

Construction of a Personalized Recommendation Service Model for Online Learning Resources

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Keywords: Personalized Recommendation, Online Learning Resources, Collaborative Filtering, User Satisfaction

Abstract: In the digital age, the role of personalized learning resource recommendation system in improving learning experience and educational effect cannot be ignored. Accordingly, this article proposes a personalized recommendation service model for online learning resources to improve the accuracy, efficiency and user attention of the recommendation system. Starting with the data collection and processing of user behavior and the metadata analysis of learning resources, a recommendation algorithm based on collaborative filtering method is designed, and the content recommendation technology is applied to solve the cold start problem. This network architecture adopts micro-service architecture, which ensures the scalability and high concurrent processing ability of the system. The maximum recommendation accuracy of the system reaches 98.3%, the recall rate reaches 99.3%, the maximum response time is 895 milliseconds, and the user satisfaction reaches 8 to 9.9. This article also discusses the current challenges, such as the privacy protection of users, the transparency of recommendation and the real-time performance of the system, and puts forward relevant potential solutions, such as data encryption, enhancing the interpretability of the model and updating the recommendation model in real time. In future work, it can study how to apply deep learning to personal recommendation with higher accuracy.

1. Introduction

With the rapid growth of online learning platform, it is an important task in the field of educational technology to provide learning resources that match learners' interests and abilities.

In the personalized recommendation system proposed in this article, user behavior data, learning resource metadata and anonymous user feedback data are analyzed to deeply capture user needs and provide efficient learning resource recommendation. In addition, this article also discusses the transparency, real-time performance and privacy protection in the recommendation system, including data anonymity, model interpretability enhancement and real-time update.

The article first introduces the research background and significance of personalized recommendation systems, clarifies the research objectives and contributions of this article. Next, the theoretical foundation and key technologies of personalized recommendation systems were

reviewed, and the shortcomings of existing research were pointed out. In the methodology section, the data collection and processing methods, recommendation algorithm design, system architecture and implementation of the recommendation system are described. The Results and Discussion section presents the performance evaluation results of the recommendation system, analyzes recommendation accuracy, recall rate, user satisfaction, and response time, and discusses the challenges and potential solutions faced. Finally, the conclusion section summarizes the main findings and contributions of this study, and provides prospects for future development.

2. Related Work

In today's digital age, personalized learning resource recommendation systems are becoming increasingly important. They analyze the behavior and preferences of learners, provide customized learning content to enhance the learning experience and improve educational effectiveness. Li Chunying proposed a personalized learning resource recommendation model for learners based on knowledge graphs to address the issues of data sparsity and cold start in personalized learning resource recommendations. This model utilizes the historical interaction information between students and courses in online learning, as well as the attribute information of online courses, to construct a course knowledge graph and assist in personalized recommendation of course resources [1]. Liu Fang focused on the problem of personalized recommendation in online learning, where single features are the main focus and multi-dimensional learner models are less studied. Based on learner model specifications and guided by relevant educational theories, she conducts detailed classification research on multi-dimensional personalized features such as learner learning style, knowledge status, cognitive ability, and interest bias [2]. Yue Pei aimed to accurately and reasonably recommend English teaching resources to users. He used web scraping technology to obtain user behavior data and English teaching resource data, extracts their features, and integrates them. He used deep learning models to establish the relationship between user behavior features and English teaching resource features, achieving personalized recommendations [3]. Zhang Xuxiang proposed a personalized learning resource recommendation method based on knowledge graph and graph embedding to address the problems of poor interpretability, insufficient recommendation efficiency and accuracy in existing methods. He constructed an online learning environment knowledge graph based on a universal ontology model for online learning, and trained the knowledge graph using graph embedding algorithms to optimize the graph calculation efficiency in learning resource recommendation [4]. Ma Hua elaborated on the hot topics of combining traditional algorithms with deep learning, knowledge graphs, cognitive diagnosis, etc., to study blended learning resource recommendation, and summarized the research trends in online learning resource recommendation that support knowledge transfer, fragmented resource integration, and dynamic recommendation [5].

