Personalized adaptive online learning analysis model based on feature extraction and its implementation

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Abstract. Modern people pay more and more attention to individualized learning. The traditional teaching method is to explain all the learning contents in a unified way. The setting of teaching contents and courseware are relatively fixed, which cannot provide individualized choices for different learners. The core of the adaptive learning system based on feature extraction studied in this paper is that the system recommends personalized learning content for learners according to the learner model. To establish and personalize the self-adaptive learning engine mechanism, a personalized self-adaptive learning content presentation based on clustering is proposed. This study can analyze the data of students' learning behavior and knowledge mastery, recommend reasonable learning path and learning resources with appropriate difficulty, give timely and accurate feedback to students' learning effect, provide personalized service intervention, and promote teaching and learning.

Keywords: Feature extraction; Personalized adaptive online learning; Learning analysis model

1. Introduction
With the development of information technology, the proportion of online learning in modern students is increasing day by day. Based on a large amount of learning behavior data generated by online learning behavior, how to use big data mining technology to analyze online learning behavior and better realize teaching decision-making, learning process optimization and personalized learning method recommendation has become the research focus [1]. Adaptive learning system is "an intelligent adjustment system that meets the needs of learners by presenting appropriate information, teaching materials, feedback and suggestions according to each learner's unique personality characteristics and specific conditions". According to the actual platform construction and application at the current stage, the calculation of students' learning characteristic portraits is in the core position [2].

In this study, the personalized adaptive learning system based on feature extraction can record learners' learning process in real time, process, process and utilize students' learning data through educational data mining, give students feedback information in time, predict students' learning trends, dynamically present personalized adaptive learning content, plan learning paths, recommend personalized learning resources, and finally realize students' personalized adaptive learning.
2. Adaptive learning system and adaptive learning technology

2.1. Adaptive learning system

Adaptive hypermedia system reflects some characteristics of users in the user model, and uses this model to adjust various parts of the system to adapt to users. In other words, this system should meet three criteria: it should be a hypertext or hypermedia system; it should have a user model; it should be able to use this model to adjust hypermedia [3-4]. In this learning system, the machine will be able to achieve effective information exchange and interaction with learners, and make corresponding adjustments in real time according to the feedback from users. After user use and certain information collection, through analysis and comparison, actively recommend and adjust relevant learning strategies, and track and plan the user's achievements [5].

It is not difficult to see that the core of the concept of adaptive learning system is that the system can automatically adjust according to the characteristics of learners to adapt to different learners. Therefore, the technical route of this paper is: taking the learner model as the center, combining with the domain knowledge model, designing and implementing the personalized recommendation mechanism of the adaptive learning system.

2.2. Adaptive learning technology

Adaptive learning is a software and platform that learners can automatically adjust to meet their individual learning needs [6]. It belongs to the category of ITAI (Information Technology Application in Instruction), specifically, it is individual learning ITAI. Adaptive learning technology takes full account of learners' own habits and needs, responds to individual user data and adjusts teaching materials accordingly, and predicts what kind of content learners need at a certain time so as to make timely follow-up [7], constantly guiding learners' learning trajectory, providing learners with a smoother learning environment with fewer obstacles in the learning process, so that they can focus on learning content more easily and improve their learning efficiency. Generally speaking, adaptive learning technology can make the platform adapt to learners, but not learners adapt to the platform.

From program teaching to ITAI, to adaptive learning technology, people have never stopped exploring personalized learning. The existence of individual differences and individualized needs is the driving force for the in-depth study of individualized learning. With the continuous progress of modern information technology, people will put forward higher demands for individualized learning, so the study of adaptive learning technology is of great significance.

3. Personalized adaptive online learning analysis model based on feature extraction

3.1. Feature extraction

The principle of feature extraction is to use an evaluation function to evaluate the importance of feature items in the candidate feature set, and set a certain threshold to eliminate feature items whose importance weight is less than this threshold, so as to achieve the purpose of feature extraction. Although the text can be expressed in vector form by vector space model. However, it is impossible to take all the words appearing in the text set as feature items. Because the larger the text set. The more words there are, the more feature items there are, and the more difficult it is to calculate by computer.

