

Retraction

Retracted: Teaching Quality Evaluation of Ideological and Political Courses in Colleges and Universities Based on Machine Learning

Journal of Mathematics

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Qiao, "Teaching Quality Evaluation of Ideological and Political Courses in Colleges and Universities Based on Machine Learning," *Journal of Mathematics*, vol. 2022, Article ID 2835029, 10 pages, 2022.

Research Article

Teaching Quality Evaluation of Ideological and Political Courses in Colleges and Universities Based on Machine Learning

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Ideological and political (IAP) education is the soul of socialist construction. As the main position for the cultivation of the “Four Haves” in the cause of socialist construction, colleges and universities shoulder an important educational mission. However, standard, scientific, systematic, and feasible evaluation index system is lacking in the teaching of IAP theory courses. Therefore, it is fervently required to use the modern science and technology for the establishment of a complete, objective, and feasible classroom teaching evaluation system, and the optimization of the evaluation process is also an important issue that needs to be resolved urgently. This paper combines teaching evaluation theory and machine learning methods, analyzes the rationality of evaluation indicators through the acquired evaluation data, and optimizes the evaluation system. By comparing the advantages and disadvantages of traditional machine learning classification algorithms, a classifier based on weighted naive Bayes is analyzed and designed for teaching evaluation, and the specific process of evaluation model construction is introduced. The experimental results show that the classification model based on the weighted naive Bayes algorithm is reasonable and feasible for teaching evaluation. Combined with the weighted Bayesian classification incremental learning principle, the performance of the classification model can be better than the traditional classification model.

1. Introduction

It has always been a top priority for both the party and the country to invest in IAP education programs, as the cornerstone of socialist creation. With the continuous advancement of the reform of the market economy system, my country's spiritual and cultural undertakings are facing unprecedented challenges. A decision was made in this regard at the Sixth Plenary Session of the Seventeenth Central Committee, which met from October 15 to October 18, 2011, and which was titled “Deepening Reform of the Cultural System, Promoting the Development and Prosperity of Socialism Culture.” Specifically, the resolution said that, in today's changing social environment, the need of encouraging the development and progress of socialist cultural endeavors, as well as the importance of giving full play to the function of cultural soft power, must be given full consideration. Nowadays, in the primary stage of socialism in our country, due to the imbalance in the construction of

material civilization and spiritual civilization, problems such as honesty and morality occur from time to time. There is an urgent need to use the socialist core value system to regulate and guide direction in life. In order to further the cultural system's reform and promote socialist culture's enormous growth and prosperity, skilled builders are required [1]. Therefore, it has become an important task to cultivate the “Four Havings People” who is capable of promoting the growth and development of socialist spirituality.

Colleges and universities are intimately linked to the molding of the “Four Havings People” intellectual and political character as the principal front for growing and creating the socialist “Four Havings People” [2], the reform of the socialist cultural system, and the realization of the goal of cultural prosperity and development. It is the primary method for colleges and universities to educate students on IAP matters [3–5]. The Sixth Meeting of the Seventeenth National Committee of the CPC Central Committee in Canada also clearly put forward the issue of promoting

cultural prosperity. IAP theory courses should be treated seriously as a means of promoting China's development of advanced culture.

There is now a steady advancement in IAP theory courses taught by applying the spirit of several programs suggested by the CPC and basically conforming to the requirements set forth in the central documents. However, there are still some problems. The quality of teaching work is the internal driving force that guarantees the effective development of courses. To improve fundamentally, it is necessary to find out the problems and make targeted improvements on the basis of scientific analysis. On the basis of this, college and university ideology and political theory courses should be thoroughly investigated and evaluated for their teaching quality [6]. However, looking at the existing research results and actual survey results in related fields at this stage, despite the fact that the study on IAP education at colleges and universities has been finished, it is not difficult to come across examples of this. A great deal of work has to be done before IAP theory courses can be considered thorough, and a number of important themes need to be addressed and investigated further.

