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Improving the Personalized Analysis of Network Education based on Recommendation Algorithms

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ABSTRACT

With the rapid development of science and technology, the internet and new media have entered the era of algorithmic recommendation. This article investigates and analyzes the new characteristics of content dissemination and discourse expression in university network education from the perspective of recommendation algorithms. Addressing the practical dilemmas of value bias at different stages of integration, decreased independent thinking ability of learners, and divergence of social values, this study explores the incorporation of algorithmic recommendation techniques into university network education. It proposes guiding strategies, such as the "guiding algorithm," "approaching algorithm," and "moving away from algorithm," to provide references for the realization of "recommendation algorithm + university network education" and promote the healthy development of university network education.

Keywords: Recommendation Algorithm, University Network Higher Education, Personalized Analysis, Guiding Strategies

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1. Introduction

According to recent statistics, by the end of 2022, over 95% of information dissemination will be accomplished by algorithms [1]. This change not only affects technology but also impacts all aspects of our lives. With the development of technology, algorithms have been endowed with increasing power, influencing social culture, directly affecting our daily actions, and even obtaining the status of truth. This change has significantly impacted education in universities, affecting not only classroom teaching and personal life but also societal ideology, leading to substantial transformations in the roles and power dynamics of individuals [2]. As algorithm technology continues to advance, it presents unprecedented development opportunities for university management, while also posing significant challenges. “Higher Education” is a fundamental course for cultivating morality and nurturing talent, but with technological advancements, it faces increasing competition. Therefore, in this competitive environment, it is necessary to take adequate measures to strengthen the practicality of “higher education” and effectively address the various issues it encounters. In recent years, numerous scholars have investigated the use of algorithms to enhance the mental health of undergraduates, and several practical solutions have been developed, resulting in significant progress [3]. However, most research remains focused on broad fields and lacks practical applications that address the mental health needs of undergraduates. By thoroughly investigating the technical nature of algorithms, we can gain a deeper understanding of how they can enhance undergraduates’ ideological and moral development and prepare them for further research in this field. The new recommendation algorithm, which combines collaborative filtering and content filtering, effectively integrates users’ past experiences, characteristics, and product features, thereby greatly enhancing the accuracy and richness of recommendations [4]. By analyzing item attribute information, including categories, tags, and keywords, an item profile is established to identify other items similar to the target item and recommend products based on the target user’s interests. The comprehensive recommendation combines collaborative filtering and content filtering, weighting or superimposing the results of the two steps to obtain a comprehensive recommendation result. Then, it ranks the recommendations based on the user’s historical behavior and item attribute information. By improving recommendation algorithms, students are provided with more accurate and personalized learning resources and services, thereby improving the quality of teaching [5]. It promotes the integration of information technology and education, advancing the rapid development of the education sector. It also provides references and insights for personalized education research in other fields. Through in-depth research, we have found that the use of excellent recommendation algorithms makes university online courses highly beneficial for students’ growth. They achieve outstanding grades and are more willing to accept new knowledge. This suggests that, under these circumstances, in designing university courses, we should pay more attention to understanding students’ individual needs to promote their growth better.

2. Related Work

With the popularization of algorithm technology, higher courses in university networks have been significantly influenced [6]. This new course approach leverages a substantial body of research findings, laboratory practice cases, and real-time monitoring to more effectively meet the needs of the audience. Furthermore, this new course approach can better understand the audience’s interests and preferences, and effectively control their mindset changes, thereby publishing course content more targeted to their community. In recent years, numerous scholars have investigated the use of algorithms to enhance the mental health of university students, and several effective solutions have shown promising progress. However, most research still tends to focus on broad fields and lacks practical applications for the mental health of university students. Nevertheless, some scholars have conducted in-depth research in this area.

Researchers, from the perspective of personalized education, have explored the innovation of the university network higher education model and proposed some new educational methods and strategies, such as personalized recommendation based on big data and interactive learning, to increase students' participation and learning effectiveness in higher education [7]. Researchers have used recommendation algorithms to delve into the application of university network higher education. Through accurate insights into students' learning behaviors and interests, they provide targeted learning resources and services, significantly enhancing teaching effectiveness and student satisfaction [8]. Scholars have discussed the innovation and practice of network-based higher education in universities, proposing new educational concepts and approaches, such as internet-based learning platforms and online interactions, to enhance the appeal and effectiveness of higher education [9]. Researchers have studied the application of personalized education in university higher education and proposed new educational strategies and methods, such as personalized tutoring and online learning communities, to promote students' personalized development and improve learning effectiveness [10].

