



Tutoring Precision Strategy of Ideological and Political Education Based on Intelligent CAD

Zhang Lei ¹ and Yao Fu ^{2*}

College of Medicine, Jingchu University of Technology, Jingmen 448000, China
¹199607016@jcut.edu.cn; ²200707024@jcut.edu.cn

Corresponding author: Yao Fu, 200707024@jcut.edu.cn

Abstract. This study explores a precision tutoring strategy for ideological and political education, leveraging Intelligent Computer-Aided Design (CAD) and big data analytics. The aim is to enhance the effectiveness of ideological education by utilizing advanced technologies to tailor educational content and delivery to the specific needs of students. By integrating big data, the system can analyze student behavior, preferences, and performance, allowing educators to create personalized learning experiences. Intelligent CAD facilitates the design of interactive and engaging educational materials, making complex ideological concepts more accessible. Under the tide of Intelligent CAD and big data, it is extremely necessary to strengthen the research on the precision of ideology education in colleges and universities (IPECU), which requires ideology educators to establish big data thinking, explore new educational methods, and constantly create a new situation of IPECU. By analyzing users' behavior on the website, the accurate recommendation system can infer users' needs so as to recommend more valuable resources to users. The accuracy of this paper's ideological and political education precision recommendation model is higher, which is 16.75% higher than the traditional algorithm. The exploration of intelligent ideology mode is helpful for teachers to use big data technology to collect students' data information scattered in cyberspace, grasp students' states in real-time, and provide accurate instructional resources according to students' different states and needs.

Keywords: Intelligent CAD; Ideological and political education; Instructional resources; Tutoring Precision

DOI: <https://doi.org/10.14733/cadaps.2025.S8.186-197>

1 INTRODUCTION

The Internet industry has driven the development of a number of other traditional industries, and its rapid development and traditional industries have embraced the Internet across borders. The cross-border of the education industry is also quietly going on. It is imperative to effectively

combine the value logic of the education industry with the operation logic of the Internet industry [1]. The purpose of IPE is to use appropriate methods to achieve people's free and all-round development, and the implementation of education cannot be separated from the application of educational methods. IPE methods are the key to the implementation of IPE, which restricts the effectiveness and development of IPE to a certain extent [2]. With the development of IT, networks have penetrated into all aspects of social life, especially IT, which has been widely used in college education, resulting in network teaching. Although many universities have implemented online teaching in IPE, the unsatisfactory construction of online instructional resources restricts the development of online teaching of Ideology courses [3]. In the age of big data, it is essential to strengthen the research on the accuracy of IPECU, which requires ideology educators to establish big data thinking, explore new education methods, adhere to being close to reality, life, and students, and constantly create a new situation of IPECU [4].

The Internet industry has driven the development of a number of other traditional industries, and its rapid development and traditional industries have embraced the Internet across borders. The cross-border of the education industry is also quietly going on, and it is imperative to effectively combine the value logic of the education industry with the operation logic of the Internet industry [5-6]. With the advent of the age of big data, it is a strategic choice for IPEs in the age of big data to drive high-end IT and transform the paradigm of intelligent IPE so that intelligent IPE presents a brand-new development trend. The rapid development of education is reshaping educational concepts, innovating educational contents and methods, and accelerating the reconstruction of educational ecology. Therefore, the construction of wisdom and ideological education has become an inevitable choice for the reform and innovation of IPE. Big data IT can provide support for the precise reform of IPECU, help IPECU comprehensively and systematically analyze the information of the subject and object of education, accurately identify the learning needs of educational objects, accurately evaluate the effect of education, accurately push educational resources, and accurately match the educational needs and educational supply for IPECU, Drive the IPECU to achieve accurate reform [7]. This paper proposes a recommendation algorithm for IPE resources based on the CF algorithm. According to users' browsing records, browsing habits, and preferences, the instructional resources that users may be interested in are recommended to them. Through design experiments, the effectiveness of the algorithm is proved.

The construction of network instructional resources is very important for the development of network teaching at IPECU. Without a rich and complete network of instructional resources, network teaching of Ideology courses in Universities will be impossible [8-9]. For the precise strategy of IPE resources, the main innovations of this paper are as follows:

(1) By analyzing users' behavior on the website, the precise recommendation system can infer users' needs so as to recommend more valuable resources to users. The recommendation quality of the recommendation system directly determines the user's dependence on the recommendation system.