The research purpose of this topic is to use machine learning methods to solve the problems of traditional classroom teaching evaluation indicators such as fuzzy and relatively single evaluation model [7, 8]. Use data mining technology to explore the internal relationship between various factors that affect teachers' teaching effect and teaching level from the teaching evaluation data and optimize the existing index system. By researching and optimizing machine learning algorithms, construct a teaching evaluation model to reduce subjective factors. Achieve a quick and objective judgment of the quality of teaching and provide effective guidance for teaching management. The study on this topic might hypothetically broaden the use of data mining technologies in education and give new ideas and technical references for the assessment of teaching methods. Solve the issue of too much subjective assessment of teachers in the old manner, try to provide a reliable teaching evaluation method for teaching workers, and improve the efficiency and credibility of evaluation. In Section 2 of this paper, we reviewed the literature related to our work. In Section 3, we explained the different methods and algorithms, including the proposed methods and algorithms. In Section 4, we executed some experiments, which used different algorithms. Then, we compared and analyzed their outcomes and confirmed the perfection of the proposed techniques. Finally, we concluded the study in Section 5.

2. Related Work

It is critical for colleges and universities to teach courses on ideology and politics as part of their overall educational mission. It is to systematically teach IAP morality courses guided by Marxism and its Chinese theoretical results [9]. It is a primary means of acquiring political and ideological knowledge, as well as a significant means of acquiring theoretical knowledge. Its purpose is to cultivate students' socialist personality through teaching activities organized by

the school. Through teaching, cultivate the defenders, builders, and successors of socialism that meet the essential requirements of socialism. An essential part of the college and university teaching mission is to teach IAP courses. However, the actual result is that the school does not pay attention to it, the teachers are hard to deal with, the students cannot be interested, and the actual teaching effect is not satisfactory.

Studying the effectiveness of professors who teach courses in political theory and ideologies at colleges and universities relies on theories and practices from both the ancient and modern cultures of China and elsewhere in the world. Chinese academics and professionals have frequently referred to Chinese and foreign traditional theories and practices since the introduction of a new program of IAP theory courses at universities [10, 11]. According to the actual situation of education and teaching of theory courses, different levels of research are carried out on the meaning, function, importance, and initiation of the indication system of the evaluation and evaluation of education and teaching quality of theory courses, accumulated a wealth of ideas, and produced different guiding roles in practice. IAP theory courses in college and university classrooms are rarely studied in terms of their educational and teaching quality. There is still much space for improvement in terms of educational and instructional quality in college and university courses on IAP theory. There is an urgent need to widen the scope of study, whether theoretical or applied.

The following are some example comments on the study's results about the guiding principle for assessing ideology and political theory courses delivered in colleges and universities. The notion of developmental assessment must be included into the evaluation process. IAP theory courses are taught for a variety of reasons, but the ultimate goal is to help students and teachers grow together, which promote the diversification of evaluation methods, the diversification of evaluation subjects, the three-dimensionality of evaluation content, and the dynamic nature of the evaluation process. Continuously realize the promotion of "learning" by evaluation, the promotion of "teaching" by evaluation, and the promotion of development by evaluation. Mei Ping pointed out in "Five Key Points of College IAP Theory Course Teaching Evaluation" that in college IAP theory course teaching evaluation, the evaluation concept of "focusing on the common development of teachers and students" is a developmental evaluation concept. An evaluation system that is based on science and the goal of sustainable human development, as well as an evaluation system that encourages individuals who have been evaluated to participate in evaluations, engage in self-reflection, and pursue professional development and comprehensive quality improvement is positioned [12]. Zhang Sheqiang pointed out in the "Three Questions of Teaching Evaluation of IAP Theory Courses in Colleges and Universities" that the evaluation of the teaching and evaluation of IAP theory courses must also adhere to the scientific development concept to achieve comprehensive, coordinated, and sustainable development of teaching evaluation and better service for education and teaching work.

