

Research on Hierarchical Interactive Teaching Model Based on Naive Bayesian Classification

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Abstract—The purpose of this research is improving the current inject classroom teaching mode that ignores individual differences and inefficiency of students. By studying classification algorithm in data mining and applying the classification method based on Naive Bayes algorithm, we designed and implemented scientific classification of students, and draw lessons from stratified and interactive teaching mode, so as to build a new effective teaching mode. The results show that through scientific classification of students, real-time hierarchical interaction teaching effectively stimulate students' interest in learning, improve cooperation ability, and improve classroom teaching efficiency.

Keywords—Naive Bayesian; student classification; hierarchical interactive; teaching model

I. INTRODUCTION

Under the background of big data era, the current teaching mode is not adapt to the cultivation of innovative talents, there are many problems, such as low efficiency of classroom, teachers' manipulation of teaching process, ignore the individual differences of students in knowledge transfer ability. Therefore, this study aimed at these problems, by studying classification algorithm in data mining and applying the classification method based on Naive Bayes algorithm, we design and implement scientific classification of students, and draw lessons from stratified and interactive teaching mode, so as to build a new effective teaching mode. The mode enable students to learn efficiently, so as to adapt to the trend of rapid development of new technology and cultivate innovative talents.

II. RESEARCH METHOD

The research and practice of the hierarchical interactive teaching model based on the Naive Bayesian classification is based on the classification of students' differences. So there are two major tasks need to do: the approaches to the students' difference measurement and grouping and the design of hierarchical interactive teaching framework. Its method flow is shown in Figure I.

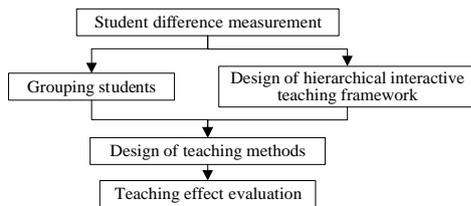


FIGURE I. RESEARCH METHOD FLOW

First of all, based on the samples, the naive Bayes algorithm according to the student's attribute value is used to test the students' differences. Then, according to the results to make a scientific difference classification to achieve effective grouping for students. At the same time, the design of the hierarchical interactive teaching framework is carried out by the two subjects (the student is the main body, the teacher is the leading part). Finally, the teaching effect is evaluated and analyzed.

III. STUDENT CLASSIFICATION DESIGN BASED ON NAIVE BAYESIAN

A. Naive Bayesian Theoretical Principle

At present, there are many kinds of algorithms in data mining, such as based on Bayes algorithm, decision tree algorithm, neural network algorithm, rough set algorithm, genetic algorithm, support vector machine algorithm and so on. In the practical application of many classification algorithms, the most widely used algorithm is Naive Bayesian algorithm model. Naive Bayes is a simple and effective classification model. From Bayes' theorem recall that:

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)} \quad (1)$$

Equation (1): $P(A)$ and $P(B)$ separate representation the probability of occurrence of events A and events B .

$P(A|B)$ indicates the probability of occurrence of event A under the premise that event B occurs. $P(A|B)$ is a priori probability, and its value is often easily obtained.

$P(B|A)$ indicates the probability of occurrence of event B under the premise that event A occurs. $P(B|A)$ is a posteriori probability, and its value is the result of the solution of the Bayesian formula.

The classifier structure diagram based on the naive Bayes algorithm is shown in Figure II. Its leaf node A_m represents the m attribute, and the root node C represents the category. Suppose $D = \{C, A, S\}$ are training samples, it includes the student category $C = \{C_1, C_2, \dots, C_i\}$ and the student attribute $A = \{A_1, A_2, \dots, A_m\}$. Suppose $S = \{S_1, S_2, \dots, S_n\}$ represents a collection of classified students, in which S_n represents n th student. Suppose $X_k = \{a_1, a_2, \dots, a_m\}$ is a student to be classified,

in which each a_m represents an attribute eigenvalue of the pending item X_k .

