Research Article

Method of Ideological and Political Teaching Resources in Universities Based on School-Enterprise Cooperation Mode

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The personalized recommendation system influences the recommendation of ideological and political teaching resources in universities, resulting in a high MAE score. As a result, under the school-enterprise collaboration paradigm, this study proposes a customised recommendation approach for ideological and political teaching resources in colleges and universities. The ideological and political teaching resource bank is developed against the backdrop of the teaching paradigm that combines universities and businesses. Learners’ browsing data history is gathered to create a learning interest model for them. A hybrid collaborative filtering recommendation method was devised, and a recommendation engine was established by Taste component, taking into account individualised resource recommendation needs and information entropy weight distribution mode. When compared to previous techniques, the developed customised recommendation method considerably enhances the recommendation quality of instructional resources and reduces MAE by 29% and 34%, respectively.

1. Introduction

People were less able to get materials when the Internet was not invented. People may now quickly get all kinds of resources, thanks to the rapid growth of the mobile Internet, but they also face the problem of “information backpacking” and “knowledge overload,” making it more difficult to discover the information they want. The lack of a tailored platform can be compensated for by customised recommendations. The technology gathers user data, creates human portraits using big data, and delivers tailored suggestions. The development and use of a personalized recommendation system have a bright future. Personalized recommendation technology is now widely employed in e-commerce, new media, education information technology, and other industries, garnering an increasing number of people’s interest. People are increasingly demanding tailored learning as modern society progresses. The rapid growth of online learning technology is due to the advent of education informatization [1]. Most contemporary online learning tools, on the other hand, are homogenized, neglecting learners’ unique peculiarities and failing to suit their specific demands. For online learners, a vast quantity of diverse learning materials might lead to cognitive overload and network trek [2]. This article will advocate for its use in the realm of educational technology. Teaching resources play a significant role in teaching as part of educational informatization. Although a network-teaching platform may offer a huge number of teaching resources, most users will have access to the same ones. Due to their various interests and activities, users have varying demands for educational resources [3]. Providing learners with learning resource suggestion services based on their characteristics can reflect individualised learning, assist learners in swiftly finding important materials, and increase the efficiency of online learning [4].

Users may uncover prospective interests and hobbies and make suggestions using a variety of recommendation technologies, allowing them to quickly and correctly locate resources suited for their learning requirements among a
vast number of instructional materials and satisfy their wants for tailored services. [5]. This article examines the features of a specific set of users on the network teaching platform for research. In addition, this article combines it with the project’s instructional resources features, as well as the design process for particular suggestions. It is capable of avoiding the sparse matrix issues that the collaborative filtering method encounters. Finally, using Apache Mahout, this study creates its own recommendation engine.

2. Design of Personalized Recommendation Method for Ideological and Political Teaching Resources in Universities under School-Enterprise Cooperation Mode

2.1. Setting up School-Enterprise Cooperation Teaching Resource Bank. School-enterprise cooperation teaching resource platform is designed to overcome the boring of traditional learning mode, enhance the fun of learning process, meet the personalized learning needs of students, and facilitate teacher-student interaction [6]. The teaching resource platform is divided into five functional modules as follows: user information management, teaching resource management, resource statistical analysis, course management, and micro-lesson management, among which teaching resource management and course management are the core parts of the platform management [7].

