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Intelligent Teaching Resource Recommendation and Optimal Allocation in Basic Education

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Abstract. In order to solve the problem of low recommendation accuracy of existing recommendation methods, intelligent teaching resources recommendation and optimal allocation in basic education are proposed. Firstly, the behavioral data of users of educational information resources are collected through collaborative filtering to obtain users' interests and preferences. Secondly, the knowledge graph is used to calculate the matching degree between users' interests and the attributes of resource entities, and to obtain the matching degree between the attributes of resource entities and semantic relations. Finally, by matching the user and educational information resource features, comparing the affiliation values of different recommendation results, judging the degree of matching with the user's interests, and generating personalized recommendation results. The experimental results show that the sparsity of the experimental group is 80%, the recommendation accuracy is 96.3%, and the proposed method achieves good matching effect and can provide more accurate recommendation content. Conclusion: The experimental group has a higher accuracy rate, obtains relatively accurate recommendation of educational information resources, and improves the recommendation quality of educational resources.

Keywords. Knowledge Graph, Educational Information Resources, Personalized Recommendation

1. Introduction

In today's information age, educational information resources show a trend of massive growth. How to quickly and accurately obtain the required content from these resources has become a major challenge in the field of education [1]. As an effective information filtering method, personalized recommendation method can provide learners with accurate and valuable educational information according to their individual needs and interests [2]. This can not only improve the learning efficiency of learners, optimize the allocation of educational resources, but also create greater value for educational institutions and learners [3]. Through personalized recommendation, on the one hand, educational information resources can be more reasonable distribution and utilization, so that quality resources can better serve learners and improve the quality of education; on the other hand, educational information resources can also be adjusted and optimized in

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real time according to the feedback and behavioral data of learners, providing learners with more personalized services to enhance their experience and learning satisfaction [4].

Personalized adaptive learning has become the new normal of digital learning. The development of education big data, artificial intelligence, data mining, machine learning and other technologies provide powerful support for the realization of personalized and accurate learning [5]. At present, the explosive growth of teaching resources information, teaching resources present a large number, fast update, the complexity of the correlation between the knowledge points and other characteristics, which brings the "information overload" and "learning lost" and other problems. Learners often spend more time in searching, querying and selecting teaching resources, which is less efficient. The traditional teaching resource management system and related search technology can no longer meet the personalized learning needs of learners [6].

The current learning resource recommendation method resorts to deep learning network, which encodes the learners' learning needs and the content features of learning resources implied in the historical learning behavior data into vector representations, and achieves the final learning resource filtering and recommendation through the feature interaction between the two vectors [7]. Personalized learning resources recommendation based on deep learning has become one of the indispensable core functions of major online learning platforms [8]. Therefore, the resource recommendation service is essential, and the recommendation methods and related systems of teaching resources are of great significance, and a high-quality recommendation system can fully consider the differences of learners and provide personalized learning resources for learners accurately and efficiently [9].

2. Methodology

2.1 System architecture

The online teaching resource recommendation system for K12 education is divided into three layers: data layer, offline layer and online layer, as shown in Figure 1.

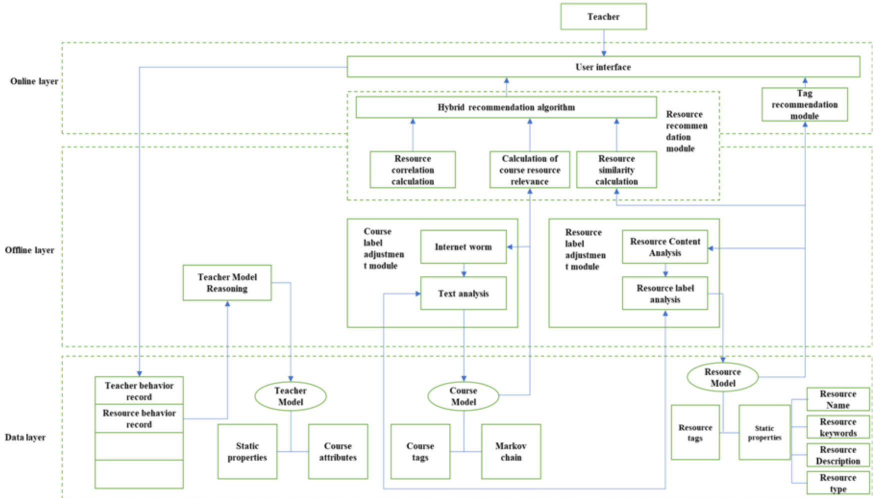

Figure1. System architecture

2.1.1 Data layer

The data layer is mainly responsible for collecting the interaction data between the online layer and users as well as model construction, including teacher behavior records, teacher model, course model and resource model [10].