The feature extraction method based on statistics is to extract features by automatically calculating the importance of features through a certain function. It does not need to build a dictionary, and has nothing to do with specific fields, but only relates to the importance of feature items. At the same time, the threshold setting will affect the number of feature items.

Information gain is one of the feature extraction methods based on statistics. Its principle is to calculate the difference between the amount of information that contains a certain feature and that that does not. The larger the difference, the greater the information gain of this feature and the stronger its importance to the text set. To calculate the information gain, we must first calculate the "entropy". For a class $n$ problem, the formula for calculating the "entropy" is shown in Formula (1). Here, $P(C_i)$
represents the probability of class \( C_i \). Then calculate the "conditional entropy" of feature \( t \), and its calculation formula is shown in formula (2) [8].

\[
H(C) = -\sum_{i=1}^{n} P(C_i) \cdot \log_2 P(C_i) \tag{1}
\]

\[
H(C|T) = P(t)H(C|t) + P(\bar{t})H(C|\bar{t}) \tag{2}
\]

\( P(t) \) and \( P(\bar{t}) \) represent the probability of feature \( t \) appearing and not appearing in the total text, while \( H(C|t) \) and \( H(C|\bar{t}) \) represent the entropy of text when feature \( t \) appears and the entropy of text when feature \( t \) does not appear. The calculation method is shown in Formula (3) and Formula (4).

\[
H(H|t) = -\sum_{i=1}^{n} P(C_i|t) \cdot \log_2 P(C_i|t) \tag{3}
\]

\[
H(H|\bar{t}) = -\sum_{i=1}^{n} P(C_i|\bar{t}) \cdot \log_2 P(C_i|\bar{t}) \tag{4}
\]

In which \( P(C_i|t) \) and \( P(C_i|\bar{t}) \) represent the probability of class \( C_i \) when feature \( t \) exists and the probability of class \( C_i \) when feature \( t \) does not exist, respectively. With the above formula, the information gain formula of feature \( t \) is shown in formula (5).

\[
IG(t) = H(C) - H(C|T) \tag{5}
\]

For each feature, this method can be used to calculate its information gain. For feature items whose information gain is less than "threshold", different thresholds can be set according to different situations.

### 3.2. Analysis of online learning behavior

Online learning platform has accumulated a large amount of user learning data, including basic information of users, online learning behavior, habit statistics, online learning effect evaluation and so on. Among them, online learning effect evaluation is an important part of online education, but the loose structure of online education and the openness of distance learning environment make it very difficult to objectively evaluate learners [9]. Therefore, this paper aims at the above problems to effectively extract the learning behavior characteristics, and uses BP neural network model to predict offline grades.

BP neural network algorithm is a supervised classification method. Its main idea is to input learning samples, and use back propagation algorithm to adjust the weights and deviations of the network repeatedly, so that the output vector is as close as possible to the expected vector. When the sum of squares of errors in the output layer of the network is less than the specified error, the training is completed, and the weights and deviations of the network are saved. Classification model completes training. After preprocessing the user's online learning behavior data, the user behavior characteristics are obtained. Using behavior characteristics to train BP neural network, the classification model is obtained.

It is assumed that the study period is calculated according to the week, and the homework is submitted according to the week. Therefore, this paper divides the week into 7 equal parts, each part spans 1 day, and the week code is 1 to 7 (for example, 1 on Monday, 2 on Tuesday, and so on). Then, the time of each login learning is mapped to this discrete time series (1, 2, 3, 4, 5, 6, 7). The actual entropy function is used to measure the time regularity coefficient of user login learning, which is defined as formula (6) [10]:

\[
\]
\[ S_x = x^2 \left( \frac{1}{n} \sum_{i=1}^{n} \Lambda_i \right)^{-1} \ln n \quad (6) \]

Where \( x \) represents the number of weeks occupied by the mapped time series; \( n \) represents the sequence number of mapping. In order to accurately extract the learning regularity of learners, \( n \) must be a continuous sequence; \( \Lambda_i \) represents the length of the shortest sequence that has not appeared before the \( i \)-th start.