(2) This paper aims to design and implement a precise learning resource recommendation strategy based on the CF algorithm. According to the user's browsing records, browsing habits, and preferences, the instructional resources that users may be interested in are recommended to users, and the CF algorithm is used to recommend precise chemistry learning resources for learners.

The rest of the chapters are arranged as follows: the second section is related work, which analyzes the research of excellent scholars in IPE and teaching recommendation; The third section constructs the IPE Resource Recommendation Model of this paper; The fourth section verifies the effectiveness of the model through experiments; The fifth section summarizes the contribution of this paper, and puts forward that in the future, it is also necessary to refine the description of the data entities of learning resources, such as the course category of learning resources, the applicable population, etc.

2 RELATED WORK

Ym, etc., think that big data has brought us a new perspective and new method to know the world, and it has promoted the reform of IPE methodology [10]. Toledo pointed out that the current integration of instructional resources in IPE has the phenomena of blind accumulation of resources, complicated resource structure, and aging resource content. Under the guidance of IPE theory, the cultivation of college students' moral quality, knowledge quality, and ability quality has become the target orientation for the integration of online instructional resources in IPE [11]. In view of the practical problems faced by the current network teaching of IPECU, Chen promotes the network teaching of IPE by improving the construction of network instructional resources [12]. Cakir et al. think that students' satisfaction with the utilization rate of online instructional resources is low, and they hold a positive attitude toward the necessity of setting up the IPE instructional resources network but think that there are big problems in the website at present [13]. Therefore, we should further optimize the Ideology course instructional resource network, enrich its content, innovate its forms of expression, and enhance its interaction so as to assist the Ideology course teaching and improve its timeliness. Using data, we can more comprehensively analyze, grasp, and predict the changes in students' thoughts and behaviors and create a new research model of IPE. Koren et al. generated the user model through the history of the user's purchase and made recommendations according to the user model [14]. Pang et al. suggested that logs can be mined to help improve the accuracy of the recommendation system [15]. Pan applied mining, association rule mining, and decision tree technology to e-commerce recommendation systems and recommended products suitable for users [16-17]. Bobadilla proposed a method of recommending current and subsequent learning materials in real time according to learners' interests and progress [18-19].

The research on the recommendation system of educational resources is not very mature. Because the popularity of the teaching assistant system in domestic education is not very high, although some universities have their own teaching assistant systems, these teaching assistant systems rarely contain instructional resource recommendation subsystems. Deeply cultivating big data in the field of IPECU and promoting the construction of a set of intelligent ideology modes with complete systems, coupled elements, coordinated development, and efficient operation will continuously improve and deepen the knowledge system and theoretical foundation of IPECU.

3 METHODOLOGY

3.1 CF Recommendation Algorithm

The enormous potential of the network is that it can connect thousands of computers, mobilize people from different regions and different responsibilities to work together and allow people from different regions to communicate with each other. Big data provides a new research paradigm and a new thinking paradigm for the research of IPECU, promotes the scientific construction of IPE, and makes accurate IPE possible. Content-based recommendation technology takes resource information as the research object, uses information retrieval technology to analyze the content of items, and usually applies neighbor function and classification technology to analyze and cluster the text content of items.

When a new user operates, the algorithm will train its neural network according to the user's operation so as to achieve accurate recommendations. By copying the global recommendation model as the recommendation model of the new user and then modifying the recommendation model according to the subsequent operations of the new user, the recommendation model is closer to the user's preference. Views of this process are shown in Figure 1.

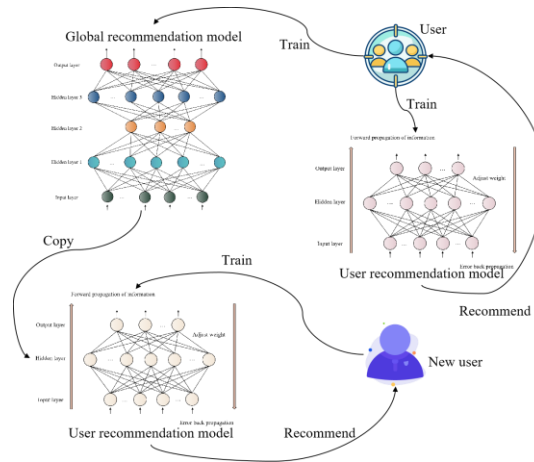


Figure 1: Precise recommendation process.

