Decision Support Algorithm for Discipline Construction of Comparative Pedagogy Based on Evolutionary Graph Data Mining

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The traditional pedagogy discipline construction decision support algorithm has the problems of poor discipline construction decision satisfaction, high decision time, and low decision recall rate. Therefore, a decision support algorithm for discipline construction of comparative pedagogy based on evolutionary graph data mining is designed. First, the programme call graph is created based on the programme execution path, and then the graph reduction method is used to decrease the call graph set and create the weighted behavior graph set. The original graph set is then reduced using the subtree reduction procedure. The interference of weights in the graph must be eliminated while mining closed subgraphs using a close graph method. The most frequent subgraph of comparative pedagogy discipline construction is then mined, and an SVM classifier is created to accomplish information mining of comparative pedagogy discipline construction in evolutionary graph data mining. Then, using the complete weighing approach, the attribute classification of comparative pedagogy discipline construction is accomplished, and the decision weight of comparative pedagogy discipline construction is established. Finally, the weight distribution scheme of comparative pedagogy discipline construction is obtained by using European distance, so as to realize the decision support of comparative pedagogy discipline construction.

The experimental results show that the decision-making satisfaction of comparative pedagogy discipline construction of this method is 97.32%, the decision-making time is only 0.9 min, and the decision-making recall rate is as high as 98.66%, indicating that the decision-making effect of comparative pedagogy discipline construction of this method is good.

1. Introduction

Decision making is a comprehensive decision-making discipline that studies decision-making principles, decision-making processes, decision-making skills, and other contents. The use of decision-making is helpful to explore reliable decision-making laws and is of great significance for the government to realize scientific decision-making [1–3]. Big data decision-making may be simply defined as the practice of making decisions based on large amounts of data. Big data decision-making, in particular, is a field that analyses how data are used and processed in the decision-making process. It not only looks at how big data are used in decision-making but also at how big data are mined and analysed. It also mentions security and privacy concerns, as well as ethical and moral concerns, that may develop throughout the large data decision-making process. The key significance of branch disciplines such as management decision-making and penetration behavior decision-making has been merged into big data decision-making. It enhances conventional decision-making, transforms it into an emerging discipline with cutting-edge content, and ushers in a new era in the area of decision-making [4]. In this study, we emphasize that the decision-making process of comparative pedagogy discipline construction should meet the requirements of the development of the times, fully understand the connotation and value of big data and educational big data, and make use of the unique advantages of big data and educational big data to affect the educational decision-making of comparative pedagogy discipline construction. It can let the relevant personnel in the educational neighborhood obtain real information to decide how to make the next decision. On this basis, it can also be used as an auxiliary tool for managers to improve
their management level [5]. Relevant scholars have studied this and made some progress.

Reference [6] proposes to design a DEA-GA-BP intelligent bid evaluation decision support algorithm for pedagogy discipline, classify the decision evaluation attributes of pedagogy discipline using adaptive learning, construct the bid evaluation decision model of pedagogy discipline using BP neural network, and finish the design of intelligent bid evaluation decision support system for pedagogy discipline using genetic method. This strategy can boost discipline construction choice satisfaction, but it has a poor decision efficiency. Reference [7] proposes an intelligent decision support algorithm of pedagogy discipline based on big data analysis, classifies the attribute of pedagogy discipline curriculum through the decision tree algorithm in artificial intelligence technology, obtains the correlation degree between pedagogy disciplines through big data analysis method, and realise the design of pedagogy discipline intelligent decision support system by using multiobjective analysis method. This method can shorten the time of curriculum decision-making of pedagogy, but the satisfaction of discipline construction decision-making is poor.

Reference [8] proposes a multidisciplinary collaborative construction decision support system based on improved K-NN and SVM, which realises the classification of multidisciplinary teaching courses using the K-NN classification method, realises the question and answer interaction of multidisciplinary teaching courses using the human-computer interaction module, and realises the similarity matching of multidisciplinary teaching courses using the SVM method. This method has low computational complexity and can improve the decision-making efficiency, but the decision-making recall rate is low.

To solve the above problems, this paper proposes a decision support algorithm for discipline construction of comparative pedagogy based on evolutionary graph data mining, which can effectively improve the decision satisfaction of comparative pedagogy discipline construction, shorten the decision time, and improve the decision recall rate.