The construction of teaching resource database is the basis of personalized recommendation of teaching resources. Usually, teaching resources include visuals, film and television, cases, pictures, and textbooks. In addition, they also include infrastructure, teaching aids, and teacher resources. The construction of professional teaching resource database includes two contents. First of all, there is need to work on the ideological and political education with the complete information about the dual currency team and complete information on it. The former is the general teacher training into a knowledgeable teacher, and the latter is the academic teachers into practice, making both fully grasp the education work to help the school to complete the personnel training goal. Secondly, a sub-database of professional teaching resources should be established, with professional courses as the core, including curriculum system, professional construction scheme, professional introduction, teaching team, professional research, social services, recruitment, and employment. In the recruitment and employment resources database, it is necessary to mention independent recruitment plan, school recruitment general rules, recruitment plan, admission number, admission score line, employment information, counterpart college entrance examination, and recruitment outline. Social service resources include participation in the social vocational skills competition, enterprise science and technology research and development, enterprise industry training, on-the-job internship, and many other contents. Secondly, a classroom is in the air. It is a course which explains the information about resource platform, including all sort of video information, curriculum, teaching courseware, and other course cooperation unit. The use of teaching materials, power materials, virtual experiment, recommendation site, interaction space, recommended books, and a series of resources, can be open to students, students learning goals, to promote their self-study ability to ascend. Thirdly, the material resource library. It is the most basic part of the entire repository. According to the classification, it can be divided into virtual simulation software, curriculum library, video library, animation library, picture library, text file library, 3D interactive library, audio library, and other media types. A variety of test questions, learning instruction, teaching materials, and other teaching documents are also considered as some of the main types of the application.

The teaching resource platform jointly built by schools and enterprises should not only include traditional teaching resource types [8] but also highlight the characteristics of enterprise practice [9]. Ideological and political education belongs to a complicated system engineering, involving students in daily life, survival skill operation, the society, and in university-enterprise cooperation personnel training mode. The goal of the teaching emphasis is on cultivating students’ creative ability, practical ability, entrepreneurial ability, and employment ability. The traditional ideological and political education teaching method is very difficult to apply, and the aspects of teaching content have changed students into the enterprise. Because after a new personnel arrangement disrupted students’ former organizational system, all activities are in accordance with the practice enterprise personnel, production situation, and production and marketing of arrangement, although the school counselor will follow instruction. However, it is difficult to pay more attention to students than in school, and the training of practical skills is also the focus in the process of practice, thus neglecting ideological and political education. Therefore, the teaching resource platform is divided into a theoretical teaching resource model and an industrial teaching resource model, and the information of each kind of teaching resource is summarized according to the format of Table 1.

The theoretical teaching model mainly presents the traditional teaching materials such as guide plans, textbooks, auxiliary materials, and exercises in a new electronic form in front of students [11], which is convenient for students to extract at any time. Industry’s main teaching model simulates the enterprise actual work scene, makes students participate in the simulation of the project in the daily learning technology application, development, and bug-fixes practice, trains students to solve practical problems and technical ability of thinking, encourages students to participate in market research, and helps students to understand the development trend of industry [12] in advance. To help students determine their future career direction, they need to master vocational skills [9]. The platform establishes a resource uploading mechanism and sharing mode [13]. The resource audit architecture is shown in Figure 1.
The curriculum is the core of students’ learning, and the teaching resource platform adopts the idea of stratification to design curriculum modules. The courseware contains the auxiliary resources required by students for learning [14] and is the smallest unit of learning in one-to-one correspondence with courses. In addition, some ideological and political curriculum practices are designed by the school-enterprise cooperation, which require students to complete within the prescribed time to exercise students’ application ability.

### 2.2. Constructing User Learning Interest Model

In order to establish the interest model of learners, it is necessary to collect and record learners’ scoring information and learning behaviors, such as learners’ scoring, browsing, collecting, sharing, and downloading of ideological and political teaching resources [15]. Explicit evaluation of learning resources by learners is the most direct and easiest data to analyze, but the operation of evaluation has no direct significance for learners themselves, and not all learners will score the learned resources [16]. Therefore, systematic personalized recommendation mainly uses implicit scoring, that is, analyzing learners’ behaviors. This study combines log mining and system operation information collection to obtain learner behavior information. The main content of information collection is listed in Table 2.

In this study, TF-IDF technology is used to interpret and reason the collected learner behavior data, and the noise is separated from it, the information related to the user’s interest is output, and the data are formatted to generate the user model with structured representation. TF-IDF is the most mature and successful text learning technology in the field of information retrieval [17].