Let C be the set of all users, and S be the set of all recommended objects. Generally speaking, the scale of the collection C and the collection S is relatively large, such as millions of online customers and hundreds of millions of commodities. Calculating the recommended object: For the recommendation degree of user C , we use the recommended utility function $u_{c,s}$, that is, $u: C * S \rightarrow R$, and R is a non-negative real number. The problem to be studied by the recommendation algorithm becomes to find the set S^* of those recommended objects with the largest recommendation degree R :

$$\forall c \in C, S^* = \arg \max_{s \in S} u_{c,s} \tag{1}$$

According to actual problems, different attribute feature information can be used when measuring and sampling users or recommended objects. Calculating the utility value u is the core problem of the recommendation algorithm, but it is not in the whole field of $C * S$, but distributed in a subspace. Certain data sets should be extrapolated first; that is, the recommended objects should be marked with the user's historical rating, and the recommended objects that have not been evaluated by the user need to be marked and extrapolated before use. Various recommendation algorithms have designed corresponding utility functions for different extrapolation and prediction strategies.

The advantage of using the content-based method for accurate recommendations is that it is simple and effective. However, there are still some problems [20]. Content-based methods need to do a lot of analysis work before recommendation, such as what the current users visit and which pages on the website are related to it. Big data IT can provide support for the precise reform of IPECU, help IPECU comprehensively and systematically analyze the information of the subject and object of education, accurately identify the learning needs of educational objects, accurately evaluate the effect of education, accurately push educational resources, and accurately match the educational needs and educational supply for IPECU, Drive the IPECU to achieve accurate reform. According to these data, the system can make accurate recommendations.

Let the number of documents contained in the document set be N , the number of documents containing the keyword k_i in the document set is n_i , f_{ij} represents the number of times the keyword k_i appears in the document d_j , and the word frequency k_i of d_j in the document TF_{ij} is defined as:

$$TF_{ij} = \frac{f_{ij}}{\max z f_{zj}} \quad (2)$$

Where z represents the keyword appearing in the document d_j . The inverse frequency IDF that k_i appears in the documentation set is defined as:

$$IDF = \log \left(\frac{N}{n_i} \right) \quad (3)$$

Where n_i represents the number of documents that contain keywords in the document. The importance W_{ij} of the keyword k_i in the document d_j is defined as:

$$W_{ij} = TF_{ij} * IDF \quad (4)$$

Assuming that the similarity between items S and U is calculated, the algorithm obtains the importance of the keyword k_i in the document d_j and then sorts the importance W_{ij} of all words in descending order to obtain the real keyword of the item. Assume that the keywords with the word frequency value ranking in the top N are selected.

By calculating the similarity between the user's interest characteristics and items or between items, the user's interest in an item can be predicted. Usually, the cosine similarity method is used to measure their similarity:

$$sim_{u,v} = \frac{u \cdot v}{|u||v|} \quad (5)$$

Vectors u and v can represent user interest model vector and commodity feature vector, respectively. If the $sim_{u,v}$ value is larger, the similarity between the two is higher, and vice versa.

With the advent of the age of big data, it is a strategic choice for IPEs in the age of big data to drive high-end IT and transform the paradigm of intelligent IPE so that intelligent IPE presents a brand-new development trend. The rapid development of education is reshaping educational concepts, innovating educational contents and methods, and accelerating the reconstruction of educational ecology. Therefore, the construction of wisdom and ideological education has become an inevitable choice for the reform and innovation of IPE. When considering users' interests, we must also consider a time problem, that is to say, the user's access records within a certain period of time are the most effective for users, and if it takes too long, the things accessed before may not be the content that users are interested in [21]. Focusing on the dimension of wisdom education, this paper holds that wisdom and ideological education is a new form of wisdom education in the field of IPE. In the construction of an intelligent education environment, the construction of an intelligent ideology cloud needs to be built and improved so as to serve teaching monitoring, online teaching, psychological counseling, resource supply, instant feedback, and so on. The content-based filtering recommendation algorithm combines the data provided by information retrieval to screen information and finally achieves the purpose of recommending items to users.