2. Decision Support Algorithm for Discipline Construction of Comparative Pedagogy Based on Evolutionary Graph Data Mining

2.1. Comparative Pedagogy Discipline Construction Information Mining Based on Evolutionary Graph Data Mining

This section proposes a decision support algorithm for discipline construction of comparative pedagogy based on evolutionary graph data mining. To begin, put the pile of the to-be-tested programme, run the test case, gather the programme execution track, and convert it to a weighted software behavior diagram. The graph mining approach is then used to extract frequent edges from closed subgraphs. To categorise all executions and detect questionable techniques, SVM is used. Finally, the suspicious method set is used as the final information mining result of comparative pedagogy discipline creation [9]. The overall framework of the method is shown in Figure 1.

The specific process of the method is roughly divided into five steps:

Step 1: building a weighted software behavior diagram. The program call graph is constructed according to the program execution trajectory, and then the graph reduction algorithm is used to reduce the call graph set and construct the weighted behavior graph set.

Step 2: mining closed subgraphs. The first step is to mine the closed subgraphs from the graph set after completing the construction of the weighted behavior graph set, retain the closed subgraphs, extract the frequently executed directed edges from the closed subgraphs, and record the frequent edge information.

Step 3: establishing SVM classification. Take frequent edges or closed subgraphs as features, train SVM to classify all executions, and record the classification accuracy before and after the execution of each method in the program.

Step 4: analyzing the classification results. Identify the methods with obvious changes in classification accuracy before and after implementation, and add them to the discipline construction information set of comparative pedagogy.

Step 5: information mining results. Finally, the information collection of comparative pedagogy discipline construction is obtained to realize the information mining of comparative pedagogy discipline construction.

2.2. Building Weighted Behavior Diagram

To get the first set of method call diagrams, the programme to be tested is inserted at the method level, all test cases are performed, and the programme execution trajectory of method granularity is gathered. At present moment, the call graph set only contains information on each method’s call during programme execution, and the execution timings of the program’s methods are not recorded. To construct a weighted behavior graph, it is required to minimise the original call graph set and add the method execution timings as a weight to the illegal call graph [10]. This study does not need to consider the number of method executions while generating the software behavior diagram and instead eliminates all duplicate edges directly, as illustrated in Figure 2.

Figure 2(a) shows successful execution and Figure 2(b) shows failed execution. The solid line represents the call relationship between methods and the dotted line represents the transfer relationship between methods. Although this kind of software behavior diagram is relatively simple as a whole, a large amount of useful information may have been lost due to the serious compression of the behavior diagram. The original graph set is reduced by subtree reduction algorithm to remove the repeated substructures in the graph. At the same time, the call times of the substructure are given as the weight to the directed edge of the call graph, and the program call graph with weight is constructed. Compared with the graph reduction method of directly deleting duplicate edges, the size of the behavior graph obtained after
subtree reduction processing the graph set is smaller, and the weight information is retained. Therefore, using the subtree reduction algorithm is considered to reduce the initial graph set and build a weighted behavior graph [11]. When mining closed subgraphs using a close graph algorithm, removing the interference of weights in the graph is necessary because the directed edges with different weights belong to different edges. Then, mining is carried out to obtain the largest frequent subgraph and record the frequent edge information contained in the graph. We record the correspondence between frequent edges and each behavior graph in tabular form, as shown in Table 1.

The first column in Table 1 shows the software behavior diagram, and an execution track corresponds to a software behavior diagram [12–15]. The last column indicates the category of the software behavior diagram, which is divided into failed execution (f) and successful execution (P). The other columns represent the frequent edges contained in the closed subgraph, and the value corresponding to the software behavior graph is the specific execution times of the method.

SVM can classify limited samples. We use support vector machine to classify all software behavior diagrams. Each software behavior diagram has a label indicating whether it belongs to failed execution or successful execution. When a method is added, the classification accuracy of SVM changes significantly, so this method can better distinguish successful execution from failed execution, which is likely to contain

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**Figure 1:** Framework of decision support algorithm based on evolutionary graph data mining.

**Figure 2:** Software behavior diagram of ccrypt-1.2. (a) Successful execution. (b) Failed execution.
The classification of discipline construction [16].