The above literature focuses on the personalized analysis of university network higher education, explores new educational methods and strategies to increase students' participation and learning effectiveness. Among them, the application of recommendation algorithms in university network higher education has also received widespread attention, providing students with more accurate and personalized learning resources and services. At the same time, these literatures propose new educational concepts and approaches, such as internet-based learning platforms and online interactions, to enhance the appeal and effectiveness of higher education. Overall, these studies provide valuable references and insights for the personalized analysis of higher education in university networks.

Recommender systems with information filtering methods can solve the problems posed in network education. [11] A recommender system aims to collect data about users' past interests, purchasing behavior, and evaluations of content they have consumed to predict further potentially interesting items for any individual user [12]. These data typically take the form of ratings given by users to items on an integer rating scale (most often 1-5 stars where more stars mean a better evaluation) but can also be unary in that a user is associated with an item only if the user has purchased, viewed, or otherwise collected it. Since the tastes and interests of users are embedded in the input data, recommendations can be provided without requiring any query or keyword. The selection of items for a particular user is based on the user's past behaviour, thereby ensuring personalised recommendations. However, the extent to which personalization might deteriorate is a function of the relentless pursuit of recommendation quality [13], [14].

Possibly, the most conventional recommendation schemes are collaborative filtering techniques. User-based collaborative filtering identifies users who are similar concerning certain items and then recommends items liked by those similar users to the target user for which recommendations are being computed. It became an area of importance in research regarding smart learning where students could predict the accuracy of recommendations through personalised learning based on the development of smart education into higher education. Even though the accuracy of prediction is enhanced through knowledge tracing models based on historical learning data of the students, the designing and application of personalized learning recommendation in conjunction to classroom teaching of higher education is a significant difficulty. [15]

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3.University Higher Education Model Based on Recommendation Algorithm

3.1 System Modeling

Firstly, the higher education course recommendation system is modeled by using singular value decomposition (SVD) to decompose the high-dimensional sparse matrix into low-dimensional matrices. Then, the behavior data of students are transformed into course preference values through the Analytic Hierarchy Process (AHP). Finally, by establishing a model mapping, the recommendation model is transformed into a Markov decision process. In real life, the student course matrix is large, but individual students have limited interests. The rating data for individual students on courses is usually tiny. The basic principle of SVD is to decompose a complex matrix into two simpler matrices, which is not only suitable for symmetric matrices but also for M×N matrices, effectively reducing the computational workload. However, when decomposing matrices using SVD, each element of the matrix must be cleared before a more compact matrix can be generated. If a student rates a course, it indicates that the student has seen the course. By observing students' rating behavior, we can infer their preferences. Therefore, we can extract this information through implicit parameters to construct the SVD model more accurately, as shown in Formula 1.

$$r_{px} = \mu + d_p + d_x + v_x^T u_p \qquad (1)$$

3.2 Layered Model for Student Interest Calculation

To analyse the implicit bias in students' course preferences, data on students browsing course introductions, collecting courses, and learning courses were first collected. Then, use the AHP to calculate students' preference values for the course. The problems that students like are categorized into three layers: target layer, standard layer, and program layer. Use browsing course introductions, bookmarking courses, and learning courses as decision-making criteria. The hierarchical model for calculating student interest is illustrated in Figure 1. A Pairwise comparison of different factors constructs the judgment matrix C. Adding bookmarks to courses is more important than browsing course introductions. Learning course content is more important than collecting courses. Therefore, the ratios are set as follows: the ratio of collecting courses to browsing courses is 3:1; the ratio of learning courses to browsing courses is 5:1; and the ratio of learning courses to collecting courses is 3:1.

3.3 Markov Decision Process

The Markov Decision Process (MDP) is a practical decision theory that transforms complex environmental variables into controllable states and actions, enabling efficient decision-making processes. It helps us better understand and predict complex decision-making processes. The objective of controlling the system in this way is to maximize the performance criteria of the model. The Markov Decision Process has been successfully applied to model various problems, including multi-agent problems, robot learning and control, and game problems. Therefore, the Markov Decision Process has become a standard method for solving sequential decision-making problems. Through reinforcement learning techniques, we can transform the reward and punishment signals of the recommendation model into a mapping relationship that enables the agent to transition from one state to another, thereby improving the prediction of student preference scores at different timestamps. For the reward and punishment functions, the values of the reward and punishment functions represent the rewards for performing actions in specific states. The definition of reward and punishment function values in this study is presented in Formula 2, where Sn represents the state, and Cn and Rn are used to guide the agent in perceiving information about the current environment.