In the similarity calculation of the CF algorithm, two user variables or two item variables need to be extracted from the system. When the numerical changes of the two variables are positively correlated, it means that the two variables have a linear relationship and the similarity between users or projects is high. When the values of the two variables change into a negative correlation,

it means that the two variables have no linear relationship and the similarity between users or projects is low. The calculation formula of the Pearson coefficient is:

$$\rho_{x,y} = \frac{\sum xy - \frac{\sum x \sum y}{N}}{\sqrt{\left(\sum x^2 - \frac{\sum x^2}{N}\right) \left(\sum y^2 - \frac{\sum y^2}{N}\right)}} \quad (6)$$

When the Pearson coefficient is applied in the user-based CF algorithm, the calculation formula of the Pearson coefficient will make a relative change, and the similarity calculation formula is as follows:

$$\omega_{u,v} = \frac{\sum_{i \in I_u \cap I_v} r_{ui} - \bar{r}_u * r_{vi} - \bar{r}_v}{\sqrt{\sum_{i \in I_u \cap I_v} r_{ui} - \bar{r}_u^2} \sqrt{\sum_{i \in I_u \cap I_v} r_{vi} - \bar{r}_v^2}} \quad (7)$$

Among them, $\omega_{u,v}$ is the similarity calculated by user u and user v based on the Pearson coefficient.

I_u is the set of items reviewed by user u , and I_v is the set of items reviewed by user v . r_{ui} is user u 's preference for item i , and r_{vi} is user v 's preference for item i . \bar{r}_u and \bar{r}_v represent the average level of preference value of user u and user v on all items, respectively.

With the help of high-end IT, such as big data, the construction of IPE will realize digitalization, integration of things, and intelligence of IPE. This will fundamentally change the traditional mode of IPE, break through the limitations of the original mode of single-subject education, and realize the cooperative education of all staff. Compared with the traditional IPE model, the intelligent IPE model highlights the concept of collaborative education and strives to build an intelligent IPE resource database, including an instructional resource database, user behavior database, educational administration information management database, etc., to provide intelligent services for all educational subjects, and to form an educational joint force of multi-linkage, multi-force, and multi-channel progress.

3.2 Precise Recommendation of IPE Instructional Resources

Users of the instructional resource-sharing module are mainly divided into student users and teacher users. Students and teachers can not only browse, search by category, search by keyword, upload, and download the resources but also rate and comment on the resources so as to realize the reasonable positioning of the resources' value. The instructional resource precision recommendation module is mainly aimed at student users. The recommendation system includes three parts: keyword layer, description layer, and user interface layer. At the bottom of the keyword layer, it provides the required keywords for the upper description and defines the dependencies between keywords. The description layer above the keyword layer defines the description of users and resources. At the top user interface layer, according to the precise rules defined in the following two layers, resources satisfying the rules are recommended to users. The recommendation method of IPE instructional resources based on CF is shown in Figure 2. Intelligent IPECU is the inevitable trend of accurate IPECU in the age of big data. With the help of big data technology, teachers collect educators' educational information in full quantity. At the same time, the corresponding α and β should be set according to the contribution degree of the weighted mean score of users and the weighted mean score of items. Where in the weighted mean score of user i is calculated:

$$r_u = \bar{r}_u + \sqrt{\sum_{k=1}^k r_{k,i} - \bar{r}_i^2} / K \tag{8}$$

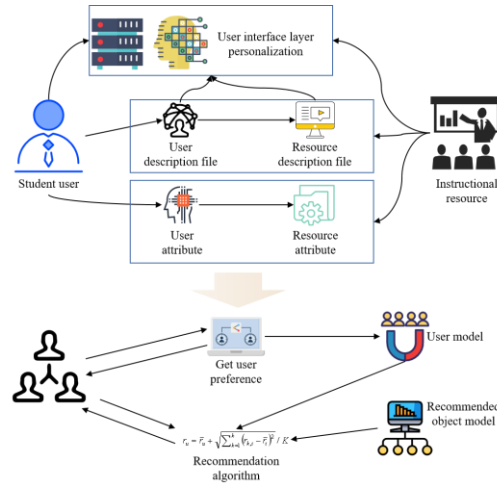


Figure 2: Recommendation method of instructional resources for IPE.