As shown in Figure 3, A, B, and C are three programs in the discipline construction program of comparative pedagogy, in which method B contains some problems. SVM is established at the return of method A to train a classifier A and classify all. Since method B containing errors is not executed, the classification result of classifier A is not much different from that of the previous method [17–19]. At the return of method B, SVM is established to train a classifier B and classify all. At this time, due to the execution of method B containing errors, the classification result of classifier B is more accurate than that of classifier A, and the improvement of classification accuracy is obvious. Therefore, method B is more suspicious and can contain errors.

2.3. Attribute Classification of Discipline Construction of Comparative Pedagogy Based on Comprehensive Weighting Method. Suppose that the classification attribute dataset \( X = \{ x_1, x_2, \ldots, x_i, \ldots, x_n \} \), \( 1 \leq i \leq n \) contains \( n \) data objects, in which each data object \( x_i = \{ x_{i1}, x_{i2}, \ldots, x_{ij}, \ldots, x_{in} \} \), \( 1 \leq i \leq n \) is described by \( m \) classification attributes \( C = \{ c_1, c_2, \ldots, c_j, \ldots, c_m \} \), \( 1 \leq j \leq m \) [20]. Attribute \( c_j = \{ c_{j1}, c_{j2}, \ldots, c_{j\ell}, \ldots, c_{jn} \} \), \( 1 \leq j \leq m, |c_j| \) values appear in dataset \( X \). For two different attributes \( c_j \) and \( c_j' \) in dataset \( X \), the relationship between classification attributes \( \ell_c(c_j, c_j') \) is defined as

\[
\ell_c(c_j, c_j') = \begin{cases} 
\diamond & 1 \leq s \leq |c_j|, 1 \leq t \leq |c_j'| \\
(c_{js}, c_{jt}') & \text{otherwise} 
\end{cases}.
\]

Among them, \( \ell_c(c_j, c_j') \) table is not the relationship between attributes \( c_j \) and \( c_j' \); \( c_{js} \) and \( c_{jt}' \) are the values of attributes \( c_j \) and \( c_j' \) in dataset \( X \), respectively, and \( \diamond \) refers to the relationship between attributes \( c_j \) and \( c_j' \) which is comprehensively reflected by the relationship between all values of these two attributes [21, 22].

Generally speaking, when we solve some practical problems, it is easy to describe specific problems in the form of several factors. At the same time, it can also be expressed by fuzzy mathematical knowledge. The combination of these interacting factors constitutes a fuzzy problem [23].

Set \( U = U_1 \times U_2 \times \ldots \times U_n \), \( A_i \in \mu(U_i) (i = 1, 2, 3, \ldots, n) \), where \( A \) is compounded by \( A_1, A_2, A_3, \ldots, A_n \). Due to the diversity of problems, the manifestations of \( A \) are also diverse.

2.3.1. Weighted Average Method. Set \( \delta_1, \delta_2, \delta_3, \ldots, \delta_n \) as a group of weights to make

\[
\delta_A(u) = \sum_{i=1}^{n} \delta_i A_i(u_i).
\]

Among them, \( u = (u_1, u_2, u_3, \ldots, u_n) \in U \).

2.3.2. Product Average Method. Set \( \alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_n \) as a group of weights to make

\[
\mu_A(u) = b \prod_{i=1}^{n} (\mu_{A_i}(u_i))^{\alpha_i} = b \prod_{i=1}^{n} (\mu_{A_i}(u_i))^{\alpha_i},
\]
where \( u = (u_1, u_2, u_3, \ldots, u_n) \in U \), \( b \) is a positive real number.

Therefore, the weight of the decision-making of the discipline construction of comparative pedagogy is obtained.

### 3. Decision Support Algorithm for Discipline Construction of Comparative Pedagogy Based on Evolutionary Graph Data Mining

#### 3.1. Evaluation of Discipline Construction Quality of Comparative Pedagogy Based on Project Response Theory

During the development of item response theory, two most important models were born, namely, three-parameter logistic regression model and Rasch model [24]. The classic three-parameter model of discipline construction quality evaluation of comparative pedagogy is as follows:

\[
E(U|x_i) = \pi(x_i) = \pi_i = c_i + \frac{1 - c_i}{1 + e^{-1.7u_i(\theta - b_i)}}.
\]  

