Multi level Recommendation System of College Online Learning Resources Based on Multi Intelligence Algorithm

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Abstract. In order to accurately grasp the actual search habits of online learning objects and establish a more reasonable multi-level recommendation scheme, a multi-level recommendation system of online learning resources in Colleges and Universities Based on multi intelligent algorithm is designed. With the help of the given topology, the multi-level recommendation behavior in the system is analyzed. Then combined with various types of Resource Recommendation application units, the hardware execution environment of the system is built. On this basis, a multiple intelligent neural network model is established. Combined with multi intelligent recommendation technology, the actual Resource Recommendation behavior related to learning objects is determined, and the software execution environment of the system is built. Combined with the structure of relevant hardware equipment, the design of multi-level recommendation system for online learning resources in colleges and universities based on multiple intelligent algorithms is completed. The experimental results show that the system designed in this paper records a larger number of learning objects, but the recommended waiting time is relatively shorter. The system can accurately grasp the actual search habits of online learning objects and establish a more reasonable multi-level recommendation implementation scheme.

1. Introduction

With the development of information technology, online learning platform is more and more personalized, intelligent and accurate services. In the face of learning resources with large amount of data, strong professionalism and complex knowledge structure, the problem of online users' learning loss is particularly prominent. Therefore, online users urgently need personalized learning path recommendation service to help them discover the knowledge information they need timely and accurately[1-2]. Learning resource recommendation system is the learning activity route and knowledge sequence selected by online users according to their learning preference, learning style, learning level and environmental factors during the learning process. Practice has proved that the resource recommendation system can realize the dynamic guidance and effective control of online users' learning behavior. The purpose of online learning behavior analysis is to identify learners' cognitive characteristics and preferences by mining and analyzing online users' learning behavior data, so as to provide more scientific prediction and intervention for the development of personalized learning.

Multiple intelligence algorithm is an artificial neural network model based on behavioral data. It is an intelligent technology that can infer and process data[3]. The data enters from the input layer, goes through the hidden layer function processing, and finally outputs from the output layer, realizing the linear classification of the learning behavior of the learning user. Assumes that each neuron corresponding to a kind of learning behavior, multiple intelligent nodes are connected by a large number
of neurons, and the variety of learning behavior of learners is formed namely an adaptive nonlinear dynamic system, the use of multiple intelligent algorithm, the classification of the user a variety of learning behavior can be obtained.

2. Hardware execution environment of learning resources multi level recommendation system

2.1. System topology
Considering the performance, availability, scalability and data isolation and other key factors, the system adopts a multi-level deployment topology. The deployment topology can be roughly divided into four levels.

The first layer is the terminal display layer, which is composed of university online learning users and smartphones. Student users use the personalized recommendation system of online learning resources through smartphones to select preferred subjects for learning.

The second layer is the communication link layer. It is composed of Wi-Fi, 4G, 5G and other wireless communication network hosts. It is responsible for the bidirectional communication of learning resource data, route selection and link data security.

The third layer is the front-end processing layer, which is composed of firewall and front-end processing server of online learning resource recommendation system. It is mainly responsible for the access rights management of student users, the management of student user context and subject resources, and gives the corresponding personalized learning recommendation list.

The fourth layer is the data storage layer, which is composed of database server. It mainly stores all kinds of information of student users, scores, subject resources and algorithm execution.

The traditional search method of recommendation system is based on keyword search, which provides recommendation service for web users by matching the keywords entered by student users. However, students often get the same search results by using the same keywords. In the face of the vast ocean of data, users need a recommendation system that can provide personalized services[4].

2.2. Multi level recommendation behavior
Compared with the traditional online learning resource recommendation system, the multiple intelligence algorithm generally has more clear and more real user identity. It is also convenient to describe the student users from the perspective of general situation. For example, the statistics of mobile student users' profile are generally obtained by filling in the form when mobile users register. Of course, some data can be used to infer the mobile user profile data (for example, on the basis of mobile license, the information on the ID card can be used to obtain the user's native place information, or some purchase behavior of the user can be used to infer the income situation, or Mobile social tools are used to mine more information of users. In addition, we can also use some other ways to obtain the relevant information of mobile users. We can use GPS to locate mobile users or record their activity routes, and use machine learning and relevant data to infer the characteristics and nature of mobile Internet users.