In the formula: K is the total number of user ratings for item i , and $r_{u,q}$ is the rating value of user k for unrated item i . The user's weighted mean rating is the sum of the mean errors of the user's average rating r_u and the user's various ratings \bar{r}_u relative to the average rating of the unrated items. Calculate the weighted mean score for i items:

$$r_i = \bar{r}_i + \sqrt{\sum_{q=1}^Q r_{u,q} - \bar{r}_i^2} / Q \tag{9}$$

Among them, Q is the total score of user u to the project space, and $r_{u,q}$ is the score value of k to user u to q . The weighted mean rating of an item r_i is the sum of the average rating of the item \bar{r}_i and the mean error of the average rating of each user in the user set for the unrated item i and the average rating of the user. Then integrate the weighted score:

$$r_{ui} = \alpha r_u + \beta r_i \quad \alpha + \beta = 1 \tag{10}$$

After obtaining the integrated weighted score of the unscored items and filling the corresponding items, any item in the matrix has a score for the items i and j , and the contribution judgment parameters α and β are introduced.

Although precise learning is also mentioned in the traditional education model, students' learning tends to keep a unified pace due to the constraints of scientific and technological levels, ideas, and other factors. To some extent, learning on the Internet is naturally characterized by precision. Learners can break through the time and space constraints and freely choose learning content, teachers, etc., in the open online learning space and shared intelligent learning platform, which has great autonomy and freedom. However, without the support of big data, teachers can't dig out the teaching rules hidden behind it through educational big data, nor can they accurately identify learners' precision needs. The intelligent teaching system automatically generates feedback reports for each learner based on accurate evaluation, gives accurate learning

suggestions, and pushes them to learners. Students can accurately orient and exert their strength, aim at the short board, target treatment, and make breakthroughs. IPE will collect and record educational data in real-time through various mobile internet application platforms, with the help of relevant IT, and conduct in-depth mining, classification, and processing so as to deeply analyze the correlation between data and obtain accurate feedback. This can not only help ideology educators to deeply understand the objective laws of teaching management but also help ideology educators to accurately grasp the "whole portrait" of students' groups in terms of ideological state, behavior dynamics, and knowledge mastery, and provide data reference for the next teaching management.

4 RESULT ANALYSIS AND DISCUSSION

Make the decision-making of data education decision-makers more scientific, and informatization becomes an important reference for decision-making. Under the general trend, the disadvantages of traditional IPE methods are increasingly prominent, and opportunities and challenges are intertwined. The appearance of disadvantages is also an important factor in promoting the further innovation of IPE methods. Through the real-time accumulation and close analysis of the data, educators can record the specific behavior data in students' lives in digital form, discover the changes in students' thoughts, develop students' personalities, and carry out targeted education through small behaviors. The informationization provided by big data can enable the educated to grasp the development trend of students from the macro level. In education, educators can predict the development trend of students' thoughts and behaviors more rationally by analyzing and grasping students' thoughts and behaviors. Using big data to accurately reveal the ideological situation of students' groups and individuals and to grasp the behavioral characteristics of students' groups and individuals can promote the combination of precise development and mass customization. Figure 3 shows the subjective scoring results of users on different recommended models of IPE instruction resources.

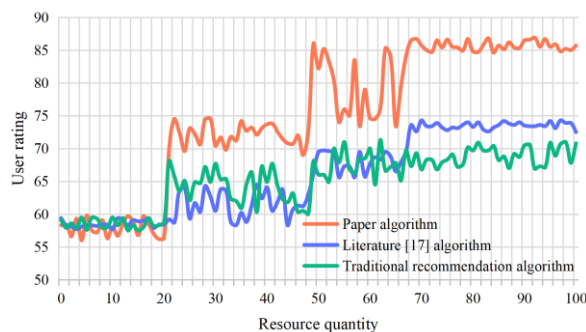


Figure 3: User subjective rating.

Most users said that the accurate recommendation system of learning resources can help them quickly locate the information they need in the massive learning resources, and the recommendation results are generally more accurate, which can meet individual needs and tap the potential interests of users. Figure 4 shows the performance comparison between algorithms when different sparsity is selected.