Teachers' behavior records are used to record teachers' various operations on the system platform and provide data basis for personalized recommendation. According to teachers' behavior objects, teachers' behavior records can be divided into resource behavior records, teaching task records and label behavior records [11]. Resource behavior record is to record the teacher's operation behavior on resources in the user interface (UI) interaction process, including downloading, scoring, collection, and browsing; Teaching task record refers to the teaching design and lesson preparation operations carried out by teachers in the process of UI interaction; Label behavior record refers to the operations performed by teachers on recommended resource labels, including selection, modification, deletion and addition .

The curriculum model is used to express the relationship between courses and the content characteristics of each course. It is composed of curriculum relationship and curriculum label based on Markov chain. In the traditional teacher centered education and teaching, curriculum design and teaching tasks are arranged according to the curriculum order of each subject book, so teachers will also use curriculum related resources in this order. Markov chain describes a state sequence, and each state value depends on a limited number of previous states. Therefore, Markov chain is used to represent the sequence relationship between courses, that is, the course prepared in the next state is only related to the current course position. Using the state transformation relationship of Markov chain, you can predict the position of teachers in the course structure when they log in to the system again, So as to more accurately recommend relevant resources. In Figure 2, α_i $1 \leq i \leq M$, M is the number of curriculum nodes) represents the probability from the status of Lesson $_i$ to the status of Lesson $_{i+1}$, β_i represents the probability from the status of Lesson $_i$ to the status of Lesson $_i$, $\alpha_i+\beta_i=1$, $\alpha_0=0$. Course tags are used to represent the content characteristics of each lesson. They are represented by Vector Space Model (VSM) and can be expressed by formula (1):

$$\text{Tag } S_{Li} = \left\{\text{tag}_k : w_k \mid 1 \leqslant k \leqslant N_t, \sum_{k=1}^{N_t} w_k = 1\right\} \tag{1}$$

Where: tag $_k$ represents the kth tag; W $_k$ is its weight; N $_t$ is the number of tag sets. The initialization and adaptive adjustment of tag sets are completed by the course tag adjustment module in the offline layer.

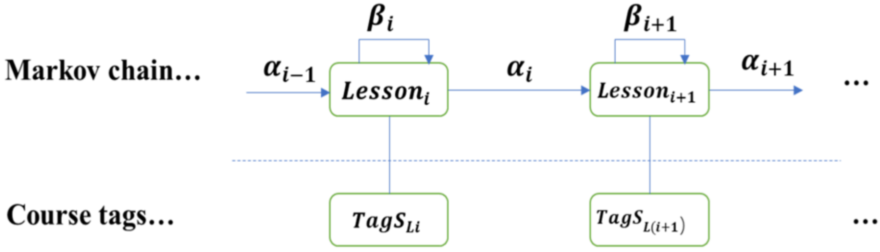

Figure 2. Curriculum model

The resource model includes: 1) static attributes, mainly the resource owner's description of the resource, including resource title, resource keywords, resource description and resource type (such as pictures, videos, audio, documents, etc.); 2) The resource tag, which represents the resource content characteristics, is represented by VSM, such as formula (2). Its initialization and adjustment process is completed by the resource tag adjustment module of the offline layer.

$$\mathrm{TagS_{Ri}} = \left\{\mathrm{tag_k}: \mathrm{w_k} \mid 1 \leqslant \mathrm{k} \leqslant \mathrm{N_{Ri}}, \textstyle\sum_{\mathrm{k}}^{\mathrm{N_{Ri}}} \mathrm{w_k} = 1\right\} \quad (2)$$

The teacher model consists of static attributes and dynamic course attributes. The static attributes are the necessary information that the user fills in when registering, such as user name, registered e-mail address, etc. The course attributes record the position of the teacher in the course model and dynamically track the user's contextual environment.

2.1.2 Offline layers

The main function of the offline layer is to analyze and process the data layer data, initialize and adjust the model, and calculate the correlation or similarity between courses and resources and resources and resources based on the content and user behavior data, so as to provide data support for the hybrid recommendation algorithm in the online layer.