In addition, Xu S developed an architecture for an adaptive recommendation model for online learning resources, modeled learners, and fragmented learning resources, exploring the personalized online learning resource recommendation problem based on mobile device-based fragmented learning [6]. Asio J M R aimed to evaluate the implementation of alternative delivery mode learning resources as the basis for the COVID-19 pandemic intervention plan [7]. Ram íez-Donoso L presented quasi experimental results in a blended learning course, in which 294 students used small online private courses as supplements to evaluate the impact of multimedia teaching on student motivation and learning resource consumption [8]. Abdi S proposed a consensus method based on matrix decomposition and pointed out how it can be used to improve the accuracy of aggregated learner decisions. He also demonstrated how to utilize student performance information and combine it with domain experts to rate a limited number of learning resources to further improve

the accuracy of results [9]. Castro M D B used meta-analysis to review literature on the effectiveness of online learning courses. The research results indicate that by providing carefully planned and designed courses and projects for higher education institutions, the effectiveness of online learning courses can be met [10]. After a comprehensive review of the research on personalized recommendation services for existing online learning resources, this article found that although some progress has been made, it still faces performance bottlenecks when dealing with large-scale datasets and real-time recommendation requirements. This study can comprehensively utilize technologies such as machine learning, data mining, user behavior analysis, and knowledge graphs to improve the accuracy, efficiency, and user satisfaction of recommendation systems.

3. Method

3.1 Data Collection and Processing

In the process of collecting user behavior data, this paper adopts a set of comprehensive data tracking and management tools, which are specially designed to capture and record all the interactive behaviors of users on the educational platform. These interactions include key activities such as course selection, video viewing duration, homework submission, search and navigation. The data collection system can handle large-scale data sets, and its capacity is enough to store and process millions of records from thousands of active users.

In the analysis stage, the data cleaning process ensures the accuracy of analysis, removes invalid or abnormal data points, and then selects representative samples from the whole data set for analysis by random sampling technology. This random sampling method not only improves the analysis efficiency, but also ensures the statistical reliability of the analysis results. The specific data are shown in Table 1:

Table 1: User Behavior Data

User ID	Course Selections	Video Watch Duration (min)	Assignment Submission Rate (%)	Search Counts	Average Page Stay Duration (sec)	Navigation Path Length	Interaction Type	Interaction Frequency
U01	5	320	80	45	360	7	Video Watching	Daily
U02	3	240	100	30	300	5	Assignment Submit	Weekly
U03	6	480	60	60	450	9	Course Searching	Every Two Days
U04	4	160	75	20	240	3	Forum Interaction	Every Three Days
U05	2	120	50	15	180	2	Material Download	Weekly
U06	8	640	90	75	540	11	Course Reviewing	After Each Lesson
U07	7	350	85	50	400	8	Social Sharing	After Every Two Lessons

By analyzing the behavioral data in Table 1, it is possible to capture the learning habits, preferred

course types, and their active time periods during the learning process of users, thus providing tailored recommendation content for each user.

The metadata of learning resources provides an understanding of course content and structure, which describes the theme, difficulty, target audience, prerequisite requirements, and teaching resources included in the course, such as videos, reading materials, and exercises, as shown in Table 2 [11-12].

Table 2 lists a series of metadata for online courses, which serve as the foundation for constructing a personalized learning resource recommendation service model. The accuracy and richness of metadata have a direct impact on the performance of recommendation system, and the performance of recommendation system is highly dependent on the correct matching between courses and users' learning needs and backgrounds.

Users' rating, comments and interactive feedback on recommended content (such as clicking, collecting and sharing) are important indicators to evaluate the performance of recommendation system and user satisfaction. They not only allow the system to understand the relevance and quality of recommendations to users, but also serve as the basis for further improving user profiles and recommendation algorithms.