From the form of collecting and using information data of big data platform, when collecting information resources of IPE, universities should comprehensively include teachers, college students, counselors, and other subjects involved in IPE activities, and comprehensively collect and sort out relevant data of their participation in education.

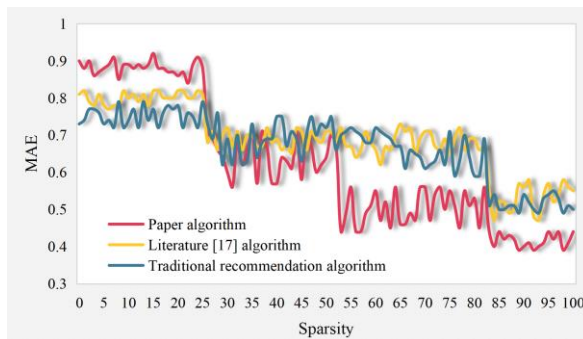


Figure 4: Performance comparison between algorithms with different sparsity.

Table 1 shows the change in model accuracy when different iterations are set. Six groups of data with iteration times between 2000 and 12000 were selected to observe the change in model accuracy.

<i>Iterations</i>	<i>Accuracy rate</i>
2000	32.6%-67.5%
4000	43.4%-71.8%
6000	61.2%-73.5%
8000	71.4%-85.6%
10000	80.3%-92.3%
12000	81.2%-93.6%

Table 1: Model accuracy with different iterations.

It can be seen that after many iterations, the accuracy of the algorithm gradually improves and tends to be stable. Under the support of big data technology, to realize the precise transformation of IPE, teachers must learn to use data to analyze and solve problems, really understand the use value of big data, and guide the use of big data technology with correct data governance concepts. The MAE results between algorithms are shown in Figure 5. The recall of different algorithms is shown in Figure 6.

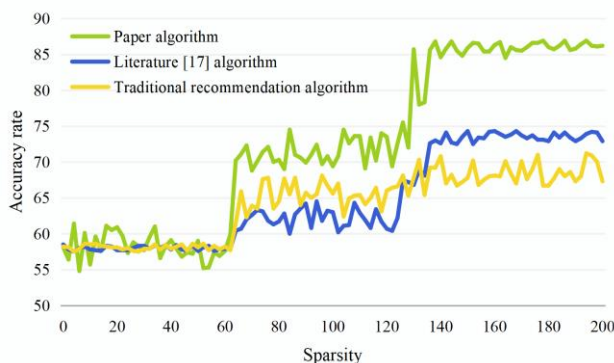


Figure 5: Mean absolute error results of different algorithms.

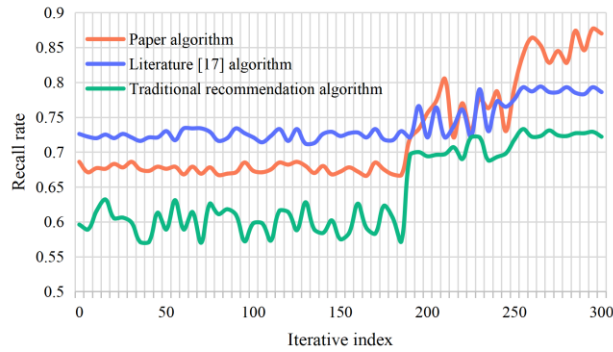


Figure 6: Recall the results of different algorithms.

Table 2 shows the experimental results of screening evaluation indexes. A comparison of recommended accuracy between models is shown in Figure 7.

<i>Model</i>	<i>Average precision</i>	<i>Average recall</i>
Weighted association rules	88.35%	90.41%
Literature [17] algorithm	83.14%	85.31%
Paper recommends model	94.25%	95.18%

Table 2: Experimental results of filtering evaluation indicators.