### 3.3. Learner data model

Determine the learner model = \{learner's basic information, learner's knowledge level, learner's interest preference, and learner's learning style\}. The following three parts of the learner model: learner's basic information, learner's knowledge level, and learner's learning style are designed, and the learner's interest preference will be reflected in the fifth chapter. The schematic diagram of learner model is shown in Figure 1, and the data models are shown in Tables 1, 2 and 3.

![Figure 1 Schematic diagram of learner model](image)

**Table 1 Learner basic information table**

| Field           | Data type | Field description                                      |
|-----------------|-----------|--------------------------------------------------------|
| Student number  | int       | Student ID number, student unique identification code  |
| Username        | string    | System registration user name                          |
| Password        | string    | Login password                                         |
| Gender          | string    |                                                        |
| Age             | int       |                                                        |
| classes         | string    |                                                        |
| E-mail          | string    |                                                        |

**Table 2 Learning style type table**

| Field                | Data type | Field description                  |
|----------------------|-----------|------------------------------------|
| Student number       | int       | Value range \{11a,9a,7a,5a,3a,a,b,3b,5b,7b,9b,11b\} |
| information processing| string    | Ditto                              |
| Perception           | string    | Ditto                              |
| Input                | string    | Ditto                              |
| Understand           | string    | Ditto                              |
### Table 3 Knowledge level table

| Field                                | Data type | Field description                                      |
|--------------------------------------|-----------|--------------------------------------------------------|
| Student number                       | int       |                                                        |
| Knowledge point number               | int       | Unique identifier of knowledge point                   |
| Goal accomplished                    | bool      | "true" or "false"                                      |

#### 3.4. Constructing domain knowledge model

Constructing domain knowledge model: domain knowledge model includes the components of domain knowledge and the relationships among them. By collecting the correlation between knowledge points, course units, course content organization and learning results, the existing domain knowledge model is optimized. According to the optimized domain knowledge model, the best learning path can be recommended for learners. According to the theory of Connectionism, this study forms the knowledge map of curriculum knowledge points in the form of directed graph. On the one hand, it constructs the domain knowledge model, on the other hand, it presents it to learners in a visual way. In addition, the existing domain knowledge model is optimized by constructing the learner experience model.

In this system, learners learn that data are recycled and updated in real time, and the contents of each module in Figure 2 are updated with the real-time update of data.

![Figure 2 Data recycling](image)

Firstly, the data generated by learners' learning enters the learner database, and the system constructs learner model, domain knowledge model and social network model according to the data of the learner database. Personalized adaptive learning engine makes prediction and recommendation according to these models and real-time behavior data of learners. Secondly, it enters the learner database, and the system continuously optimizes the learner model, domain knowledge model and social network model according to the new learning process data. Finally, combined with learners' current learning data, prediction and recommendation are made, and the dynamic results are presented to learners. This process goes round and round, and the system can continuously evolve, improve and upgrade itself, making the recommended and predicted content more suitable for learners.

#### 4. Implementation of adaptive learn system

**4.1. Initialization and Update of Learner Model**

From the perspective of learner information individuation, a learner model is established, which includes four parts: learner basic information, interest preference, learning style and knowledge level. Completed the initialization and update of learner model. Among them, the basic information and interest preference of learners are initialized by registration information. In the learning style part, when the user logs in the system for the first time, the learner's learning style is initialized by Solomon Learning Style Scale. Learners' interest preferences and learning styles are updated by analyzing their learning behaviors. Learners' knowledge level is initialized and updated through test questions. The
initialization and update process of learner model is shown in Figure 3.

![Figure 3 Process diagram of learner model initialization and update](image)

4.2. Personalized adaptive learning engine

The presentation of personalized adaptive learning content is mainly reflected in two aspects. On the one hand, it is aimed at the first learning of learning content, clustering learners according to the preschool test situation, and providing personalized adaptive learning content for different types of learners; On the other hand, according to the unit test after learning, the learner knowledge model is constructed or updated according to the answer data. If the test passes, the unit study is completed; if the test fails, the learning content suitable for learners is automatically fed back according to the detailed answer data.