$$R_{gm}\left(s_n^{(p)}, c_n^{(p)}\right) = s_{n+2}^{(p)} - r_{px} \qquad (2)$$

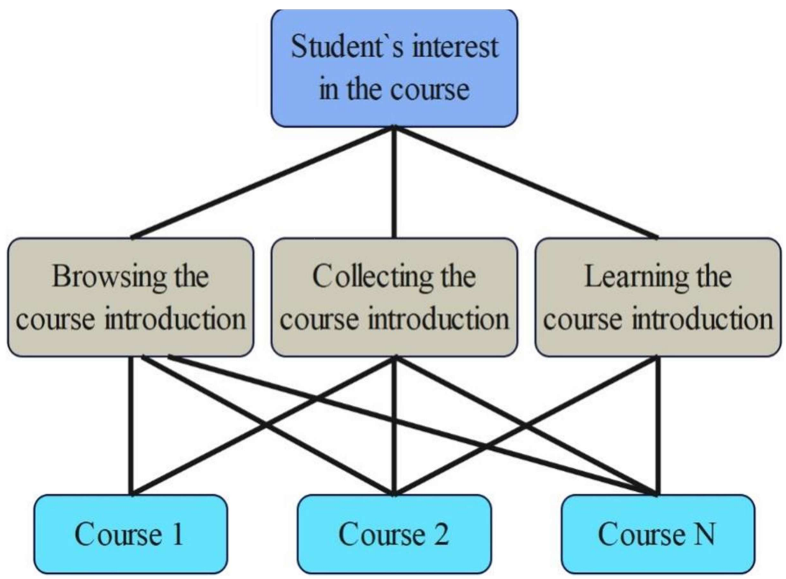

Figure 1. Hierarchical Model

3.4 Recommendation Model Kernel

Based on the knowledge point mining and weight calculation results of political thought courses, as well as the knowledge features involved in user interest modeling, a university political thought course recommendation model is established. According to the function, the model is divided into three parts: the input part, the processing part, and the output part. To address the issue of traditional recommendation methods ignoring user behavior sequences and multiple user interests, a hybrid recommendation model of Backpropagation (BP) and Recurrent Neural Network (RNN) is designed. The behavior sequence includes almost all the information that interests the user. The system's input is the user's behavior, and its output is a description of events that occurred within a specific period. In the input layer, the size of the input vector depends on the number of items; generally, the number of active items is 1, and the rest are 0. Both the RNN and BP neural networks have the same output layer. The network's foundation is to integrate the input and output layers to obtain a single result, which can be represented using Formula 3.

$$Z = \sum_{i=1}^{N}\left(f_1\left(\sum_{i=1}^{N} z_i w_{ki} - \theta_i \right) - Y_k \right) \qquad (3)$$

4. Experimental Design and Analysis

4.1 Experimental Design

To evaluate the effectiveness of the proposed algorithm for a university political thought course that accommodates multiple user interests, an experimental analysis was conducted. It was compared with common recommendation algorithms, such as personalized recommendation algorithms based on user behavior feature mining and those integrating trust relationships, time factors, and tag information. The system had 13 registered users and provided 680 courses related to computer science, English, and political thought. The system collected 17,080 valid learning records and evaluation results, with the training set achieving a hit rate of 118%, amounting to 200,000 records, and the test set achieving a hit rate of 30%, amounting to 30,000 records. Using web crawling technology, valuable, reliable, and actionable content could be searched from a large number of political thought courses and related user groups. Different types of learning content could be retrieved one by one from the specified category column on the webpage. Using an ID code table, the initial IDs could be extracted from multiple categories of ID codes and adjusted to 1 for quick retrieval of the required user information from the data set and verification of the reliability of these ID codes. Then, by viewing the detailed information of each ID code, their learning situation could be understood. To address the lack of targetedness and inability to form personalized recommendations for university political thought education courses, a political thought education recommendation system was proposed, divided into the following three points. By introducing collaborative filtering algorithms and reinforcement learning reward-punishment mechanisms, a novel method was developed to enhance students' academic performance. This method used timestamps to measure students' interests and used the Analytic Hierarchy Process (AHP) to determine their preference levels. To meet the educational needs of different categories, a new collaborative filtering algorithm was developed, which effectively identifies and selects university political thought courses with specific features. The algorithm combined hybrid filtering technology with an incremental forgetting curve to enhance the efficiency and flexibility of traditional collaborative filtering algorithms, thereby better meeting the needs of the education market. By adopting historical preference fusion technology, the individual characteristics of each student were grouped into distinct categories and combined to create a customized historical preference fusion database, enabling the measurement of the educational effectiveness of political thought courses. To validate the effectiveness of the algorithm, this paper selected representative matrix factorization algorithms, direct trust matrix factorization algorithms, and indirect social relationship matrix factorization algorithms for comparison in the experiment. All experiments were conducted 10 times, and the results were averaged. By examining the data in the table, it is evident that the error value of this algorithm is lower than that of the other compared algorithms, and as the training set increases, the error comparison becomes more pronounced. The more extensive the training set, the lower the error rate of the algorithm.