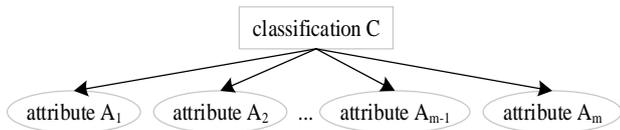


FIGURE II. THE CLASSIFIER STRUCTURE DIAGRAM

B. Design the Individualized Attributes of Students

The student classification method based on the naive Bayes algorithm is used the information of the past students as the sample set, which is used to construct the naive Bayes classifier.

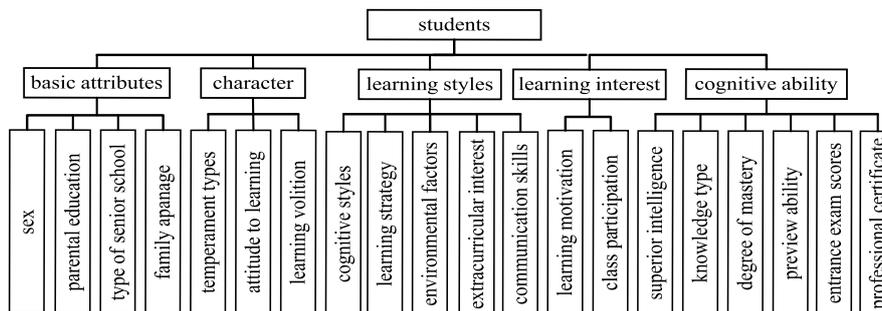


FIGURE III. INDIVIDUALIZED ATTRIBUTES OF STUDENTS

C. Student Classification Design Based on Naive Bayesian

The process based on the naive Bayes classification is shown in Figure IV.

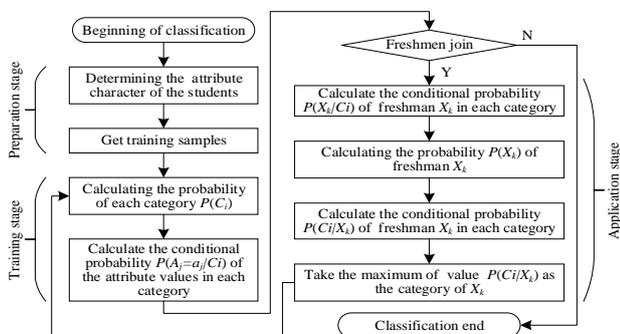


FIGURE IV. STUDENT CLASSIFICATION CYCLE FLOW CHART BASED ON NAIVE BAYES ALGORITHM

1) $P(C_i)$ is set to indicate the frequency of the occurrence of the student category C_i in the training sample concentration, that is the category probability. For sample data sets, there are different levels of students in each category, which avoids the discrimination of students.

$$P(C_i) = \frac{Count(C_i)}{n} \quad (2)$$

Students are classified according to the information of the students' attributes. The students divided into the same category are not simply using the score as criterion of evaluation. Its are classified by comprehensive evaluation after combination of other attributes.

The difference classification based on the naive Bayes algorithm is select the individual attributes of the students as shown in Figure III. The students which 8 attribute values similar in the two dimensions (character and learning style) are put into one category, while the 12 attributes values of the three dimensions of personal basic situation, learning interest and cognitive ability are different. The purpose of the classification is to carry out differential teaching to implicit dynamic stratification and heterogeneous cooperation for students' cognitive ability, learning interest and basic information.

The function $Count(C_i)$ represents the number of students belonging to category i which is in the entire student sample collection of S . n represents the total number of the entire student sample collection of S .

