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Design of a Student Recommendation Platform Based on Learning Behavior and Habit Training

Xiaoyun Zhu*

Yunnan Open University, Kunming 650500, Yunnan Province, China

***Corresponding author:** Xiaoyun Zhu, 15812040598@139.com

Abstract: This study innovatively built an intelligent analysis platform for learning behavior, which deeply integrated the cutting-edge technology of big data and Artificial Intelligence (AI), \mined and analyzed students' learning data, and realized the personalized customization of learning resources and the accurate matching of intelligent learning partners. With the help of advanced algorithms and multi-dimensional data fusion strategies, the platform not only promotes positive interaction and collaboration in the learning environment but also provides teachers with comprehensive and in-depth students' learning portraits, which provides solid support for the implementation of precision education and the personalized adjustment of teaching strategies. In this study, a recommender system based on user similarity evaluation and a collaborative filtering mechanism is carefully designed, and its technical architecture and implementation process are described in detail.

Keywords: Big data analysis; Collaborative filtering; Learning behavior analysis; Personalized recommendation; Intelligent matching

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1. Research background

In the wave of digital education, given the challenges of college students' confusion in learning, insufficient interaction, difficulty in finding partners, and difficulty in understanding the learning situation of teachers, we have created a new comprehensive communication platform based on deep behavior analysis [1]. Relying on big data and AI technology, the platform accurately analyzes the learning trajectory and realizes the personalized push of resources and intelligent matching of partners. For students with weak self-management and lack of interaction, cutting-edge algorithms, and multi-dimensional data fusion are used to create an active interactive, and autonomy-driven learning ecology. At the same time, detailed student portraits are provided for teachers to help precise teaching and optimize teaching strategies [2]. This platform is not only an efficient tool for students to improve their growth but also a key support for teachers' smart teaching and quality improvement [3].

2. Recommendation based on similarity and collaborative filtering algorithm

2.1. Calculate the similarity between two students using the Euclidean formula

The Euclidean distance is calculated as follows:

$$E(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \ldots + (p_n - q_n)^2} = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \quad (1)$$

The Euclidean distance is a non-negative number, with a maximum of positive infinity, but similarity values are generally in the range [-1,1]. You can invert it to get the result between [0,1]. The denominator +1 is to avoid the divisible by 0 error. Finally, Euclidean's formula for calculating the similarity between two students is:

$$similarity\,(p, q) = \frac{1}{1 + E(p, q)} \quad (2)$$

The larger the distance between two students, the smaller the similarity, and the smaller the distance, the larger the similarity [4]. In this application, we can use the following steps to generate the user similarity matrix [5]:

(1) Collect user data and extract feature vectors for each user.

(2)Compute the similarity between any two users using the Euclidean algorithm.

(3)Store the calculated similarity values in a matrix, where the rows and columns represent the users, and each element in the matrix represents the similarity value between the two users.

(4)This matrix can be used in recommender systems, cluster analysis, and other tasks [6].

2.2. Use a collaborative filtering algorithm to generate a user prediction rating matrix

The user-based collaborative filtering algorithm, a widely used strategy in recommendation systems, identifies groups of users with similar interests to the target user. Based on the preferences of these similar users, it recommends courses that the target user may find appealing. The detailed execution process of the algorithm is as follows.

(1) User similarity matrix construction: Using the Euclidean distance calculation method or other suitable similarity measurement methods, the system calculates the similarity between each pair of users and then constructs a user similarity matrix [7]. This matrix is the basis for subsequent steps to measure the similarity of users' interests.

(2) Filter neighbor users: According to the constructed user similarity matrix, the algorithm will filter out the user group with high similarity to the target user as the "neighbor users." These neighbor users are considered to have strong predictive power for the course preference of the target user due to their high consistency in interests.

(3) Predict the ratings and construct the matrix: The user similarity matrix is combined with the rating information of these neighbor users to predict the potential ratings of the target users for the courses that they have not yet followed by matrix operations (such as weighted average) [8].

(4) Generate a personalized recommendation list: Based on the ratings in the predictive rating matrix, we sort the candidate courses in order of the predicted ratings and generate a personalized recommendation list [9]. This list contains a series of course resources the system thinks the target user will most likely be interested in.

Although collaborative filtering algorithms have shown excellent performance in user-based recommendation systems, their performance may become a limiting factor when dealing with large-scale data sets. To overcome this problem, we introduce advanced dimensionality reduction techniques to simplify the data processing process and reduce the computational complexity. Simultaneously, we implement a data sparsification strategy to effectively reduce the amount of data required for calculation.