4.2 Experimental Result Analysis

The personalized recommendation algorithm based on user behavior feature mining and the personalized recommendation algorithm integrating trust relationships, time factors, and tag information were compared with the proposed algorithm. The experiment selected the recommendation list length as 1, 5, 10, 15, 20, 25, and 30, and the comparison results of the precision of the three recommendation algorithms under different recommendation list lengths are shown in Figure 2. From the graph, it can be observed that when the recommendation list length is between 5 and 15, the precision of the proposed algorithm does not show a significant improvement trend. As the recommendation list length increases, the precision of the proposed algorithm improves significantly, reaching a maximum accuracy rate of 97%. The personalized recommendation algorithms, based on user behavior feature mining and the integration of trust relationships, time factors, and tag information, do not exhibit significant changes in recommendation accuracy. The experimental results indicate that, compared to the other two recommendation algorithms, the proposed algorithm consistently achieves the highest precision, and this advantage becomes more pronounced as the recommendation list increases. The experiment demonstrates that the proposed algorithm yields better recommendation results.

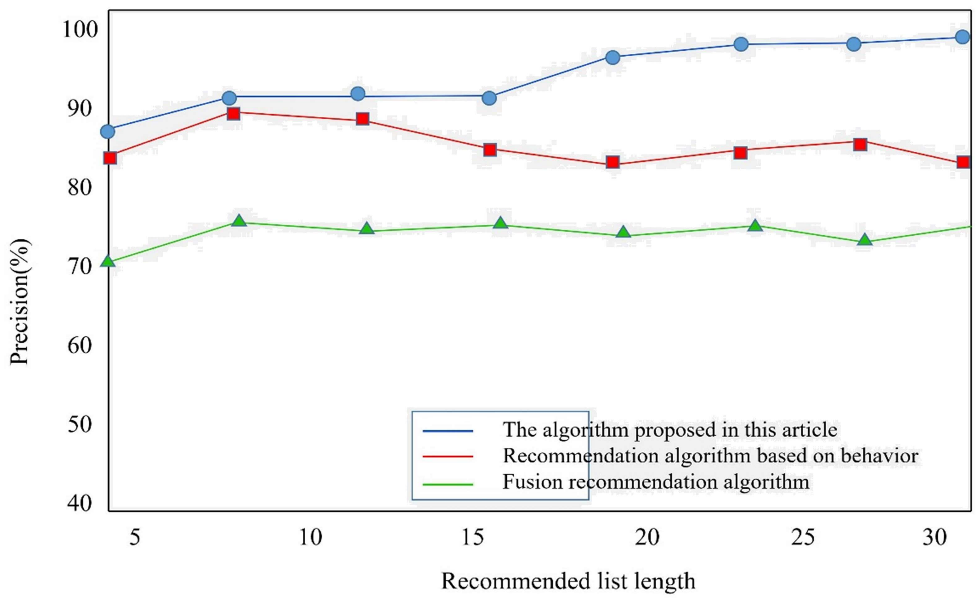

Figure 2. Precision Comparison Results

The proposed algorithm achieves a maximum user coverage of 98% through analysis at various iteration times. The user coverage of the personalized recommendation algorithm based on user behavior feature mining is highest at 78%. The personalized recommendation algorithm, which integrates trust relationships, time factors, and tag information, achieves a maximum user coverage of 72%. At different user numbers, the maximum user coverage of this algorithm is 92%. The personalized recommendation algorithm, based on user behavior feature mining, achieves the highest user coverage of 61%. The personalized recommendation algorithm, which integrates trust relationships, time factors, and tag information, achieves a maximum user coverage of 64%. By comparing the above data, the effectiveness of this algorithm is verified, and it can recommend suitable political thought courses to a more significant number of students. As shown in Figure 3, the proposed algorithm generally exhibits high optimization ability, with an optimization ratio above 0.75. It can be seen that using this method for recommending political thought courses has good optimization ability and convergence. At the beginning of the iteration, the error value of the algorithm is approximately 1.38. By observation, it can be seen that the error value of the algorithm in the first iteration is less than 0.38. As the number of iterations increases, convergence and maximum error are achieved only after 20 iterations. However, the algorithm indirectly