### Table 1: Information sheet on teaching resources.

| Attribute          | Type          | Description                                                                 |
|--------------------|---------------|-----------------------------------------------------------------------------|
| Resource ID        | Bigint        | Upload time                                                                 |
| Resource type      | Varchar (20)  | Including media materials, question banks, test materials, cases, literature, frequently asked questions, resource directory index, online courses record the uploader of the resource, record the time the resource was uploaded |
| Professional code  | Varchar (20)  | It is numbered according to the national standard discipline classification and code [10] of the People’s Republic of China |
| Education level    | Varchar (20)  | Doctor, master, undergraduate, vocational college                           |
| Name of the resource | Varchar (100) | Display the name of the resource                                            |
| Content abstract   | Varchar (100) | Provide a brief introduction to the content of the resource                 |
| Author             | Varchar (60)  | Record the uploader of the resource                                         |
| Upload time        | Date          | Record the upload time of resources                                         |

![Figure 1: Resource audit framework.](image)
Using user-project evaluation matrix representation, the presentation and establishment of a specific group user model. In this study, the user-item scoring matrix is adopted to input the membership degree into the membership function, each has its limitations. So far there is a set \( [19] \). Although there are many methods to establish a personalization model, the membership function of users' interest lies in teaching resources. The membership function uses a fuzzy set to elaborate and analyze a certain fuzzy phenomenon, that is, the membership function is used to describe the degree of object elements belonging to a certain set \([19]\). Although there are many methods to establish membership function, each has its limitations. So far there is no law to follow, mainly based on the practical experience related to domain knowledge and common sense to give a membership degree. In this study, the user-item scoring matrix is adopted to input the membership degree into the matrix, which shows the user’s preference for the project and the group user’s interest bias. It is suitable for the representation and establishment of a specific group user model. Using user-project evaluation matrix representation, the user interest model \( \Lambda \) is expressed as follows:

\[
\Lambda = \begin{bmatrix}
R_{11} & R_{12} & \cdots & R_{1n} \\
R_{21} & R_{22} & \cdots & R_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
R_{m1} & R_{m2} & \cdots & R_{mn}
\end{bmatrix}
\] (2)

In formula (2), \( R \) represents matrix elements, \( m \) represents the number of students in colleges and universities, and \( n \) represents the total number of ideological and political teaching resources. Each element in the matrix represents the evaluation score of learners on ideological and political learning resources, which is generally an integer value within a real number range. Generally speaking, a higher score indicates a higher degree of user preference for the item. A null value indicates that the user has not yet rated the item.

### 2.3. Designing a Hybrid Collaborative Filtering Recommendation Algorithm

In order to recommend, the teaching resources the result showing the details about personalized learning and ideological and political courses, make better resources recommended and in the actual application to avoid based on the user and the defect of the collaborative filtering algorithm based on the project, this article puts forward will be based on user and collaborative filtering algorithm based on the project, the combination of design of hybrid collaborative filtering recommendation algorithm. Collaborative filtering automates the process of ideological and political learning in real life and provides personalized resource recommendations to users according to the preferences of other users with similar tastes. According to the user’s rating information of the project, we find the nearest neighbor set with similar interest to the target user and then predict the project that the target user may be interested in by combining the nearest neighbor user’s rating information in this set. The most intuitive description of collaborative filtering recommendation is to form a matrix of users and resource items. The interest matrix of university learners is listed in Table 3 by referring to the user interest model.

According to the \( M \times N \)-order interest matrix composed of \( M \) users and \( N \) resource items, the existing value is the user’s score on the corresponding resource items, and the score ranges from 1 to 10, while the null value (unknown value) in the matrix is exactly what the recommendation system needs to calculate through prediction. The prediction process rules and the actual are more conformed to the law, the unknown value of prediction is more accurate, and information filtering effect is better. There is collaboration in filtering the most important link needed based on nearest neighbor users to set user similarity scores of information and resources information, and it was used to calculate the target users for its entry resources prediction score evaluation. Finally, it formed according to the score to the teaching of the ideological and political target users personalized resource recommendation.