(4)

where \( \pi_i \) represents the correct answer probability of \( i \) on the test question of students with \( \theta \) ability level after the application of pedagogical discipline decision-making method, and \( a_i, b_i, c_i \) are the discrimination, difficulty, and guess measurement parameters of the test question, respectively. Although Rasch model is derived based on different theoretical systems, it can be regarded as a special case of three-parameter model in form; that is, it does not include test item discrimination and guessing measure [25]. Generally speaking, if a test consists of \( n \) test questions, when considering the three-parameter model, the likelihood function of the test is

\[
L(U|\theta) = \prod_{i=1}^{n} \pi_i^{u_i} (1 - \pi_i)^{1-u_i},
\]  

(5)

where \( U \) is the answer vector of students with ability level of \( \theta \) on the test after applying the decision-making method of pedagogy, and the values are 0 (right answer) and 1 (wrong answer). At this time, the evaluation function of discipline construction quality of comparative pedagogy is

\[
L(U|\theta) = \sum_{i=1}^{n} [u_i \ln \pi_i + (1-u_i)\ln(1 - \pi_i)].
\]  

(6)

Data must be used to solve the three criteria of students’ ability level and test question quality. The simplest basic method for determining the equation parameters is to use maximum likelihood estimation. Because the equation generated by deduction does not have an explicit solution, it must be solved repeatedly using a numerical approach to achieve the assessment findings of discipline construction quality in comparative pedagogy.

#### 3.2. Decision Support for Discipline Construction of Comparative Pedagogy Based on European Distance

Using Euclidean distance to describe the weight distribution scheme \( \beta \) alternative weight allocation scheme \( \alpha \), the feasible degree is calculated as follows:

\[
d(\alpha, \beta) = \left( \sum_{i=1}^{m} |a_i - \beta_i|^2 \right)^{1/2}.
\]  

(7)

The selection method of indicator weight allocation scheme can be defined according to \( d \). Let \( W_i = \{w_{i1}, w_{i2}, \ldots, w_{i|}\} \) be a weight allocation scheme, and the number of indicators is \( s \), according to the weight set of each single indicator in the same category. Suppose that the set of different index weight distribution schemes designed by several experts is \( \tilde{W}_s = \{W'_1, W'_2, \ldots, W'_s\} \), and the number of index weight distribution schemes designed by experts is \( s \). Select a weight distribution scheme that can meet all other weight distribution schemes in \( s \) distribution schemes; that is, select one \( W' \) and \( W'' \) within \( \tilde{W}_s \), which must be representative to make it meet:

\[
W' = \arg \max \sum_{i=1}^{s} d(W''_i, W'_i).
\]  

(8)

According to the above weight distribution scheme, the decision support for the discipline construction of comparative pedagogy is carried out, and the corresponding discipline construction and development scheme of comparative pedagogy is given.

### 4. Experiment

#### 4.1. Experimental Scheme

The experiment was carried out using 11 classification attribute datasets from the University of California Irvine’s UCI machine learning repository 4, an open source data collection. The dataset utilised in the experiment contains a wide range of data properties, including the number of data items, classification attributes, and categories. As a consequence, the experimental findings based on these 11 datasets may precisely demonstrate the suggested method’s efficiency.

#### 4.2. Evaluating Indicator

(1) Decision satisfaction \( R_Q \):

The \( R_Q \) index of decision satisfaction is calculated as follows:

\[
R_Q = \frac{1}{T} - \frac{1}{T} \sum_{i=1}^{T} \sum_{j=1}^{\mid C_i \mid} d^2(x_{ij}, c_i)
\]  

(9)

where \( n \) is the number of data objects in the dataset, \( T \) is the number of categories, \( |C_i| \) is the number of data objects in class \( i \), \( c_i \) is the class center of class \( i \), \( c \) is the center of the dataset, and \( x_{ij}^g \) is the \( g \) data object in class \( j \).

(2) Decision time: the longer the decision-making time, the lower the decision-making efficiency. On the contrary, the shorter the decision-making time, the lower the decision-making efficiency.

(3) Recall rate of construction decision is \( R_c \):

The calculation method of \( R_c \) index is as follows:
4.3. Experimental Result


By analyzing Table 2, we can see that different methods have different satisfaction with the decision-making of pedagogy discipline construction. When the number of iterations is 50, the decision satisfaction of comparative pedagogy discipline construction of reference [6] method is 67.53 percent, comparative pedagogy discipline construction of reference [7] method is 68.97 percent, comparative pedagogy discipline construction of reference [8] method is 70.21 percent, and comparative pedagogy discipline construction of this method is 98.75 percent.