corrected the student's preference vector and achieved convergence after 15 iterations, followed by recommendation efficiency. Due to the optimization of preference vectors and feature vectors from both the student and course perspectives, the algorithm achieved convergence with a smaller error value in the fourth iteration. The experimental results further validate the accuracy and convergence performance of the proposed algorithm's recommendations.

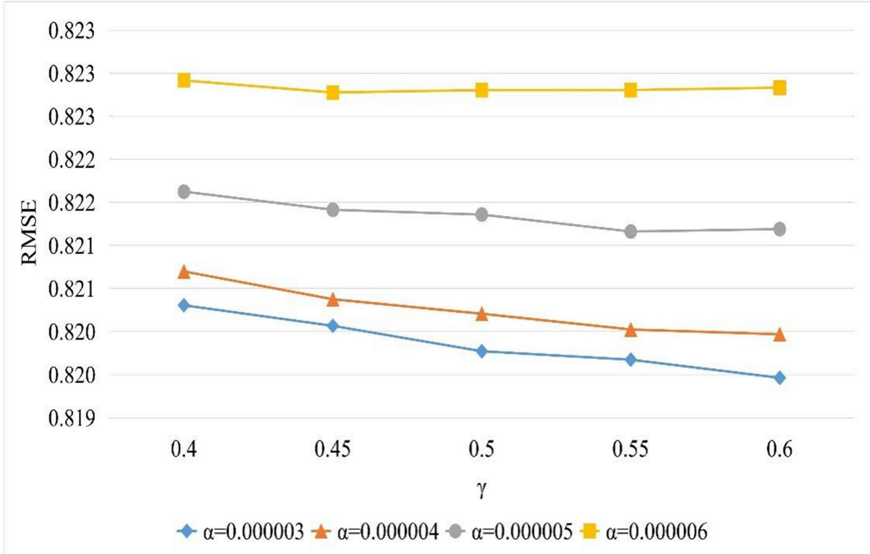

Figure 3. The Impact of Different γ on RMSE

5. Future Directions

Higher education is about begetting ethical citizens and building professionals worldwide. However, generative AI, like ChatGPT, presents unique opportunities and challenges to the older education model. (16) Many educators and policymakers are curious about what Genai can and cannot do. (17). These AI chatbots and lesson-interactive books allow students to converse with machines regarding learning and thus improve their communication skills through ongoing dialogue with such technologies. (18-21). Recommender Systems have a broader scope in using AI technologies for network education. The analysis shows that Recommendation Systems make suggestions considering recommendations from similar users according to user preferences (22, 23, 24, 25, 26) and make recommendations as per learning style and diagnosis/student progression and knowledge group. (27-31).

6. Conclusion

Political thought courses encompass the entire process of higher education teaching and serve as a necessary system for universities to cultivate high-quality skills and abilities. In light of this, this study aims to develop a new method to cater to the personalized needs of political thought education courses. This method employs a multidimensional hierarchical analysis process and incorporates an enhanced collaborative filtering algorithm. This research presents a personalized recommendation algorithm tailored to multiple user interests in political thought courses at universities, aiming to provide personalized recommendations for political thought education courses. The experiments demonstrate that it offers advantages regarding recommendation accuracy, user coverage, recommendation efficiency, optimization, and other key aspects. The influencing factors are deeply understood by treating students' course ratings at different intervals as a Markov decision process. The behavior data of students are transformed into course preference values through the hierarchical analysis process. Combining a collaborative filtering algorithm with a reinforcement learning reward and punishment process improves the predictive effect by adjusting the influencing factors. The experimental results demonstrate the feasibility of the proposed system, showing good accuracy and convergence performance. Improving the algorithm's accuracy in cases of insufficient training data is a future research direction.

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