Current advances in data mining have had a significant impact on education-related research during the last several years, most notably in data collection, storage, analysis, and decision-making. The area of educational data mining has received a lot of interest from academics and researchers alike. It is possible to acquire a huge amount of student information, teacher information, and teaching data during the educational process. However, the information hidden behind these large amounts of data cannot be effectively used. The introduction of data mining technology can dig out more valuable knowledge. Since 2005, the topics of many international conferences have been intelligent mining of educational data. The ongoing evolution of education has also facilitated the progressive expansion of study into the theory and implementation of educational data mining. In 2008, Montreal, Canada hosted the first International Conference on Educational Data Mining. Eight conferences have been successfully hosted to date, as has the Journal of Educational Data Mining (JEMD) [13].

The process of teaching evaluating has changed from a single qualitative assessment to a mix of qualitative and quantitative evaluations as new technologies have been developed. However, it is frequently important to develop a sound data model in order to do quantitative analysis on a variety of data sources. The weighted average approach, expert evaluation technique, AHP analytic hierarchy process [14], fuzzy comprehensive evaluation method [15], neural network model method [16], and Markov chain method [17] are the most extensively used approaches for assessing instruction in the United States and worldwide. Currently, scholars decide the weight of the evaluation index mostly using the fuzzy comprehensive evaluation approach and the analytic hierarchy process [18–20]. For instance, scholars such as Li Xingmin integrated the analytic hierarchy method with fuzzy comprehensive evaluation of teaching quality, resulting in a very scientific quantitative procedure that enhanced the scientificity and reliability of the evaluation outcomes.

The use of rough set theory to overcome the issue of irrational index weights is one aspect of relevant research into integrating machine learning technology into teacher assessment systems [21], the introduction of decision trees to analyze teaching data [22], and an investigation into the effects of teaching quality factors using association rule algorithms. Additional research has found that artificial neural networks can be used to model education in order to evaluate it [23, 24]. Peng Juping, for example, applied artificial neural network theory, developed related mathematical models, quantified the indicators in a comprehensive manner, and then constructed a Bayesian neural network model to obtain a more reasonable evaluation result [25]. It has been proposed in the literature [26] to use wavelet neural networks to construct a mathematical model for evaluating the quality of teaching. There are a lot of disadvantages to using neural networks as an application approach, including a predisposition for falling into local extreme points and a high degree of sample reliance.

To summarize, in recent years, scientists have made significant advances in the field of teacher evaluation

research. However, the depth of research on teaching evaluation theory is greater, the content of research on evaluation technique and technology is less, and the technology employed is very straightforward. In order to overcome the shortcomings of qualitative and quantitative evaluation in traditional classroom evaluation, more research in data mining and machine learning is required.

3. Method

The primary focus of this chapter is the development of a methodology for evaluating classroom instruction. To begin, let us have a look at some of the more established methods of classification. The Naive Bayes algorithm is found to have more advantages in teaching evaluation through theoretical and experimental verification. The weighted naive Bayes algorithm incremental learning algorithm is suggested as an evaluation model for teaching.

3.1. Evaluation Method Based on Traditional Classification Algorithm. As part of the supervised learning process, classification is a significant issue. Analyze the training data and identify a model or correct description for each class to summarize its properties. The model may infer the class to which these new data with unknown labels belong using the created class description. This description is then used to categorize future test data in the data set. Learning and classification are the two fundamental processes that make up the classification challenge. A suitable learning approach is utilized to learn a classifier based on the training data set in the learning process. The new input instance is utilized to classify the new input instance in the classification process.

Naive Bayes, support vector machines, K-nearest neighbors, decision trees (DT), neural networks, and so on are all common classification techniques in machine learning. The Naive Bayes (NB) algorithm is a classification approach based on Bayes' theorem among them. A simple classification model is used to introduce the hypothesis of feature condition independence. This type of classification model is known as a support vector machine (SVM). Classifiers are constructed using a linear classifier, which defines the greatest interval in the feature space. Using K-nearest neighbor (KNN), it is assumed that a training data set and an instance category have been established. Suppose you already know the class labels of the k closest training examples and you want to predict the class using majority voting or some other approach. An instance of the DT paradigm is represented by a tree structure, which symbolizes the process of classifying instances based on their qualities. Feature selection, decision tree creation, and decision tree pruning are all common phases in decision tree learning. Nonlinear comprehensive evaluation can be solved by using an artificial neural network. Any complicated nonlinear relationship can be fully approximated, and the nonlinear process can be modelled without knowing the underlying cause of the information.