3. Technical scheme

We built a comprehensive curriculum learning platform, which has a clear design logic and is divided into several core levels from top to bottom: interactive interface layer, data collection layer, data analysis layer, recommendation algorithm design based on collaborative filtering, and data application layer. It not only realizes the closed-loop process from data collection to analysis and then to personalized recommendation but also ensures seamless integration and efficient collaboration between each component. The specific system framework is shown in **Figure 1**.

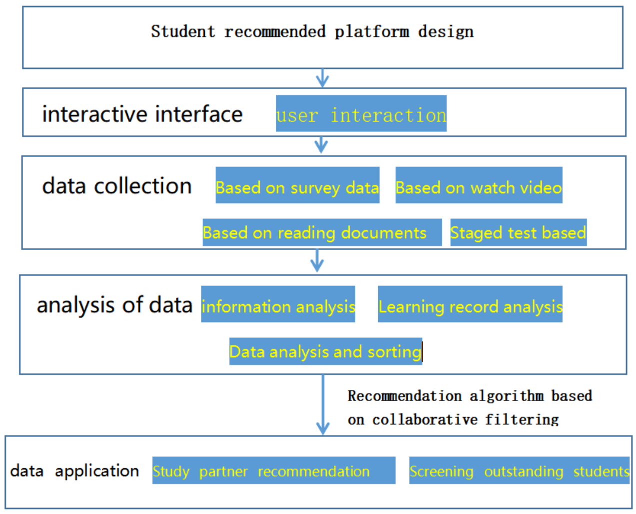

Figure 1. System frame diagram

(1) Interactive interface layer functions: Through carefully designed questionnaires, we can flexibly collect data for specific needs [10]. These data are like a window, allowing us to deeply understand students' interests, learning habits, and basic information, laying a solid and clear path for subsequent data analysis, and ensuring the reliability and pertinence of the analysis results.

(2) Data collection layer functions: In the part of learning documents, we are committed to laying a systematic way for users to learn by themselves, eliminating information fragmentation, helping users to plan their learning process efficiently, and saving valuable time [11]. In terms of video tutorials, we have gathered the latest and most popular learning resources to ensure that every learner can enjoy a smooth, efficient, and focused learning experience. On this basis, we also innovatively introduce a phased self-testing mechanism to encourage students to consolidate knowledge and test the effect immediately after completing the document reading and video learning of each chapter. The platform will comprehensively track and record each student's learning process and test score, providing data

support for subsequent personalized learning evaluation and guidance.

(3) Data analysis layer function: We first analyze the collected data in depth, clarify the data structure by drawing an accurate entity relationship diagram, and then build a comprehensive and efficient database system. This step not only ensures the integrity of the data but also lays a solid foundation for subsequent advanced analysis.

(4) Algorithm design layer function: Facing the personalized recommendation problem of massive learning resources in online education platforms, we abandon the traditional content-oriented or single-user feature recommendation framework, and instead deeply explore the analysis of user behavior characteristics to capture the similarity between users from a refined perspective [12]. Through the original comparison of the similarity of learning behavior sequences, we implement an enhanced user-based collaborative filtering strategy, which goes beyond the limitations of single-dimensional analysis, and penetrates the broad user community to accurately identify users with similar learning interests, and then integrates these users' preference data to predict and meet the personalized learning needs of current users. Despite the challenges posed by data sparsity and other issues, collaborative filtering still firmly occupies the core position in the field of personalized recommendation due to its excellent ability to deal with complex data structures and significant advantages in recommendation performance. In practice, we use the "k-nearest neighbor" algorithm to accurately locate a user's "learning partners," and according to the preferences of these partners, we tailor an accurate learning resource recommendation scheme for each user.

(5) Data application layer: Integrates document learning, video learning, and stage test data, calculates the similarity between students through the Euclidean distance, and calculates its reciprocal value to identify similar learning partners, forming the first data support [13]. Then, the user-based collaborative filtering algorithm was used, and the Euclidean algorithm was used to calculate the user similarity again, the user neighbor set was constructed, and the similarity matrix was generated. Combined with the user-course rating matrix, the user's rating of unfollowed videos was predicted, and the predicted rating matrix was obtained by matrix multiplication, which was used as the second key data support to jointly optimize the learning partner recommendation.