The mobility of recommender system supported by multiple intelligent algorithms can be interpreted from three aspects: the mobility of users, the mobility of devices and the wireless access of devices. There are also great differences between the behavior of student users and Internet users, which makes the basis and data of mobile recommendation system and Internet recommendation system different. Student users show their preference for learning resources by scoring on a five-point scale. This multi-level scoring mechanism can fully reflect the multi-level of student users' preference. However, many researches only describe the preferences of student users by simply dividing them into like and dislike. However, this simple structure can not fully reflect the multi-level of user preferences. Therefore, under the effect of multiple intelligent algorithm, researchers began to use rating preference to describe user rating qualitatively, and to reflect the multi-level structure of user preference. According to the relationship between user rating and user preference, a personalized recommendation system based on tag rating is proposed by combining rating with personalized recommendation system based on multiple intelligence algorithm.
Nowadays, virtual interaction between online students becomes more and more frequent. For example, student users can share their information in various online learning networks. After mastering the social behavior of users, we can establish all kinds of communication networks. Because the mobile phone can be closer to the user, it can make the mobile social communication possible. The various behaviors of mobile users in social networks can reflect the real behaviors of users more accurately and objectively. As a social recommendation derived from the mobile Internet, mobile social recommendation must establish a thorough mobile social network. Then find and analyze the social relationship between users, and finally use online learning behavior to make mobile recommendation.

3. Software execution environment of multi level recommendation system for learning resources

3.1. Multiple intelligent neural network model
In learning resource retrieval, by comparing documents and query items to compute sorting, documents and keywords must be matched and weighted to compute sorting. Because the neural network is a good matching mode, it can be used to study information retrieval. Neural networks are an oversimplified graphical representation of the interconnected network structure of neurons in the brain[5]. As shown in figure 1, the neural network model is generally composed of three layers: query item layer, keyword layer and document layer. Query item nodes start the inference process by signaling keyword nodes. Document nodes can also signal keyword nodes. Keyword node connects query item node and document node, and establishes the relationship between them.

Figure 1. Neural Network Model Structure

3.2. Multiple Intelligent Recommendation Technologies
In the traditional research of multi-level recommendation system technology for learning resources, multi-intelligence algorithm is the earliest and most successful personalized recommendation technology studied so far. It is based on the assumption that the best way to find content that is interesting to students is to find users with similar interests to the target user and then recommend those users' interests to the target user.

Based on the assumption that if some student users have similar interests and preferences in the past, they will have similar interests and preferences in the future, and their preferences will remain the same over time. User-based multiple intelligence algorithms use statistical methods to select several neighbor users that are most similar to the preferences of the target user and recommend items of interest to the target user[6]. First, the similarity between users is calculated by comparing the user's behavior, and a set of ε neighbor users most similar to the target user is found. Then, the preferences of users in the
neighbor user collection are calculated, and Top-N items with higher preferences are selected as the recommended items collection.

Although multiple intelligence algorithms based on student users have been successfully applied in many fields, they still face serious challenges[7]. When faced with large-scale online learning sites, tens of thousands of student users and project classification information must be processed. The amount of computation will increase dramatically, and scalability issues will seriously affect the real-time performance of the recommended system. Set $\alpha_0$ to represent the minimum recommendation for online learning resources in Colleges and Universities Based on multiple intelligent algorithms. Combining the above physical quantities, the system multiple intelligent recommendation technical standard can be defined as:

$$\sum_{\alpha_0} \sin(\beta_1 \cdot p_1) \times (W_n - W'_i)_{\alpha_0} + \sum_{\alpha_0} \sin(\beta_2 \cdot p_2)_{\alpha_0}$$

$$R = \tfrac{\sum_{\alpha_0} \sin(\beta_1 \cdot p_1) \times (W_n - W'_i)_{\alpha_0} + \sum_{\alpha_0} \sin(\beta_2 \cdot p_2)_{\alpha_0}}{\sum_{\alpha_0} \sin(\beta_1 \cdot p_1)_{\alpha_0}}$$