Table 3 shows that the decision-making efficiency of comparative pedagogy discipline construction is different under different methods. When the number of iterations is 50, the decision-making time of comparative pedagogy discipline construction of reference [6] method is 12.7 min, the decision-making time of comparative pedagogy discipline construction of reference [7] method is 15.9 min, and the decision-making efficiency of comparative pedagogy discipline construction of this method is 0.3 min. When the number of iterations is 50, the decision-making time of comparative pedagogy discipline construction of reference [8] method is 12.8 min, and the decision-making efficiency of comparative pedagogy discipline construction of this method is 0.3 min. When the number of iterations is 200, the decision-making time of comparative pedagogy discipline construction of reference [6] method is 28.4 min, the decision-making time of comparative pedagogy discipline construction of reference [7] method is 27.9 min, the decision-making time of comparative pedagogy discipline construction of reference [8] method is 21.9 min, and the decision-making time of comparative pedagogy discipline construction of this method is 0.9 min. This method always has high decision-making efficiency of comparative pedagogy discipline construction, which shows that this method has high decision-making efficiency of comparative pedagogy discipline construction.

4.3.3. Recall Rate of Decision-Making in Discipline Construction of Comparative Pedagogy. In order to verify the decision-making efficiency of comparative pedagogy discipline construction of this method, reference [6] method, reference [7] method, reference [8] method, and this method are used to test the recall rate of decision-making of comparative pedagogy discipline construction. The results are shown in Table 4.

Table 4 shows that there are differences in the recall rate of decision-making of comparative pedagogy discipline construction under different methods. When the number of iterations is 150, the recall rate of comparative pedagogy discipline construction of reference [6] method is 76.83%, the recall rate of comparative pedagogy discipline construction of reference [7] method is 72.54%, the recall rate of comparative pedagogy discipline construction of reference [8] method is 69.86%, and the recall rate of comparative pedagogy discipline construction of this method is 72.26%. When the number of iterations is 50, the recall rate of comparative pedagogy discipline construction of reference [6] method is 68.23%, the recall rate of comparative pedagogy discipline construction of reference [7] method is 69.38%, and the recall rate of comparative pedagogy discipline construction of reference [8] method is 76.83%, and the recall rate of comparative pedagogy discipline construction of this method is 72.26%. When the number of iterations is 300, the recall rate of comparative pedagogy discipline construction of reference [6] method is 69.38%, the recall rate of comparative pedagogy discipline construction of reference [7] method is 72.54%, the recall rate of comparative pedagogy discipline construction of reference [8] method is 68.38%, and the recall rate of comparative pedagogy discipline construction of this method is 72.26%.
decision of reference [8] method is 82.89%, and the recall rate of comparative pedagogy discipline construction decision of this method is 98.66%. This method always has a high recall rate of decision-making of comparative pedagogy discipline construction, which shows that the decision-making effect of comparative pedagogy discipline construction of this method is good.

5. Conclusion

This paper proposes a decision support algorithm for discipline construction of comparative pedagogy based on evolutionary graph data mining. The graph reduction method is used to decrease the call graph set and produce the weighted behavior graph set, and the programme call graph is built according to the programme execution trajectory. The original graph set is reduced using the subtree reduction technique, and an SVM classifier is created to enable comparative education discipline information mining and evolutionary graph data mining. Then, using the complete weighting approach, the attribute categorization of comparative pedagogy discipline construction is achieved, and the weight distribution scheme of comparative pedagogy discipline construction is established utilising the European distance. In this way, the decision support of comparative pedagogy discipline construction is realized based on evolutionary graph data mining. The following conclusions are drawn through experiments:

(1) When the number of iterations is 200, the decision satisfaction of comparative pedagogy discipline construction of this method is 97.32%. It shows that this method’s comparative pedagogy discipline construction decision-making effect is better.

(2) When the number of iterations is 200, the decision-making time of comparative pedagogy discipline construction in this method is only 0.9 min. This method always has high decision-making efficiency of comparative pedagogy discipline construction, which shows that this method has high decision-making efficiency of comparative pedagogy discipline construction.

(3) When the number of iterations is 300, this method’s recall rate of comparative pedagogy discipline construction decision-making is 98.66%. This method always has a high recall rate of comparative pedagogy discipline construction decision-making, which shows that the effect of comparative pedagogy discipline construction decision-making of this method is good.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The author declares no conflicts of interest.

References