There are a range of features for each classification technique, and the effect of classification is often determined

by application environment and data properties. It is impossible to find a classifier that works for all kinds of problems and attributes. The following is a side-by-side comparison of the several common classification algorithms that were previously mentioned, see Table 1.

Classification algorithms can be used in the teacher evaluation process depending on the requirements. Class labels are based on a sequence of evaluation attribute values, and the evaluation grades are utilized as input. As an evaluation result, the new evaluation attribute's value will be assigned a most likely class label by a classification method. To ensure the validity of the evaluation results, it is essential to select a suitable algorithm for the classifier. Performance can be evaluated by the accuracy of classifiers. A measure of the relationship between the number of samples that the classifier correctly classifies and the total number of samples in a particular test data set. The formula is shown as follows:

$$\text{Acc} = \frac{S_n}{S}. \quad (1)$$

where Acc represents the accuracy rate, S_n represents the number of samples correctly classified, and S is the total number of samples.

3.2. Design of Evaluation Classifier Based on Weighted Naive Bayes. In order to describe the design of evaluation classifier on the basis of WNB, the principle of NB algorithm is given, where we proposed three algorithms which can be combined together to determine the category of the test data. Additionally, evaluation attribute weight determination algorithm is proposed.

3.2.1. Principle of Naive Bayes Algorithm. Bayesian classification, which is derived from the theory, is an example of a classification approach that makes use of Bayes' theorem. To estimate the prior probability of each category in the classification process, a considerable amount of training data must be learned, which is the core premise of classification theory. After that, determine the likelihood that an object X can be classified into multiple groups. In the end, the class with the highest posterior probability is deemed to be the instance. Suppose T is the training data set, $P = \{P_1, P_2, \dots, P_n\}$ is the attribute variable set, and n is the number of attributes. $Q = \{Q_1, Q_2, \dots, Q_m\}$ is the set of class variables, and m is the number of categories, then a training sample can be expressed as $\{s_1, s_2, \dots, s_n, Q_i\}$, $i \in m$, where Q_i signifies that the sample's class label is well-known. S can be represented as $\{s_1, s_2, \dots, s_n\}$, and to determine the test sample's chance of being a given type, the formula is

$$p(Q_i|S) = \underset{Q_i}{\operatorname{argmax}} \frac{p(S|Q_i)p(Q_i)}{p(S)}. \quad (2)$$

In the field of Bayesian classification, the Naive Bayes classification algorithm (NB algorithm) is one of the most efficient algorithms. Using a categorization model is advantageous since it is simple to understand, efficient to compute, and stable. When compared to other classifiers,

such as decision trees and SVMs, it performs better in some situations. Figure 1 shows the naive Bayes model's simplest mesh structure:

The root node Q is a class variable, and the leaf nodes $P = \{P_1, P_2, \dots, P_n\}$ are attribute variables. In spite of the fact that the NB classification model is based on the traditional Bayesian classification model, this model does not suffer from the restriction of independence among attributes. When $p(S)$ is a constant in the real world, the calculation formula for the NB method can be written as follows:

$$p(Q_i|S) \propto \underset{Q_i}{\operatorname{argmax}} p(S|Q_i)p(Q_i), \quad (3)$$

where $p(Q_i)$ is the class prior probability, which can be learned through training data. The calculation formula is

$$p(Q_i) = \frac{t_j}{t}. \quad (4)$$

where t_j represents the amount of classes, Q_i in the training samples, and t represents the total number of training samples.