(1)

In formula (1), $\bar{y}$ represents the average amount of access for online learning users in a unit time, $\beta_1$ and $\beta_2$ represent two different search conditions for learning resources, $p_1$ and $p_2$ represent two different storage vectors for learning resources, $W'_1$ represents the application storage conditions for online learning resources in the first level host, $W'_n$ represents the application storage of online learning resources in the $n$th level host. Conditions.

In learning resource information retrieval, each recommended document can be described by a representative set of keywords. Student users query documents by submitting query items. Keyword establishes the relationship between documents and query items, and determines whether documents and query items are related or not. The information retrieval system achieves the purpose of recommending documents by sorting the retrieved documents and then returning the retrieved results to the student users. The more top-ranking documents are, the more relevant they are to student user queries.

3.3. Recommendation Technology Based on Learning Objects

The system recommendation technology based on learning objects is the continuation and development of learning resource filtering technology. It is based on the content information of the item to make recommendations, and does not require the evaluation opinions of students and users on the item[8]. User information needs of students are filtered by combining natural language processing, artificial intelligence, probability statistics and machine learning, and then expressed as a user model in vector space to represent user interests. At the same time, a project feature vector is generated to represent the resource model by indexing the features of the project and weighting the word frequency statistics[9]. Recommend information by comparing the similarities between user interest models and resource models, and between resource models and resource models.

In a multi-level recommendation system based on learning objects, items are defined by attributes of related features. The system evaluates the characteristics of objects, learns users'interests, and inspects the matching degree of user data and items to be predicted. Users' data models depend on the learning methods they use, which include decision trees, neural networks, and vector-based methods. The user data model is based on the user's historical data and may change with the user's preferences[10-11].

4. System Utility Detection

To verify the practical application ability of the multi-level recommendation system of online learning resources in Colleges and Universities Based on multiple intelligent algorithms, the following
comparative experiments are designed. In the established network environment, two host components with identical built-in structure are used as the experimental objects. The experimental group hosts a multi-level recommendation system for University Online Learning Resources Based on multiple intelligent algorithms, and the control group hosts a traditional recommendation system. In the same experimental environment, the specific changes of related index parameters in experimental group and control group were analyzed.

Two groups of students were logged into the experimental group and the control group recommendation system, and their actual search and learning habits were recorded under the same experimental environment. Then input these information parameters into the data analysis host to study the specific numerical trend of experimental indicators in experimental group and control group.

Table 1 recorded the actual changes of the number of learning objects in the experimental group and the control group.

Table 1. Comparison of Numeric Quantities of Learning Objects

| Experimental Time/min | Learning Object Numeric Quantity/Person |
|-----------------------|----------------------------------------|
|                       | Experience group | Control group |
| 5                     | 66              | 31            |
| 10                    | 73              | 45            |
| 15                    | 89              | 57            |
| 20                    | 100             | 62            |
| 25                    | 100             | 63            |
| 30                    | 100             | 64            |
| 35                    | 100             | 65            |
| 40                    | 100             | 70            |
| 45                    | 100             | 71            |
| 50                    | 100             | 72            |

Analysis of table 1 shows that the number of subjects in the experimental group keeps increasing during the first 15 min. Starting from the 20 min, the upward trend tends to stabilize gradually. All 100 students participating in the experiment have been fully connected to the recommendation system host. In the control group, the number of learning objects kept increasing throughout the experiment. However, the increase of the values in the pre-experiment period was significantly higher than that in the post-experiment period, and the global maximum was only 72 people, which was 28 people lower than that in the experimental group. To sum up, a multi-level recommendation system for College Online Learning Resources Based on multiple intelligent algorithms is applied. It can quickly increase the number of learning objects that have been accessed and help control the host to better record the students' actual search and learning habits.