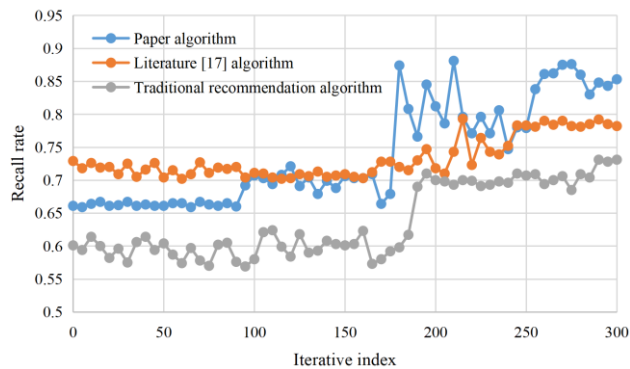


Figure 7: Recommendation accuracy results of different models.

It is not difficult to see that the recommendation algorithm in this paper has a high accuracy, which is 16.75% higher than the traditional recommendation algorithm. The user's evaluation of the accuracy of the recommendation results of the learning resource precision recommendation system is scattered. The construction of IPECU's network instructional resources can greatly promote its network teaching. Its in-depth development can realize the sharing of network instructional resources of IPE, enrich the content of network teaching of IPECU, stimulate students' learning enthusiasm, and improve the effect of network teaching of IPECU. A large part of the reason lies in the fact that there are not many users and resources in the system at the early

stage of transportation. Most of the recommendations can only be made according to the user-resource label, and the CF algorithm fails to exert its real evaluation ability. When the number of users and resources on the system reaches a certain number, the recommended results will be more accurate.

5 CONCLUSIONS

The construction of IPECU's network instructional resources can greatly promote its network teaching. Although many universities have implemented online teaching in IPE, the development of online teaching of ideology courses is restricted by the unsatisfactory construction of online instructional resources. Its in-depth development can realize the sharing of network instructional resources of IPE, enrich the content of network teaching of IPECU, stimulate students' learning enthusiasm, and improve the effect of network teaching of IPECU. In this paper, the CF algorithm is used to analyze user preferences. The exploration of intelligent ideology mode is helpful for teachers to use big data technology to collect students' data information scattered in cyberspace, grasp students' states in real-time, supply accurate instructional resources and design targeted teaching plans according to students' different states and needs.

Zhang Lei, <https://orcid.org/0009-0009-1165-058X>

Yao Fu, <https://orcid.org/0009-0006-2237-3563>

REFERENCES

- [1] Lei, W.; Qing, F.; Zhou, J.: Improved Personalized Recommendation based on Causal Association Rule and Collaborative Filtering, *International Journal of Distance Education Technologies*, 14(3), 2016, 21-33. <https://doi.org/10.4018/IJDET.2016070102>
- [2] Gaynor, J. W.; Brown, D.: An Online Booking System Encourages Self-Directed Learning and Personalization of Study, *Journal of Chemical Education*, 89(8), 2012, 1019-1024. <https://doi.org/10.1021/ed200446p>
- [3] Pérez-Milans, M.: Being a Chinese newcomer in Madrid compulsory education: Ideological constructions in language education practice, *Journal of Pragmatics*, 43(4), 2011, 1005-1022. <https://doi.org/10.1016/j.pragma.2010.10.003>
- [4] Kravet, S. J.; Wright, S. M.; Carrese, J. A.: Teaching Resource and Information Management Using an Innovative Case-based Conference, *Journal of General Internal Medicine*, 16(6), 2010, 399-403. <https://doi.org/10.1046/j.1525-1497.2001.016006399.x>
- [5] Bian, W.; Ding, S.; Jia, W.: Collaborative filtering model for enhancing fingerprint image, *Iet Image Processing*, 12(1), 2017, 149-157. <https://doi.org/10.1049/iet-ipr.2017.0059>
- [6] Ito, H.; Yoshikawa, T.; Furuhashi, T.: A study on improvement of serendipity in item-based collaborative filtering using association rule, *IEEE International Conference on Fuzzy Systems*, (15), 2014, 977-981. <https://doi.org/10.1109/FUZZ-IEEE.2014.6891655>.
- [7] Zhu, T.; Ren, Y.; Zhou, W.; et al.: An effective privacy-preserving algorithm for neighborhood-based collaborative filtering, *Future Generation Computer Systems*, 36(jul.), 2014, 142-155. <https://doi.org/10.1016/j.future.2013.07.019>
- [8] Nilashi, M.; Ibrahim, O. B.; Ithnin, N.: Hybrid recommendation approaches for multi-criteria collaborative filtering, *Expert Systems with Applications*, 41(8), 2014, 3879-3900. <https://doi.org/10.1016/j.eswa.2013.12.023>
- [9] Yz, A.; Hao, L. A.; Ping, Q. A.; et al.: Heterogeneous teaching evaluation network based offline course recommendation with graph learning and tensor factorization - *ScienceDirect, Neurocomputing*, 415(10), 2020, 84-95. <https://doi.org/10.1016/j.neucom.2020.07.064>
- [10] Ym, A.; Me, A.; Jb, A.; et al.: Social Collaborative Filtering Approach for Recommending Courses in an E-learning Platform, *Procedia Computer Science*, 151(11), 2019, 1164-1169. <https://doi.org/10.1016/j.procs.2019.04.166>