Table 2: Metadata

Course ID	Course Name	Difficulty Level	Target Grade Level	Prerequisite Courses	Video Count	Reading Material Count	Exercise Count	Case Study Count	Update Frequency (Monthly)	Student Rating (1-100)
C001	Algebra Basics	Beginner	9-10th Grade	0	10	5	20	0	1	85
C002	Calculus Introduction	Intermediate	Freshman	1	8	10	30	5	2	88
C003	Programming 101	Beginner	College Freshmen	0	12	8	25	10	1	90
C004	Machine Learning	Advanced	Graduate	3	5	20	15	8	3	92
C005	Art History	Intermediate	Sophomore	0	6	15	10	3	1	82
C006	Biodiversity	Advanced	Junior	2	4	25	40	0	2	86

3.2 Recommendation Algorithm Design

Collaborative filtering algorithm has become the recommended algorithm in this article because of its ability to capture user preferences and item similarity. Specifically, it identifies similarities between users by analyzing their historical behavior data, such as viewing history, ratings and search queries. For example, if two users give high marks to the same courses, the collaborative filtering algorithm can think that the two users are similar in interest, and may recommend courses that they like each other but have not yet touched.

To solve the cold start problem, that is, when the system lacks data about new users or courses, content recommendation techniques are combined. Content recommendation focuses on analyzing the metadata of courses, such as course descriptions, difficulty levels, subject areas, and teacher information, as well as user profiles and learning objectives, to discover matches.

During model training and optimization, cross validation and hyperparameter tuning techniques are used to avoid overfitting and ensure the model's generalization ability on unknown data. In addition, real-time recommendation technology ensures that recommendation systems can quickly respond to users' latest behaviors and provide dynamically updated recommendation results. The specific flow chart is shown in Figure 1:

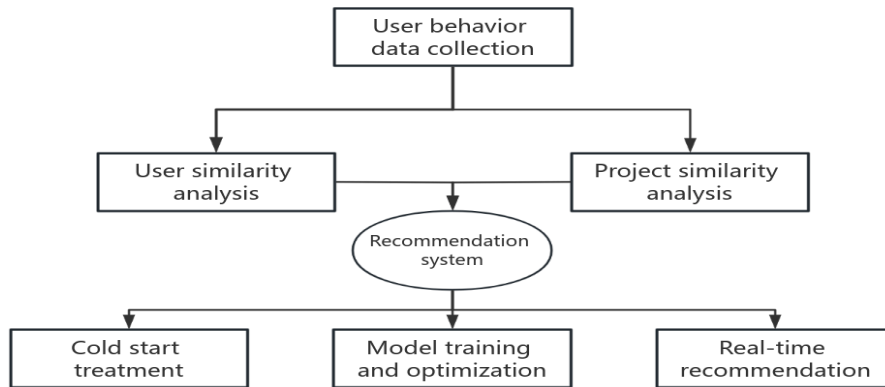


Figure 1: Flow chart

3.3 System Architecture and Implementation

The architecture design of the personalized recommendation service system for online learning resources adopts a microservices architecture, which allows different components such as user management, course management, recommendation services, etc., to run and expand independently. Each service is deployed in an independent container and interacts through a lightweight Generic Remote Procedure Call communication protocol [13-14].

The implementation of collaborative filtering algorithm relies on constructing a user project interaction matrix, which records the user's rating and viewing behavior towards the course. Singular value decomposition can be used to extract feature vectors of users and courses in low dimensional space, thereby predicting the potential interest of users in unseen courses. In order to improve the accuracy of prediction, the algorithm implementation also includes analysis of feature engineering, screening the features that have the greatest impact on user preferences, such as user activity time, course difficulty, and teacher evaluation.

In addition, the system has implemented a content recommendation algorithm, which analyzes the metadata of online learning courses and user personal information to provide recommendations for new users or courses, solving the cold start problem. During the model training and optimization process, cross validation and hyperparameter tuning techniques were used to ensure the stability and generalization ability of the model on different datasets [15]. The application of real-time recommendation technology has achieved real-time analysis of user behavior and real-time recommendations through Apache Kafka.