Table 2 records the specific changes of the recommended waiting time in the experimental group and the control group when the number of students is relatively large.

Table 2. Recommended wait time comparison

| Access Student Number Value/Person | Recommended waiting time/s |
|-----------------------------------|-----------------------------|
|                                   | Experience group | Control group |
| 10                                | 2.1              | 3.7           |
| 20                                | 2.1              | 3.8           |
According to table 2, with the increase of the number of students, the waiting time of recommendation in the experimental group always keeps a step-by-step upward trend. However, the duration of numerical stability in the later stage of the experiment is significantly lower than that in the early stage of the experiment, and the global maximum value can only reach 2.4s. In the control group, the waiting time of recommendation kept rising. The rising range in the early stage of the experiment was significantly greater than that in the later stage, and the global maximum value reached 6.6s. Compared with the extreme value of the experimental group, it increased by 4.2s. To sum up, the application of multi-level recommendation system based on multiple intelligent algorithm can effectively save the recommended waiting time required by the system. It can assist the control host to establish a more reasonable multi-level recommendation scheme.

5. Conclusion
Under the effect of multiple intelligent algorithm, a new efficient online learning resource multi-level recommendation system combined with neural network model is proposed. While analyzing the application forms of online learning resources recommendation, it can accurately analyze the access behavior of learning objects. From the practical point of view, with the increase of the number of participants, the waiting time of recommendation is effectively controlled. The system can help the control host master the actual search habits of online learning objects, so as to establish a more reasonable multi-level recommendation scheme.

References
[1] Jeong H, Park B, Park M, et al. Big data and rule-based recommendation system in Internet of Things[J]. Cluster Computing, 2019, 22(1):1837-1846.
[2] Liu Y, Yang C, Ma J, et al. A social recommendation system for academic collaboration in undergraduate research[J]. Expert Systems, 2019, 36(2):1-17.
[3] Singh M K, Rishi O P. Event driven Recommendation System for E-commerce using Knowledge based Collaborative Filtering Technique[J]. Scalable Computing, 2020, 21(3):369-378.
[4] Yadav U, Duhan N, Bhatia K K. Dealing with Pure New User Cold-Start Problem in Recommendation System Based on Linked Open Data and Social Network Features[J]. Mobile Information Systems, 2020, 2020(4):1-20.
[5] Manju G, Abhinaya P, Hemalatha M R, et al. Cold Start Problem Alleviation in a Research Paper Recommendation System Using the Random Walk Approach on a Heterogeneous User-Paper Graph[J]. International Journal of Intelligent Information Technologies, 2020, 16(2):24-48.
[6] Akram S, Hussain S, Toure I K, et al. ChoseAmobile: A Web-based Recommendation System for Mobile Phone Products[J]. Journal of Internet Technology, 2020, 21(4):1003-1011.
[7] Kumar M S, Prabhu J. Hybrid Model for Movie Recommendation System Using Fireflies and Fuzzy C-Means[J]. International Journal of Web Portals, 2019, 11(2):1-13.
[8] Lee J, Lee J. Juice Recipe Recommendation System Using Machine Learning in MEC Environment[J]. IEEE Consumer Electronics Magazine, 2020, 9(5):79-84.
[9] Liu S, Li Z, Zhang Y, et al. Introduction of key problems in long-distance learning and training[J]. Mobile Networks and Applications, 2019, 24(1): 1-4.
[10] Liu, S., Glowatz, M., Zappatore, M., et al. (Eds.). e-Learning, e-Education, and Online Training [M]. 2018, Springer International Publishing, 1-374.
[11] Liu S, Liu D, Srivastava G, et al. Overview and methods of correlation filter algorithms in object tracking[J]. Complex & Intelligent Systems, 2020, doi: 10.1007/s40747-020-00161-4.