4. System implementation

This recommendation system deeply integrates big data analysis technology, carries out comprehensive evaluation and refined classification recommendations of students, promotes accurate pairing between learning partners, and assists teachers in accurately discovering outstanding students in programming [14]. Students need to register and log in to the system when they first use it. Through a carefully designed interest survey questionnaire, the system initially depicts each student's personalized interest profile, and then intelligently pushes course materials and video tutorials closely linked to their interests. During the learning process, the system dynamically monitors students' stage assessment scores, learning trajectories, and homework submissions, and deeply excavates their learning patterns and specialties. Based on these rich multi-dimensional data, the system uses advanced algorithms to accurately match learning partners that resonate with students' interests and have suitable abilities. The system's built-in elite recognition engine can also automatically select students who show extraordinary talent in the field of programming and give feedback to teachers.

5. System test

Representative results for the user recommendation accuracy test are shown in **Table 1**.

Table 1. User recommendation accuracy test

User information	Recommended user information	Is it best?	Description
Document score: 36 Video score: 42 Stage test score: 91	Document score: 38 Video score: 46 Stage test score: 89	Yes	The difference between the two users in the stage test scores is relatively small. Their similarity is relatively high.
Document score: 63 Video score: 24 Stage test score: 14	Document score: 67 Video score: 26 Stage test score: 17	Yes	The two users are more similar in the document score, but less similar in the video and stage test.
Document score: 130 Video score: 150 Stage test score: 130	Document score: 121 Video score: 145 Stage test score: 153	Yes	The average score similarity between two users are high, and the recommendation algorithm is within the budget.

After a 60-day testing period, our platform demonstrated an ability to provide valuable learning resources to support students in extracurricular learning and foster their interest in learning. In assessing learning ability, a sample survey revealed that approximately half of the students showed limited point accumulation, which directly reflected lower levels of motivation. Meanwhile, only a small number of students excelled, achieving high scores. These results not only highlight the differences in students' learning abilities but also confirm that our evaluation system effectively identifies and recognizes excellent learning performance.

6. Concluding remarks

In exploring the integration of learning behavior training and student recommendation platforms, we are committed to creating an ecosystem that promotes both personalized learning and peer support. Through accurate data analysis and intelligent recommendation, the platform not only helps students optimize their learning habits and improve learning efficiency but also virtually weaves a close learning network so that each student can find like-minded partners and move forward together [15]. Looking forward to the future, we will continue to optimize the function of the platform, deepen the application of educational technology, and contribute to the cultivation of more future talents with innovative spirit and practical ability.

Disclosure statement

The author declares no conflict of interest.

References

[1] Ye J, 2015, Improvement of Middle School Chemistry Teaching and Research Based on Data Analysis of Academic Quality Monitoring Platform. Invention and Innovation: Vocational Education, 2015(05): 25–29.

[2] Zhang Y, 2024, Analysis of Student Behavior Based on Big Data Technology, thesis, North China University of Water Resources and Hydropower.

[3] Ren M, 2019, Big Data Personalized Recommendation Analysis. Internet of Things Technology, 9(11): 62–64 + 67.

[4] Li C, 2021, Research on the Correlation Discovery and Application of Online Learning Behavior and Achievement, thesis, Tianjin University.

[5] Fan Z, 2014, Mahout Algorithm Analysis and Case Practice. China Machine Press, Beijing.

[6] Liu X, Zhang JM, 2008, A Survey of Recommender Systems for E-commerce. Journal of Shopping Malls Modernization, 2008(28): 51.

[7] Liu J, 2016, An Improved Location-based Recommendation Algorithm. Software Guide, 15(09): 39–41.

[8] Wang Y, 2019, Construction of Personalized Learning Platform Based on Intelligent Algorithm. Journal of Tianjin Vocational College of Commerce, 7(6): 7.

[9] Zhou X, 2022, Design and Implementation of University Book Recommendation System Based on Students' Learning Behavior, thesis, East China Normal University.

[10] Yan T, Wen X, Zhao J, et al., 2017, Design and Implementation of Visual Data Analysis Platform Based on Python. Computer Times, 2017(12): 54–56.

[11] Chen J, Fang H, Lin X, et al., 2018, Based on Online Learning Behavior Analysis of Personalized Recommendation. Journal of Computer Science, 45(B11): 6.

[12] Sun G, 2010, Research Status and Analysis of Online Learners' Learning Behavior. China Education Informationization: Higher Vocational Education, 2010(15): 18–21.

[13] Geng N, Chen M, 2018, Research Status and Development Trend of Personalized Recommendation of Online Learning Resources. China Education Informatization (Higher Vocational Education), 2018(21): 1–6.

[14] Ye X, 2013, Analysis of the Hierarchical Teaching Method of Junior High School Mathematics under the New Curriculum Standard. New Curriculum Learning (Academic Education), 2013(09): 102.

[15] Zhou X, 2022, Design and Implementation of University Book Recommendation System Based on Students' Learning Behavior, thesis, East China Normal University.

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