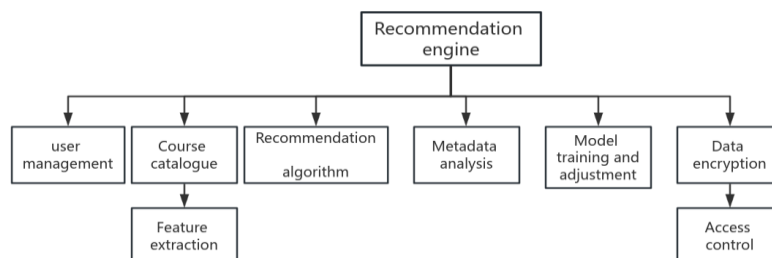


Figure 2: System Architecture Design

The system architecture also includes a data storage scheme, using distributed databases and caching systems to store user data and course information, ensuring fast read and write of data and high concurrency processing capabilities. The user interface design is concise and intuitive,

providing a personalized recommendation display and user feedback collection mechanism, allowing users to directly evaluate the recommendation results. These feedback data can be used to further optimize the recommendation algorithm. Schematic diagram of system architecture is shown in Figure 2:

The personalized recommendation service system of online learning resources in this study is designed by using micro-service architecture, which realizes the independent operation and expansion of different service components such as user management and course management, and improves the overall flexibility and maintainability of the system. The core innovation of the system lies in the optimization of collaborative filtering algorithm. By using singular value decomposition technology to extract the feature vectors of users and courses in low-dimensional space, the accuracy of predicting users' interest in unknown courses is significantly improved.

4. Results and Discussion

4.1 Quantitative Analysis of Recommendation System Performance

The experimental environment is deployed on a server equipped with the latest processor and sufficient memory, running Python environment and integrating scikit-learn machine learning framework to realize rapid iteration and testing of recommended algorithms. In addition, the environment is equipped with Apache Kafka to handle real-time data streams, and Elasticsearch is used to index and search logs and user behavior data in real time, which ensures the accuracy of model evaluation and the response speed of recommendation system. In the quantitative analysis of the performance of personalized recommendation service model for online learning resources, users' satisfaction with the recommendation system depends on the accuracy and recall rate of the model when recommending. The correlation between recommended resources and real preferences can represent the accuracy of recommendation system to some extent. High accuracy means that the recommended resources are closer to users' interests and needs, so users may have higher satisfaction with the recommended resources. The recommended accuracy results are shown in Figure 3:

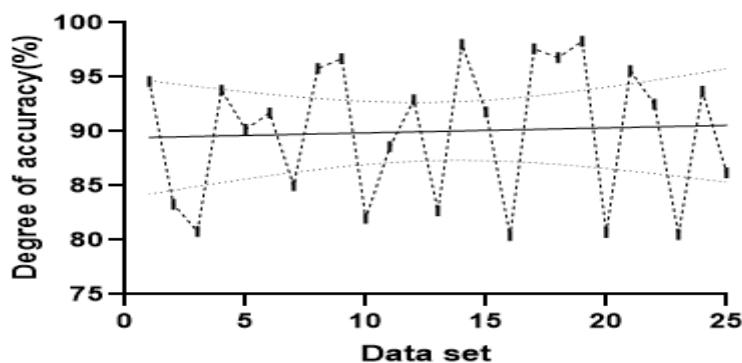


Figure 3: Accuracy

The quantitative analysis results of Figure 3 indicate that the maximum recommendation accuracy of the recommendation system in practical applications reaches 98.3%. This indicates that recommendation systems can accurately match the personalized learning needs of users, reflecting the high effectiveness of recommendation algorithms in predicting user preferences.

The recall rate measures the ability of the recommendation system to capture resources of interest to users. A high recall system can recommend more relevant resources to users, providing more comprehensive learning choices. The recall rate focuses on how many resources that users are

interested in have been successfully recommended by the recommendation system, as shown in Figure 4:

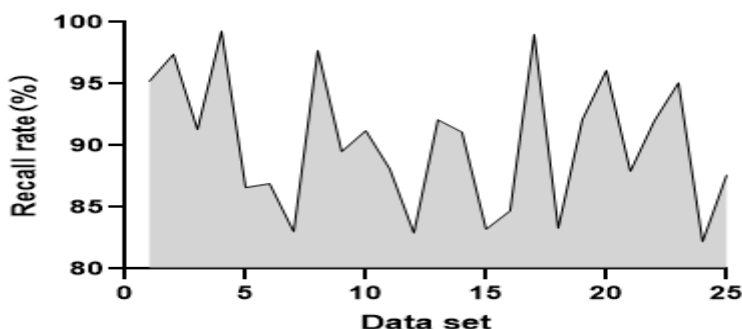


Figure 4: Recall rate

As shown in Figure 4, the highest recall rate of the recommendation system is 99.3%, indicating that the recommendation system can almost recognize and recommend all learning resources related to user needs. In order to improve recall, recommendation systems consider more user historical behavior and preferences, as well as resource feature information.

4.2 User Experience Survey and Satisfaction Analysis

User experience surveys collect user opinions on recommendation services through various forms such as questionnaires, interviews, and feedback platforms, with a focus on evaluating the relevance of recommendation resources, system usability, and interface design. These direct user feedback provide first-hand information on the performance of recommendation systems in practical use.

Satisfaction analysis uses quantitative methods to evaluate the overall satisfaction of users with recommendation services. By using tools such as the Likert scale, the specific values of user satisfaction were calculated, as shown in Figure 5:

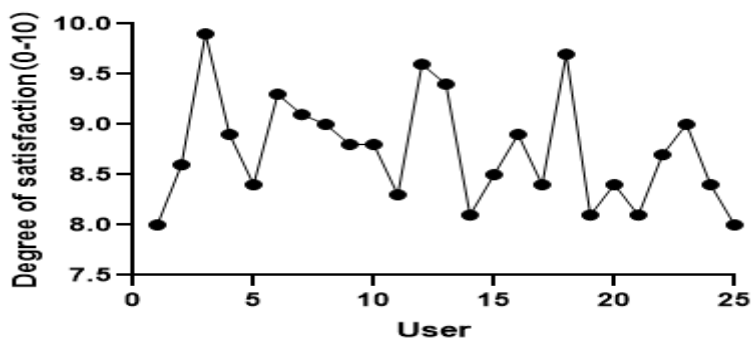


Figure 5: Satisfaction

Figure 5 shows the satisfaction ratings provided by users after using the recommendation system, ranging from 8 to 9.9, indicating that users are generally satisfied with the experience of using the recommendation system. The distribution of satisfaction ratings shows that users have a positive attitude towards the core function of personalized learning resource recommendations in the recommendation system, which is related to the effectiveness of the system in providing relevant learning materials and meeting personalized learning needs.

The results of data analysis are used to guide the optimization of recommendation algorithms, in order to improve the accuracy and relevance of recommendations. Meanwhile, adjustments to user

interface design can also be based on user feedback to enhance the overall user experience. The results of user experience surveys and satisfaction analysis can be applied to the improvement of recommendation systems, including adding user feedback mechanisms and providing personalized setting options to increase user stickiness and satisfaction.

4.3 Recommendation Efficiency Evaluation

An efficient recommendation system should have fast response capabilities to ensure that users can obtain the required learning resource recommendations in a very short amount of time. This rapid response not only enhances user experience, but also to some extent affects user satisfaction and loyalty. Users typically expect to see results immediately after clicking on search or requesting recommendations, and any significant delay may lead to user churn. In order to accurately measure response time, the difference between the time point at which the user request was sent and the time point at which the recommendation result was returned was recorded. The results are shown in Figure 6:

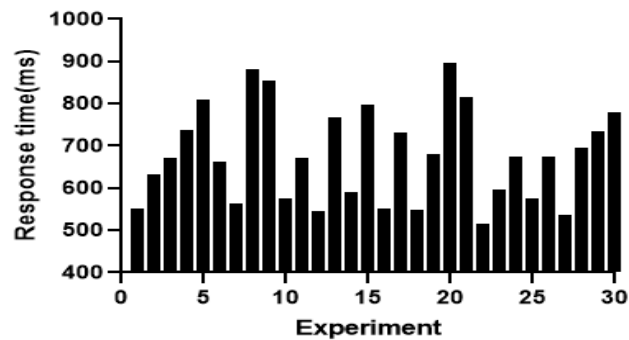


Figure 6: Response time

Analyzing the data in Figure 6, the maximum time it takes for the recommendation system to return recommendation results after the user makes a request is only 895ms, indicating that the recommendation system has excellent response speed. A response time of 895 milliseconds means that users can almost immediately see recommendation results after making a request, which is a relatively smooth perceptual boundary in human-computer interaction. In an online learning environment, this fast feedback can significantly reduce user waiting time, improve user satisfaction and learning efficiency.