The collaborative filtering recommendation algorithm generates recommendations for target users based on the preferences of the nearest neighbors. When selecting the nearest neighbors, the similarity between the target user and other users in the user group is calculated first, and then \( K \) users with the highest similarity are selected to constitute the nearest neighbors of the target user. It can be seen from the above that user similarity calculation plays a crucial role in collaborative filtering recommendation algorithm, and its accuracy plays a decisive role in the recommendation quality of the recommendation algorithm. The relationship between teaching resources in the recommendation system will not change much within a certain time range. Therefore, the similarity between ideological and political teaching resources can be offline in advance and stored in a special database table, which can be updated regularly as a reference parameter for a personalized recommendation. In this study, cosine similarity is used to calculate, and the cosine value of the angle between two vectors is used to measure the similarity. The larger the value is, the higher the similarity degree is. In the collaborative filtering recommendation system, the scoring matrix can be regarded as n-dimensional vector space, and each row can be regarded as a row vector.
In collaborative filtering, the predicted score of the target user for resource item 1 can be calculated by the following formula:

$$P_x = \mu_x + \sum_{y \in U} \left( \frac{\text{Sim}(x, y) \times \mu_y}{\sum_{y \in U} \text{Sim}(x, y)} \right).$$  \hspace{1cm} (4)$$

In formula (4), $x$ represents the target user, $P$ represents the predicted score, $\mu_x$ represents the score of the target user on the resource item, $U$ represents the nearest neighbor user set, and $\mu_y$ represents the score of user $y$ on the teaching resource item. This prediction score calculation formula is a central-weighted calculation method, which takes the average score of the target user on the resource item as the center, takes the score of the users in the nearest user set on the specified resource item as the weight value, and combines to generate the predicted value. The formation of neighbor users is the process of finding the most similar neighbor users for a target user who needs personalized resource recommendation service. The nearest neighbor user set is found according to the preset selection threshold. In collaborative filtering, the predicted score of the target user to other resources not participating in the evaluation is calculated according to the score data of the neighboring user set and the user set. The recommendation principle of hybrid collaborative filtering is shown in Figure 2:

In the personalized recommendation of ideological and political teaching resources, the hybrid collaborative filtering recommendation algorithm needs to classify learners through second-order clustering method and assign weight to learners' behaviors. The implementation of the recommendation algorithm includes five steps, including input of learner ID and behavioral characteristic data, judgment of the data category, calculation of the behavioral characteristic data of the learner, judgment of the similarity of the learner so far, generation of recommendation list according to the nearest neighbor of similar learners and TOP-N output after ascending order.

However, the recommendation of teaching resources is affected by the behavior of learners. Considering that the behavior is a variable feature item, in order to enhance the recommendation quality of resources, the weight index is set in the recommendation algorithm. Firstly, the number of users' ideological and political learning behaviors is determined, and the number of learners' behaviors is standardized to eliminate the influence that data cannot be compared due to different indicators. The standardization method is as follows:

$$Q_{l,k} = \frac{B(I, k) - \text{Min}(B(I, k))}{\text{Max}(B(I, k))}.$$  \hspace{1cm} (5)$$

In formula (5), $B$ represents the number of learning behaviors, $I$ represents learners, $k$ represents learning behaviors, $Q$ represents the number of behaviors after standardized processing, $\text{Min}$ represents the minimum number of behaviors, and $\text{Max}$ represents the maximum number of behaviors. Then, the behavior information entropy behavior is calculated according to the definition. Information entropy means that the more uniform the distribution of behavior times, the greater the information entropy of behavior, the weaker the personalized characteristics of behavior. In the process of determining user behavior weight, the larger the information entropy of ideological and political learning behavior, the smaller the corresponding behavior weight value. To sum up, the information entropy calculation formula of learning behavior of college learners is as follows:

$$I_k = -\sum_{l=1}^{L} \eta(Q_{l,k}) \times \eta(Q_{l,k}) = \frac{Q_{l,k}}{\sum_{l=1}^{L} Q_{l,k}}.$$  \hspace{1cm} (6)$$

| The user | Item 1 | Item 2 | Item 3 | Item 4 | ... | Item N |
|---------|--------|--------|--------|--------|-----|--------|
| User 1  | 8      | 4      | 3      | 8      | ... | 9      |
| User 2  | 5      | 7      |        |        |     |        |
| User 3  | 7      | 6      | 10     | 6      | ... | 7      |
| ...     | ...    | ...    | ...    | ...    | ... | ...    |
| User M  | 1      | 8      | 8      | 4      | ... | 5      |

The items without scoring are filled with 0 by default. Assuming that the scoring information of two learners in the two-dimensional resource item space is represented as vector $S_i, S_j$ respectively, the similarity between them can be defined as follows:

$$\text{Sim}(i, j) = \cos(S_i, S_j)$$  \hspace{1cm} (3)$$

In formula (3), $i, j$ represent similarity and represents two learners. Using the above learner similarity calculation results, the predicted scores of target users on ideological and political teaching resource items are obtained. Assuming that the nearest neighbor user set of user $X$ can be represented as $U$, the predicted scoring ruler of the target user for resource item 1 can be calculated by the following formula:

$$\text{Sim}(x, y) \times \mu_y$$

In formula (4), $x$ represents the target user, $P$ represents the predicted score, $\mu_x$ represents the score of the target user on the resource item, $U$ represents the nearest neighbor user set, and $\mu_y$ represents the score of users $y$ on the teaching resource item. This prediction score calculation formula is a central-weighted calculation method, which takes the average score of the target user on the resource item as the center, takes the score of the users in the nearest user set on the specified resource item as the weight value, and combines to generate the predicted value.
In formula (6), $I$ represents information entropy, and $\eta$ represents the probability of learning behavior $k$ appearing in behavior records. Finally, according to the calculation formula of behavior information entropy, the information entropy value of each behavior can be calculated. On the basis of information entropy, behavior weight indexes corresponding to different behavior items can be calculated, and the calculation formula is as follows:

$$W_k = \frac{1 - I_k}{\phi - \sum_{k=1}^{\phi} I_k}$$  \hspace{1cm} (7)

In formula (7), $W$ represents the weight of behavior and $\phi$ represents the total number of learning behaviors. Combined with the calculation results of the above information entropy weight value, users’ preferences for different ideological and political teaching resources are calculated respectively. Teaching resource items with high preference degree, that is, teaching resource items with high predicted score are selected, and the items that are not in the set of items rated by users are generated as recommendation sets.

2.4. Realizing Personalized Recommendation of Teaching Resources. In order to realize the efficient recommendation of selected personalized ideological and political teaching resources set, this study uses the Taste component in Apache Mahout to establish the recommendation engine, which is a Java-based component. And it not only realizes the most basic hybrid collaborative filtering recommendation algorithm but also provides an extended interface, makes users can easily define, and implements its own recommendation algorithm. At the same time, Taste is not just for Java applications. It can be used as a component of an internal server to provide recommended logic to the outside world in the form of http and web services. Taste is designed to meet the performance, flexibility, and scalability requirements of enterprise recommendation engines. The main components of Taste are shown in Figure 3; Taste consists of the following five main components:

Data model. The data model is an abstract interface of user preference information, and its concrete implementation supports extracts user preference information from any type of data source. Taste provides JDBC data model and file data model by default, which can read user preferences from databases and files respectively.

User similarity and item similarity. User similarity is used to define the similarity of two users. It is the core part of the recommendation engine based on collaborative filtering and can be used to calculate the user’s "neighbor." Here, we call the user with similar interests to the current user as his neighbor. Item similarity is computed between items.