It is assumed that all attribute variables are conditionally independent of one another and do not have any relationship in order to ensure the correctness of the NB approach. If the data collection contains a large number of attributes, the computational cost of $p(S|Q_i)$ is extremely high. By introducing the assumption of conditional independence, the computing cost can be reduced while sacrificing some computational accuracy. The computation formula for $p(S|Q_i)$ can be simplified as follows:

$$p(S|Q_i) = \prod_{a=1}^n p(s_a|Q_i). \quad (5)$$

If the training data is sufficient, $p(s_1|Q_i), p(s_2|Q_i), \dots, p(s_n|Q_i)$ can all be learned from the training data. It is possible to determine the category of the test data by combining the three algorithms listed above.

3.2.2. Evaluation Attribute Weight Determination Algorithm. Naive Bayes is a computationally efficient method. Conditions are presumed to be unrelated, and the weight assigned to each conditional attribute in the decision classification is set to one, which implies that they are all of equal value. When all weights are set to one, the accuracy of classification is lowered by default. According to this study, the weight allocated to an attribute is determined by how well the attribute contributes in data categorization using the weighted Naive Bayesian (WNB) approach. As well as maintaining the fast speed of the Naive Bayes algorithm, it minimizes a classifier's reliance on the conditional independence assumption. The formula for the computation is presented as follows:

$$p(Q_i|S) = \underset{Q_i}{\operatorname{argmax}} p(Q_i) \prod_{a=1}^n p(R_a|Q_i)^{w_a}. \quad (6)$$

During categorization, for example, the weight of the feature R_a is represented by w_a in order to quantify the relevance of different characteristics in the same category. As

TABLE 1: Comparison and analysis of classification algorithms.

Algorithm	Advantage	Disadvantage
Naive Bayes	Stable classification efficiency	Low efficiency when there are many attributes
Support vector machines	Less training set used	The training speed is slow when many samples
K-nearest neighbor	No need for parameter estimation	Large sample size and high space complexity
Decision tree	Readable and fast classification	Easy to overfit and ignore correlation
BP network	Able to adapt and have certain fault tolerance	Slow convergence speed, strong sample dependence

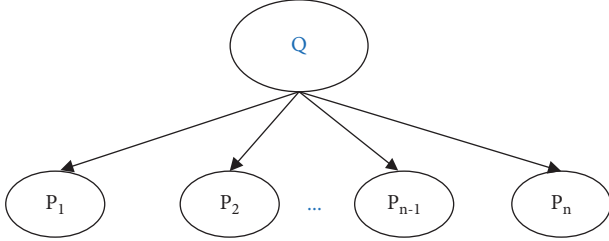


FIGURE 1: Naive Bayes classification model.

w_a increases, so does the importance of the associated characteristic R_a in categorization. What matters the most in specific applications is determining the weights assigned to each attribute in the weighted naïve model.

Using data from instructional evaluation data to investigate the relationship between each assessment feature of the instructional evaluation data and the overall evaluation value, it was discovered that the value of each index had varying degrees of influence on the evaluation conclusion. This study investigates in detail the approach given in this paper for computing the weight of each assessment characteristic by using the relative probability of the class attribute. Each attribute R_a may have G different values. Use r_g to indicate its specific value, where $g \in G$. Assuming a specific instance S , when the attribute R_a of S takes the value r_g , for category Q_i , the calculation formulas for the relative probability $p(R_a|Y)$ and irrelevant probability $p(R_a|N)$ of attribute R_a with respect to Q_i are as follows:

$$p(R_a|Y) = \frac{\text{num}(R_a = r_g \wedge Q_i)}{\text{num}(R_a = r_g)}, \quad (7)$$

$$p(R_a|N) = 1 - p(R_a|Y),$$

where count represents the statistical number. When the value of the attribute R_a is r_g and belongs to the Q_i category, the calculation formula of the attribute weight is as follows:

$$w(R_a, r_g, i) = \frac{p(R_a|Y)}{p(R_a|N)}. \quad (8)$$

As a consequence, the precise calculation formula for the weighted naïve Bayes classification method is as follows:

$$p(Q_i|S) = \operatorname{argmax}_{Q_i} p(Q_i) \prod_{a=1}^n p(R_a|Q_i)^{w(R_a, r_g, i)}. \quad (9)$$

There are n characteristics in a data collection T if the class labels are m . There are g potential values for each

property, hence the total weight of all attributes is $m * n * g$. The particular value and weight of the same property differ. Different categories assign different weights to attributes with the same value. Final step: each characteristic value is converted into a weighted average, and the resulting values are compared across all categories. The result of the categorization is the category that has the across all categories. The result of the categorization is the category that has the maximum number of points.