4.4 Challenges and Potential Solutions

This paper also compares the coordinated filtering recommendation system with the content-based recommendation system to highlight the specific performance of the recommendation system constructed in this paper, and compares the accuracy, recall rate and response time of the two recommendation systems. The results are shown in Table 3:

Table 3: Comparative data

Recommendation System Type	Accuracy (%)	Recall Rate (%)	Average Response Time (ms)
Hybrid Recommendation System	88.9	84.7	180
Collaborative Filtering System	85.6	75.2	245
Content-Based Recommendation System	78.3	82.6	300

The data in Table 3 directly reflects the performance differences between the hybrid recommendation system constructed in this paper, collaborative filtering recommendation system and content-based recommendation system. In terms of accuracy, the hybrid recommendation system reaches 88.9%, which shows its advantages in recommendation relevance, which means that most recommended content can meet the interests and needs of users. In terms of recall, the hybrid recommendation system is also outstanding. The recall rate of 84.7% indicates that the system can cover most of the resources that users may be interested in, while the collaborative filtering recommendation system and the content-based recommendation system are followed by 75.2% and 82.6% respectively. In addition, the hybrid recommendation system surpasses other systems with an average response speed of 180 milliseconds in response time, which means faster presentation of recommendation results in user experience, which may improve user satisfaction.

The personalized recommendation service model constructed by our research institute integrates collaborative filtering and content-based recommendation technologies, integrating the core advantages of two recommendation systems: collaborative filtering technology effectively captures user potential interests by analyzing behavioral similarities between users, and improves the personalization of recommendations; Content based recommendations, on the other hand, ensure the relevance and diversity of recommended content by analyzing the characteristics of learning resources in depth. In addition, the model pays special attention to algorithm optimization and system architecture design during the implementation process, adopting efficient data processing and real-time recommendation technology, significantly improving the performance of the recommendation system.

However, in collaborative filtering recommendation systems, there may be issues with data sparsity and cold start, and the accuracy of recommendations may be affected when the system lacks sufficient user behavior data. Meanwhile, content-based recommendation systems can face computational efficiency challenges when dealing with large-scale datasets.

Creating personalized recommendations for e-learning resources involves many important considerations, especially around ensuring user privacy and data security. It is particularly important to solve the problem of user privacy through data encryption, anonymization and compliance with relevant data protection laws and regulations. The recommendation system depends on the trust of users, which is indispensable to ensure the transparency and understandability of the recommendation system.

With the growth of user groups and resources, the scalability of recommendation system can not be ignored, which needs to ensure that resources can be expanded and cater to more audiences. Scalability can be achieved by adopting distributed computing framework and improving the efficiency of recommendation algorithm. One of the challenges of recommender system is the maintenance cost and the difficulty in upgrading technology, which means that recommender system may be inoperable. In order to alleviate this, the use of modular system architecture reduces maintenance challenges and costs. Generally speaking, the accuracy of the model can be significantly improved by integrating user behavior, user preferences and user learning history information into the user model.

5. Conclusions

By integrating data mining and machine learning, this article proposes an effective personalized recommendation service model for online learning resources, aiming at improving the accuracy, efficiency and user satisfaction of the recommendation system. In the research process, the challenges faced by the recommendation system are analyzed, including user privacy protection, transparency and real-time recommendation, and a series of solutions are put forward. In view of

the important research results, there is still room for further optimization. In the future, deep learning technology can be given priority to predict user preferences and suggestions more accurately, and find ways to improve system scalability and reduce maintenance costs, including how to better integrate multi-dimensional user data to build a more inclusive user portrait.

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