1) Recommendation of the best learning path based on sequence mining and association rules

The learning path contains two levels of content: one is the resource organization path within the knowledge point, because each knowledge point may contain a variety of different resources; The other is the learning path between knowledge points. Learners can freely choose the learning order of knowledge points, not necessarily according to the order of textbooks, but possibly according to the learning path of peers.

After the collection of learners' behaviors, it is necessary to analyze the information of learning behaviors and establish a model of learners' interest in learning resources. The interest model of learners is the interest matrix of learners to resources. The calculation method of learners' interest in resources is as follows.

The interest degree $P_1$ is calculated from the log information, as shown in equation (7).

$$P_1 = \alpha \times \sum_{i=1}^{n} \frac{T_i}{B}$$  (7)

Where $n$ is the number of times to browse the resource, $T_i$ is the duration of each browsing, and $B$ is the byte number of the resource. $\alpha$ is the resource media type coefficient [11].

The system operation information is assigned, and the score corresponding to the learner’s behavior can be set to the value shown in Table 4. When a learner has multiple learning behaviors for a certain learning resource, the score is the sum of the scores corresponding to the learning behaviors, and the degree of interest $P_2$ is obtained.

### Table 4 Learning behavior score

| Learner behavior | Score |
|------------------|-------|
| Collect          | 1.5   |
| Share            | 2     |
| Download         | 2.5   |

Finally, the interest degree obtained from log information and system information is weighted and
summed to obtain the learner's interest degree $P$ of resources, as shown in Formula 4. $\mu$ is the weight value of $P$.

$$P = \mu \times P_1 + (1 - \mu) \times P_2$$

Sequence mining mode is to find all frequent subsets, that is, subsequences whose frequency is not less than the minimum support threshold. Through the method of sequence mining, we can find out the related pages and shorten the distribution distance of related content pages as much as possible. When users learn some content, we can predict the next learning needs of users and provide convenient path guidance for users. In this study, the learner experience model is established by collecting the data of learning sequence and achievement of learners' knowledge points, and the correlation between learning sequence and achievement is analyzed by association rules, so as to obtain the best learning path, which can be used to optimize the knowledge model and recommend learning path.

2) Personalized resource recommendation based on collaborative filtering and social network

Collaborative filtering is one of the best recommendation algorithms at present, and its core idea is to calculate the similarity of preferences among users and make recommendations. In this study, we build a social network of communication and cooperation among learners to calculate the similarity of interests and preferences among learners, and then make recommendations. The most obvious advantage of this recommendation is that it can be recommended with better results without studying the content of the resource itself. After all, it is difficult to analyze and study the content of the resource itself.

4.3. Visualization of knowledge structure

According to the concept of connectivism, the contents of chapter learning are presented to students in the way of knowledge map visualization, which can effectively organize knowledge, clearly represent the logical relationship between knowledge and knowledge on the basis of conforming to learners' visual processing habits, reduce learners' cognitive load, and promote learners' meaningful learning, long-term memory and active construction and transfer of knowledge.

When learning a certain knowledge point, learners can choose from the knowledge structure map, or click on the knowledge tree on the left side of the adaptive learning system. The system will adaptively push the best learning resource sequence (expressed in different importance, difficulty coefficient, semantic density and media type) and learning example sequence according to the characteristics of learners' learning style and cognitive ability, which can provide adaptive learning and self-organizing learning for learners. It is beneficial for learners to construct knowledge learning by forming the correlation between new knowledge and original knowledge and knowledge to be learned.

5. Conclusion

Network online education provides a new way for learners to receive education, and the diversity of its educational models fully mobilizes learners' learning initiative and enthusiasm; The accurate collection of educational data can enable educational administrators to grasp learners' learning situation in time, and provide timely intervention and guidance. The personalized self-adaptive online learning analysis model based on big data effectively realizes the mining of learners' learning behavior and reveals the relationship between various data. By calculating each index of students' learning behavior characteristics, students can be classified in more detail, and the adaptive learning engine can calculate the best learning and testing resource list and the combination of learning order more accurately. It provides a good decision-making basis for students' personalized education, thus effectively achieving the goal of comprehensive and high-quality education.

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