- [11] Toledo, R. Y.; Mota, Y. C.: An e-Learning Collaborative Filtering Approach to Suggest Problems to Solve in Programming Online Judges, *International Journal of Distance Education Technologies*, 12(2), 2014, 51-65. <https://doi.org/10.4018/ijdet.2014040103>
- [12] Chen, L.; Lee, M Y.; Wu, J.: Analysis of higher education and management model based on cognitive anthropology, *Cognitive Systems Research*, 52(DEC.), 2018, 909-916. <https://doi.org/10.1016/j.cogsys.2018.08.017>
- [13] Cakir, O.; Simsek, N.: A comparative analysis of the effects of computer and paper-based personalization on student achievement, *Computers & Education*, 55(4), 2010, 1524-1531. <https://doi.org/10.1016/j.compedu.2010.06.018>
- [14] Koren, Y.: Factor in the neighbors: Scalable and accurate collaborative filtering, *Acm Transactions on Knowledge Discovery from Data*, 4(1), 2010, 1-24. <https://doi.org/10.1145/1644873.1644874>
- [15] Pang, Y.; Jin, Y.; Zhang, Y.; et al.: Collaborative filtering recommendation for MOOC application, *Computer Applications in Engineering Education*, 25(1), 2017, 120-128. <https://doi.org/10.1002/cae.21785>
- [16] Pan, W.; Liu, M.; Zhong, M.: Transfer Learning for Heterogeneous One-Class Collaborative Filtering, *IEEE Intelligent Systems*, 31(4), 2016, 43-49. <https://doi.org/10.1109/MIS.2016.19>
- [17] Li, J.; Yang, J. J.; Yu, Z.; et al.: Enforcing Differential Privacy for Shared Collaborative Filtering, *IEEE Access*, 5(1), 2017, 35-49. <https://doi.org/10.1109/ACCESS.2016.2600258>
- [18] Zhang, Y.; Wu, J.; Wang, H.: Neural Binary Representation Learning for Large-Scale Collaborative Filtering, *IEEE Access*, 7(99), 2019, 60752-60763. <https://doi.org/10.1109/ACCESS.2019.2915331>
- [19] Bobadilla, J.; Serradilla, F.; Bernal, J.: A new collaborative filtering metric that improves the behavior of recommender systems, *Knowledge-Based Systems*, 23(6), 2010, 520-528. <https://doi.org/10.1016/j.knosys.2010.03.009>
- [20] Li, D.; Chao, C.; Qin, L.; et al.: An algorithm for efficient privacy-preserving item-based collaborative filtering, *Future Generation Computer Systems*, 55(FEB.), 2016, 311-320. <http://dx.doi.org/10.1016/j.future.2014.11.003>
- [21] Albadvi, A.; Shahbazi, M.: Integrating rating-based collaborative filtering with customer lifetime value: New product recommendation technique, *Intelligent Data Analysis*, 14(1), 2010, 143-155. <https://dl.acm.org/doi/10.5555/2691093.2691104>
- [22] Pan, W.; Chen, L.: Group Bayesian personalized ranking with rich interactions for one-class collaborative filtering, *Neurocomputing*, 207(sep.26), 2016, 501-510. <https://doi.org/10.1016/j.neucom.2016.05.019>
- [23] Hsu, C. K.; Hwang, G. J.; Chang, C K.: A personalized recommendation-based mobile learning approach to improving the reading performance of EFL students, *Computers & Education*, 63(apr.), 2013, 327-336. <https://doi.org/10.1016/j.compedu.2012.12.004>