The course tag adjustment module initializes and adjusts the course tag in the course model, so that the course tag can more accurately and comprehensively represent the content characteristics of the course. This module is composed of web crawler module and text analysis module. The web crawler module uses the course name as a query term, simulates the search process, and crawls relevant web pages. The text analysis module uses the Term Frequency Inverse Document Frequency (TF-IDF) algorithm to analyze the web page content obtained by the web crawler, or extract the content features of the teaching task records in the data layer, so as to realize the adjustment of the course tag: in the course of course tag initialization, the extracted content features are directly used as the course tag; In the course of course label adjustment, content characteristics are obtained by analyzing teaching task records, common words and labels with low weight are deleted by statistical methods, curriculum label matrix is constructed by potential semantic analysis, matrix decomposition method is used to solve the eigenvector of the matrix, distance measurement method is used to analyze the eigenvector, and the nearest neighbor of the label is solved to expand the collection of course labels, Dynamically adjust course tags to improve course tags[12].

The resource tag adjustment module initializes and adjusts the resource tag in the resource model. Different from the adjustment of course tags, due to the differences in the types of resources (including videos, pictures, documents, audio, etc.), it is impossible to analyze the content of resources based on TF-IDF algorithm. At the same time, because the static attributes of resources are relatively short to describe the text content, the document frequency (DF) is used in the initialization process Methods Analyze the static attributes of resources, filter common words, and extract keywords as tag sets. The tags obtained from resource names, resource keywords, and resource descriptions have different weights; The process of resource tag adjustment is similar to the process of curriculum tag adjustment. According to the feedback behavior of teachers on resource tags, use statistics, potential semantic analysis, etc. to adjust and optimize the set of resource tags.

Based on course content characteristics (course labels) and resource content characteristics (resource labels), the course resource correlation calculation module and resource similarity calculation module calculate the similarity between courses and resources, resources and resources respectively according to similarity measurement and K nearest neighbor algorithm, and establish the correlation between courses and resources, and the similarity between resources and resources.

Resource relevance calculation module analyzes the resource behavior records of teachers and transforms them into a "shopping basket" problem, i.e., the resource of each user login operation is transformed into a purchase record of the user, and the relevance between resources is calculated by using association rule mining.

Teacher model inference is based on the teacher's behavioral records of the resources in the system, combined with the results obtained from the course resource relevance calculations, to reason about his/her current position in the context of the course model, and then to predict the course that the teacher is going to prepare the next time he/she logs in, based on the Markov chain structure of the course model.

2.1.3 Online layer

The online layer includes hybrid recommendation algorithm, resource label recommendation and user interface. Based on the data layer model and the data obtained from the offline layer, the hybrid recommendation algorithm is weighted to recommend teaching resources, and resource labels are recommended during the user's use of the resources. The online layer is also responsible for collecting the user behavioral data generated at this stage to prepare the data for the analysis of the offline layer.

When it is a search process, it is based on the results of resource relevance and resource similarity calculations, then weighted fusion, and recommended in reverse order according to the size of the weights; if it is any other process, it is based on the teacher's course attributes, combined with the calculation of the relevance of the course resources, to find a list of resources associated with the teacher's course attributes, and each of the resources in the list is weighted based on the relevance and similarity of resources, and the final result is also recommended in reverse order according to the size of the weights. For each resource in the list, weighting calculation is performed based on resource relevance and resource similarity, and the final result is also recommended in reverse order according to the size of the weighting.

2.2 User preference analysis of the collaborative filtering method

The data collection of user reading behavior and the collection and processing of user information of educational information resources is the first step to realize the personalized recommendation of resources. According to the demand of resource recommendation, this paper uses the web crawler to crawl the user behavior information, and sets the crawling period according to the actual situation. When the data in the list meets the requirements, the web crawler sends the data information to the database through wireless network, thus realizing the collection of user behavioral data information of educational information resources. The formula of the collected data information is as follows.

$$x = (a, b, c) \tag{3}$$

Where, a is the user identification number, b is the resource information, and c is the resource type. Since there may be duplicate data in the collected data information, in order to reduce the amount of subsequent recommendation calculations and avoid information overload, the proposed method needs to identify and delete the duplicate data in the original data, and obtain the user's interest preference by collaborative filtering of the collected user behavior data of educational information resources, so as to estimate the user's interest relationship with a certain attribute. When a certain attribute of the resource accounts for a large proportion, it means that the user's interest in the resource is low. When collaborative filtering the raw data according to this principle, this paper needs to consider the inverse frequency of the user's attributes of educational information resources, and estimate the user's interest in the resource by calculating the frequency. The expression of the user's interest in books G is as follows.

$$G = R_{Gx}Kl(z) \tag{4}$$

Among them, R_{Gx} is the user's evaluation frequency of educational information, K is the resource attribute, and l (z) is the reverse frequency of the attribute. The collaborative filtering method can effectively analyze user preferences and provide strong support for achieving better recommendation results.