User neighborhood. Used in recommendation methods based on user similarity. The recommended content is generated based on finding "neighborhood users" with similar preferences to the current user. User neighborhood defines methods for determining neighborhood users. The specific implementation is generally based on user similarity calculation.

Recommender. Recommender is an abstract interface of recommendation engine and a core component of Taste. In the program, it provides a data model, which can calculate the recommended content for different users. In practical application, generic user-based recommender or generic item-based recommender is mainly used to implement the recommendation engine based on user similarity or content-based recommendation engine.

3. Test

3.1. Experimental Data Set and Environment. In order to verify the application effect of the personalized recommendation method of design teaching resources in this study, an experimental test was carried out. The experimental data came from the ideological and political teaching department of a university, which collected 6200 evaluation data of 1200 teaching resources from 80 students. The sparse level of the data set is also considered in the experiment, which is defined as the percentage of items that are not graded in the user-item scoring matrix. The data sparse of this experiment is 1–6200/(80 * 1200)–0.935417, and the evaluation value ranges from 1 to 5. The higher the value is, the higher the user’s preference for the resource is. According to the literature, the scoring data were divided into training sets and test sets with a ratio of 0.8. The classification of 1200 resources is listed in Table 4:

The experiment is run on Windows XP. The collected data set is used to compare the recommendation method based on particle swarm optimization and neural network with the personalized recommendation method of designing teaching resources in this study, analyzing the recommendation quality of ideological and political teaching resources in the same training set and test set.

3.2. Experimental Evaluation Criteria. The evaluation of the recommendation system is an important problem. If the results of recommendation meet the requirements of users, it will improve user experience, increase the viscosity of users to the system, thus bringing corresponding economic or social effects and achieving the purpose of recommendation. However, if the recommendation system recommends inappropriate things to users, users will not only doubt the quality of the recommendation but also likely lose users.

The average absolute deviation MAE, which is the most widely used and intuitive measurement method of statistical accuracy, is used as the evaluation standard. During the experiment, the data set is divided into a training set and test set. The algorithm works in the training set and predicts the items in the test set through the data in the training set. MAE is the average of the absolute value of the actual and predicted resource ratings by all users in the test set. The smaller the MAE value is, the higher the recommendation quality is for target users. MAE value can be calculated as follows:
In formula (8), \( f \) represents the number of all users, \( o \) represents the target user, \( p_o \) represents the predicted value of the target user scoring the recommended resource, and \( q_o \) represents the actual value of the target user scoring the recommended resource.

3.3. Analysis of Experimental Results. The results of resource personalized recommendation of different methods were analyzed, and formula (8) was used to calculate the MAE values of the three recommendation methods, were obtained as shown in Figure 4.

As can be seen from the figure, when the number of neighbors is the same, the MAE value of the recommendation method based on particle swarm is almost the same as that based on neural network. However, the MAE value of the personalized recommendation result of ideological and political teaching resources designed by the method in this study is 0.54, which reduces the MAE value by 29% and 34% compared with the other two methods. It greatly improves the quality of teaching resource recommendation.
4. Conclusion

This study first elaborated on the ideological and political teaching under the school-enterprise cooperation mode, clarified the research significance of personalized recommendation of teaching resources, and understood the relevant theories and technologies of personalized recommendation. In the context of the rapid development of education informatization and online learning, this study analyzes the behavior data of college learners and outputs personalized recommendation results of teaching resources with the combination of hybrid collaborative filtering recommendation algorithm. Experiments show that the design method in this study is feasible and makes the recommendation results more humanized. Although the learning peer recommendation strategy proposed in this study is reasonable and innovative compared with previous studies in some aspects, while certain research results have been achieved, there are also many shortcomings that need to be further explored and improved. In the experiment of the current algorithm, although it can determine the type of newly added learners, in the future application, it can be considered to set a certain frequency to update the whole cluster center value after new users are added, so as to make the judgment more accurate.

Data Availability

Data are available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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