2) $P(A_j = a_j | C_i)$ is set to represent the conditional probability of each characteristic attribute value of the student in the category.

$$P(A_j = a_j | C_i) = \frac{Count_{C_i}(A_j = a_j)}{Count(C_i)} \quad (3)$$

$A_j = a_j$ indicates that the value of the j attribute is a_j . The function $Count_{C_i}(A_j = a_j)$ represents the number of students which the attribute name is A_j and attribute value is a_j in the i student category.

3) $P(X_k | C_i)$ is set to represent the conditional probability of the students X_k to be classified in the student category C_i , m represents the number of attributes that describe student differences.

$$P(X_k | C_i) = \prod_{j=1}^m P(A_j = a_j | C_i) \quad (4)$$

4) $P(A_j = a_j)$ is set to represent the probability of the student's attribute A_j when the value is a_j .

$$P(A_j = a_j) = \frac{\text{Count}(A_j = a_j)}{n} \quad (5)$$

The function $\text{Count}(A_j = a_j)$ indicates the number when the value of attribute j is a_j .

5) $P(X_k)$ is set to indicate the probability that the student X_k should be classified in the training sample concentration.

$$P(X_k) = \prod_{j=1}^m P(A_j = a_j) \quad (6)$$

6) $P(C_i | X_k)$ is set to represent the conditional probability that the student X_k should be classified to category i .

$$P(C_i | X_k) = \frac{P(X_k | C_i)P(C_i)}{P(X_k)} \quad (7)$$

7) $P(C_{\max} | X_k)$ is set to represent the maximum category probability of the student X_k which should be classified to the student category.

$$P(C_{\max} | X_k) = \max \{P(C_1 | X_k), P(C_2 | X_k), \dots, P(C_i | X_k)\} \quad (8)$$

C_{\max} indicates the maximum category of conditional probability which is obtained by (8).

Finally, (8) is used to calculate the maximum category probability of the students to be classified in the students category. That is the category of the students to be classified. At this point, one classification ends.

IV. THE DESIGN OF THE HIERARCHICAL INTERACTIVE TEACHING FRAMEWORK

The hierarchical interactive teaching model is an independent, inquiring and cooperative teaching model based on the classification of the naive Bayes algorithm. This model breaks the original classroom structure, and takes the interaction of teachers and students as the carrier, and also group autonomy, and let the students as the subject of the class. This model is guided by the task of the problem, and it is based on the students' self-study, and it aims at the completion of the task of the group. This model creates an ecological chain class based on group mutual learning to solve problems. It pays attention to the state of learning and the quality of life for every student. The design of the hierarchical interactive teaching model framework is shown in Figure V.

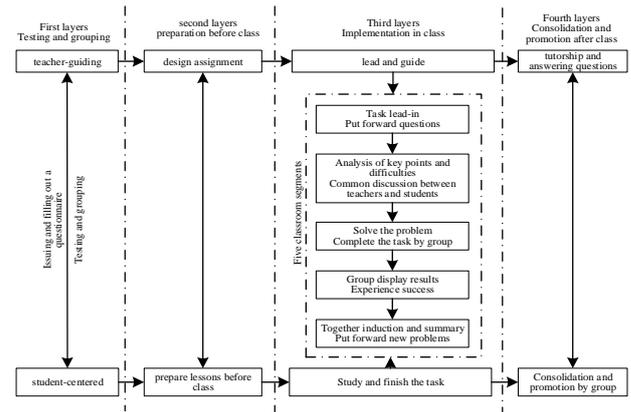


FIGURE V. THE HIERARCHICAL INTERACTIVE TEACHING MODEL FRAMEWORK

The four layers of the hierarchical interactive teaching model are closely related to each other, and support each other dynamically with the spiral. The five segments drive each other to form a whole, interlace and connect with each other. This teaching mode makes the classroom an active area for teachers and students to resonate with their ideology and to show their personality together.

V. ANALYSIS OF TEACHING EFFECT

In this paper, the teaching effect is analyzed from two aspects by using the method of questionnaire and comparative experiment. First, the experimental class's comparative analysis before and after the experiment is carried out. Then, a comparative analysis between the experimental class and the contrast class is carried out.