2.3 Knowledge mapping method of interest matching

In terms of interest matching,in this paper,the knowledge graph method can be used to establish the matching relationship between the results analyzed by the user's interest and the attributes of the educational resources,so as to carry out more accurate recommendation. The program establishes a semantic matching matrix based on knowledge graph, and sets the triad of knowledge graph as (h,r,t), then the vector representation of resource entities in the semantic relation space is$\overrightarrow{hr}$In the relational space,by placing$\overrightarrow{hr}$Mapping to the solid space and adjusting, we can get the solid vector, the$\overrightarrow{tr}$In the process of semantic matching, if the number of layers of the knowledge map hidden layer is k, then the resource entities at layer k are matched with user interests. The calculation formula of interest similarity h_k between resource entities and users at layer k is:

$$h_k = f(h, t)k \tag{5}$$

According to the resource entity and semantic relationship, the method sets the weights of the feature vectors, and obtains the interest matching matrix corresponding to the resource entity and semantic relationship by calculating the matching degree between the user's interest and the resource entity's attributes. The matching degree M of user interests and resource entity attributes is calculated as follows.

$$M = \alpha \text{sim}\ (h, t) + \beta \text{sim}\ (h, t) + \chi \text{sim}\ (r, t) \tag{6}$$

Where α, β and χ are weight coefficients; Sim (·, ·) indicates the interest similarity between the two. This paper calculates the matching degree of users' interest in different resources through equation (6), and then can make recommendations. In practical application, the recommender can also adjust the parameters in the mathematical formula according to specific needs to achieve better interest matching effect.

2.4 Personalized Resource Recommendations

Firstly, according to the interest matching matrix constructed, the program inputs the keywords of educational information resources and the user's past behavior data. Then, by analyzing these data, the program obtains the user's interest level in different resources, and then forms a semantic matching matrix; finally, the program transforms the data in the semantic matching matrix into feature vectors, which are input into the recommendation model as objective vectors. These feature vectors represent the user's interest in educational information resources. After obtaining the feature vectors, this paper builds a recommendation model and matches the user's feature vectors with the features of educational information resources to produce personalized recommendation results. At the same time, this paper adopts the weighted fuzzy calculation to derive the recommendation level of knowledge of educational information resources, and the calculation formula is as follows.

$$\alpha = \int \lambda\beta \frac{\eta}{2} d \tag{7}$$

Wherein, λ is the recommended control quantity, β is the positioning of resource entities in space, and η is the associated attribute of resources. In the recommended hierarchy space obtained by calculation, this paper calculates the correlation between the education information input by university users and the matching matrix, and through calculation, we can determine the education information resource knowledge that matches the user's interest. In order to further clarify the accuracy of personalized recommendation, the proposed scheme needs to carry out membership assignment, so as to obtain the degree of conformity between different recommendation results and user interests. By comparing the membership values of different recommendation results, the matching degree with the user's interest is judged, so as to determine the accuracy of personalized recommendation. This paper calculates the precision of personalized recommendation according to the size of the assigned value, and the calculation formula is:

$$c = \sum_{q>1} \frac{\alpha}{w} \tag{8}$$

Where q is the number of active recommendations of educational information resources, and w is the boundary range of recommendations of educational information resources. According to the calculated personalized recommendation accuracy, the recommended educational information resources are determined, the recommended educational information resources are adapted to the user's specific needs, and the adapted educational information resources are transferred to the knowledge expression framework, so that the complex educational information resources can be clearly expressed, thus completing the personalized recommendation of educational information resources.

