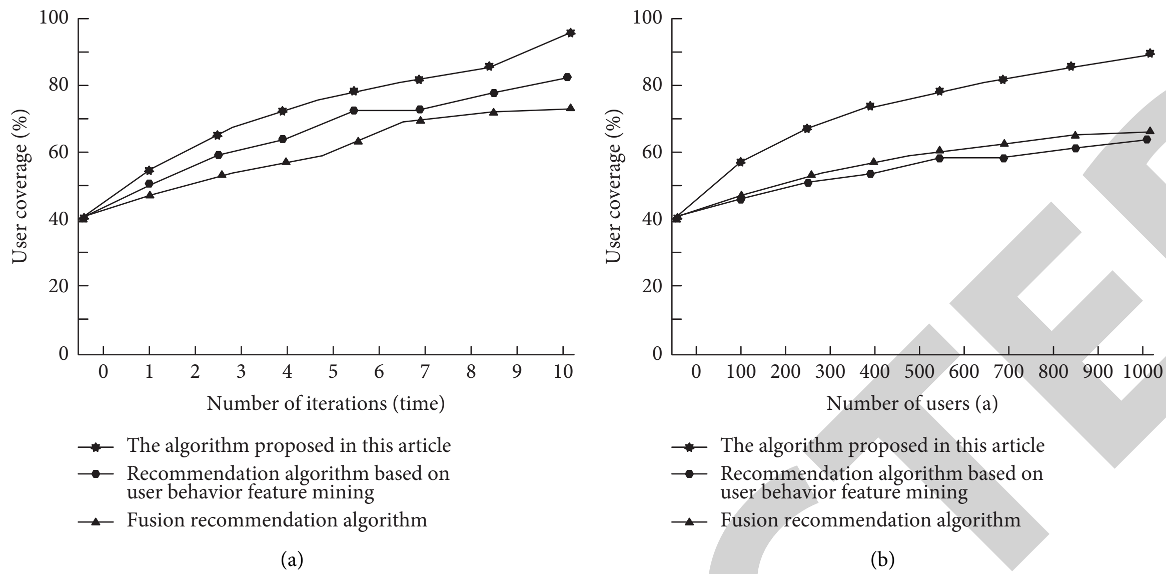


Figure 5: Comparison results of user coverage. (a) Different iteration times, (b) the number of different users.

Table 4: Comparison results of course recommendation time.

| No. of iterations/time | The algorithm proposed in this article | Personalized recommendation algorithm based on user behavior feature mining | Personalized recommendation algorithm integrating trust relationship, time factor, and label information |
|---|---|---|---|
| 1 | 1.28 | 1.90 | 2.18 |
| 2 | 1.24 | 2.90 | 2.09 |
| 3 | 1.36 | 2.90 | 3.12 |
| 4 | 1.22 | 2.91 | 3.59 |
| 5 | 1.34 | 3.92 | 2.61 |
| 6 | 1.27 | 3.93 | 1.98 |
| 7 | 1.29 | 3.94 | 1.54 |
| 8 | 1.13 | 2.93 | 2.07 |
| 9 | 1.24 | 3.57 | 3.16 |
| 10 | 1.90 | 3.61 | 3.99 |

factor, and label information is 64%. Through the above data comparison, the effectiveness of this algorithm is verified, which can recommend appropriate political and ideological courses for more students.

*4.3.3. Recommended Time.* Compare the course recommendation time of the three recommendation algorithms, and the comparison results are shown in Table 4. From Table 4, it can be seen that the course recommendation time of the traditional recommendation algorithm is long, and the user's problem cannot be solved in time. The recommendation of the algorithm in this paper takes a short time and has a strong topic concentration, which can help users solve problems. Through comparison, it can be seen that the algorithm in this paper is better than the traditional recommendation algorithm.

*4.3.4. The Ability to Find the Best.* In order to further check the effectiveness of the proposed algorithm, test its optimization ability, and the result is shown in Figure 6.

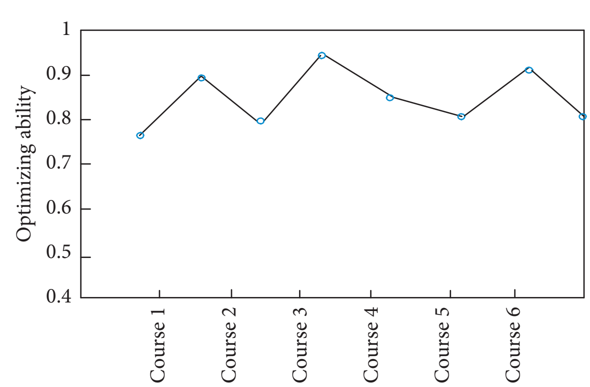


Figure 6: Results of the optimization ability test.

According to the analysis of Figure 6, the optimization ability of the algorithm in this paper is generally high, and the optimization ability can reach more than 0.75. Therefore, it can be seen that the optimization capability and convergence of political and ideological course recommendation using this method are good.

## 5. Conclusions

The political and ideological curriculum encompasses the full procedure of higher education teaching and is a necessary system for colleges to develop high-quality skills and abilities. Keeping these in mind, this study offers a personalized recommendation algorithm for college political and ideological courses under multiple user interests in order to accomplish personalized recommendations of political and ideological education courses. Experiments show that it has advantages in terms of recommendation accuracy, user coverage, recommendation efficiency, and optimization. However, some labels in the algorithm described in this article may be unable to communicate content features, affecting the interaction between courses and resources and reducing recommendation accuracy. I intend to improve the proposed system in the future, which will need the ongoing collection and analysis of teacher data. The use of feedback recordings and content optimization tools improves the accuracy of recommendation results.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The author declares that he has no conflicts of interest.

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