The comparative data of the experimental class before and after the experiment are shown in Figure VI. From Figure VI, it can be seen that 85.72% of the students have an attitude of approval towards the application of the hierarchical interactive teaching model based on the naive Bayes algorithm in the teaching. There are 70.13% of the students satisfied with the improved teaching effect. At the same time, it can be seen that the students' interest in learning and the ability to communicate and cooperate have improved obviously.

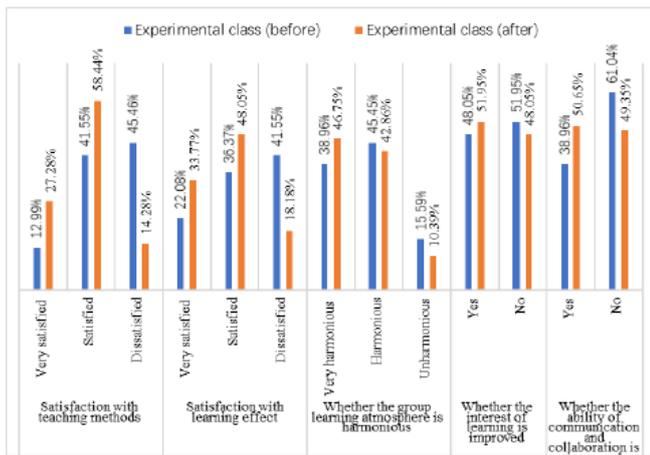


FIGURE VI. THE COMPARATIVE DATA OF THE EXPERIMENTAL CLASS BEFORE AND AFTER THE EXPERIMENT

The comparison between the experimental class and the contrast class is shown in Figure VII. From Figure VII, we can see that students' satisfaction degree, teaching effect satisfaction and group learning atmosphere based on Naive Bayes algorithm classification are higher than those of the contrast class. At the same time, it can be seen that the students' interest in learning and the ability to communicate and cooperate have also been improved.

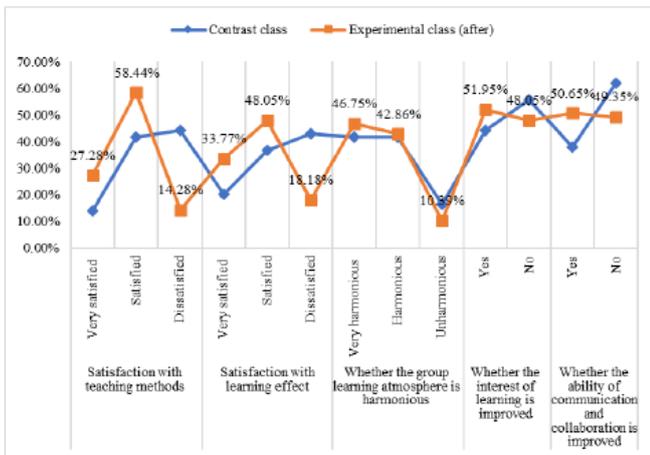


FIGURE VII. THE COMPARISON BETWEEN THE EXPERIMENTAL CLASS AND THE CONTRAST CLASS

VI. CONCLUSION

The comprehensive analysis shows that, in the implementation of the hierarchical interactive teaching model based on the naive Bayes algorithm, the new teaching mode was accepted by the students, it was welcomed by the students. The new teaching mode can improve the ability of learning interest and collaboration of students. It has a very good teaching effect. Experiments show that the classification algorithm based on Naive Bayes has better feasibility and effectiveness in solving student classification problem.

However, due to the limited personal time and ability, there are still some shortcomings in the study. In order to better achieve hierarchical interaction teaching mode based on Naive

Bayes algorithm and improve teaching effect, we still need to further improve the limitation of applying naive Bayes algorithm, that is, suppose the attributes of students are independent.

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