2.5 Experimental tests

In this paper, TRP ontology building tool is used to establish a simulation environment. Collect data on learning resources and user behavior, and classify and number the selected educational information resources. The experimental data comes from the access data set of an educational school platform, with 450 user behavior data and 300 learning resources. This paper selects the general Scikit-learn library for the implementation of recommendation algorithm functions. According to the size of the dataset and the complexity of the recommended algorithm, this paper selects Windows 11 system for operation and Eclipse software for integrated development. In order to facilitate the classified management of resources, labels are used for labeling. This paper establishes a resource scoring data table as a scoring matrix to feed back users' interest preferences. Three groups were set up, of which the group using the method in this paper was the experimental group, and the two groups using the similarity recommendation method and the association rule recommendation method were the control groups 1 and 2. The experiment uses learner behavior data to predict the comprehensive score, thus completing the sparse part of the scoring matrix, finding similar user sets through similarity, and calculating the prediction score of resources accordingly, and finally obtaining the recommendation results.

3. Results and discussion

In order to prove the effectiveness of the recommended method in this paper, the results under the scoring matrix are calculated to obtain the sparsity index. According to different learning time periods, this paper carries out 5 experiments and takes the average value as the final result.The sparsity calculation results of the 3 groups are shown in Figure. 3.

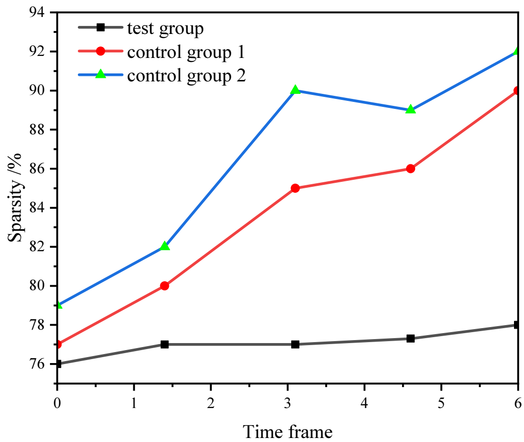

Figure 3. Comparison of the results of sparsity calculation

As can be seen from the figure, the sparsity obtained from the calculation of the comprehensive scoring matrix of the control group is in the range of 90%~95%, and the recommendation accuracy decreases with the increase of the sparsity. This indicates that when the centralized label distribution is sparse, the recommendation effect cannot meet the specific recommendation requirements. Compared with the control group, the sparsity of the experimental group is 80%, which is about 10% lower than the sparsity of the control group, and achieves a good recommendation effect. This suggests that the recommendation method in this paper can effectively enhance the usability of the scoring matrix on the one hand, through the analysis of the user's behavioral logs, get the user's implicit preference for teaching information resources, which increases the number of ratings and improves the sparsity; on the other hand, the proposed method can make more effective use of the learner behavioral data to improve the completeness of the scoring matrix, so as to provide more accurate recommendation results.

At the same time, in order to verify the rationality of the recommendation method in this paper, the recommendation accuracy of educational information resources is calculated. Different order of magnitude indicators EG1-EG8 in the recommended list are used for analysis and testing. Taking the accuracy rate of the recommended results as the indicator, calculate the indicator evaluation results of the three groups, and the specific evaluation results are shown in Table 1.

Table 1. Comparison of the results of the evaluation of the indicators of the recommended methods

Indicators	The experimental group	Control group 1	Control Group 2
EG1	100	85	86
EG2	95	82	54
EG3	98	84	35
EG4	97	82	58
EG5	93	90	85
EG6	95	85	84
EG7	96	83	78
EG8	97	87	86

From the results in the table, it can be seen that for the same index, the results of recommendation accuracy of the experimental group, control group 1 and control group 2 are 96.3%, 83.2% and 56.8% respectively. After comparison, it is found that the experimental group has a higher accuracy rate, obtains relatively more accurate recommendation of educational information resources, and improves the quality of recommendation of educational resources. This shows that the recommendation method in this paper can benefit from the in-depth description of subject knowledge system and learner characteristics by knowledge map and the optimization of recommendation algorithm. The proposed method can better understand user needs and interests, and provide more accurate recommended content.

4. Conclusion

This paper proposes intelligent teaching resources recommendation and optimal allocation in basic education. In the field of education, personalized recommendation helps to improve the learning efficiency of learners, optimize the allocation of educational resources, enhance the quality of education, promote the rational allocation of educational information resources, and improve the learning effect and satisfaction of learners. In this paper, starting from the personalized recommendation of educational information resources, a personalized recommendation method of educational information resources based on knowledge graph is studied by using knowledge graph. The recommendation method based on knowledge graph can correlate learners' personal characteristics with the knowledge structure in the knowledge graph, so as to provide personalized learning resources recommendation for them.

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