3.3. Incremental Learning for Weighted Bayesian Classification. With the continuous increase of data, the form of putting all the training sets into the memory for calculation at one time cannot solve practical problems well. The adoption of the principle of incremental learning might therefore minimize the computer's performance needs. Because Bayesian classifiers allow for incremental learning, the algorithm's time consumption can be reduced by a major portion of the calculation process being completed incrementally. Furthermore, the quality of the training data has an impact on the effectiveness of the classification algorithm when it comes to prediction. As a rule, a larger training sample improves both predictive and generalizability abilities. A classifier's training samples cannot be completed all at once in the real world, thus they must be completed progressively.

The classification algorithm in this paper mainly uses the weighted Naive Bayes method. The Bayesian incremental learning process actually updates the original class prior probability $p(Q_i)$ and attribute conditional probability $p(s_a|Q_i)$. Because incremental learning of the classifier does not require retraining the classification model, it is simple to feed the newly collected data into the classification model and to make the necessary adjustments to the model's parameters as needed. The specific correction formula is as follows:

Modification formula of prior probability of Bayesian incremental algorithm:

$$P(Q_i) = \begin{cases} \frac{M}{M+1} \cdot p(Q_i) + \frac{M}{M+1}, & \text{when } Q_t = Q_i, \\ \frac{M}{M+1} \cdot p(Q_i), & \text{when } Q_t \neq Q_i. \end{cases} \quad (10)$$

Conditional probability modification formula of Bayesian incremental algorithm:

$$P(s_a|Q_i) = \begin{cases} \frac{M_{Q_i}}{M_{Q_i} + 1} \cdot p(s_a|Q_i) + \frac{1}{M_{Q_i} + 1}, & \text{when } Q_t = Q_i \text{ and } s_a = r_g, \\ p(s_a|Q_i), & \text{when } Q_t \neq Q_i, \\ \frac{M_{Q_i}}{M_{Q_i} + 1} \cdot p(s_a|Q_i), & \text{when } Q_t = Q_i \text{ and } s_a \neq r_g, \end{cases} \quad (11)$$

where $P(Q_i)$ and household $P(s_a|Q_i)$ are the updated class prior probability and attribute conditional probability after adding a new sample, M represents the total number of original data records, M_{Q_i} represents the total number of original data records belonging to category Q_i , and r_g represents the value of a certain feature.

It is also necessary to recalculate the attribute value of the newly added sample set in order to account for the number of samples in each category that have been added. In each attribute, update the relevant probability and irrelevant probability values by combining the statistical value of the preceding sample data and then update the weights of each attribute as a result of the update. Using formula (10) and formula (11) and weighted Bayesian formula (9), the probability $P(Q_i|S)$ of the category Q_i of each data record S can be calculated.

4. Experiment and Analysis

In this section, we carried out the experiments for the proposed method and algorithms. The results of these experiments are investigated and analyzed.

4.1. Experimental Results Based on Traditional Classification Algorithms. Experimenting on an existing teaching evaluation data set, this section uses the abovementioned five machine learning classification techniques to evaluate the algorithm's feasibility. The python machine learning sklearn package provides an algorithm function that is used to compare the experimental outcomes of each classification method. For the experimental, there are 200 pieces of training data and 100 pieces of test data. After 10 iterations of cross-validation, the average classification accuracy is computed using formula (1). The results of the study are shown in Figure 2.

Figure 3 shows the average time consumption of each algorithm for the same experimental data set.

Because the Naïve Bayes method's classification accuracy on this data set is reasonably good, and its running time is the lowest, and the naive Bayes algorithm is employed to design the teaching evaluation model, as demonstrated above in the experimental findings.

4.2. Experimental Results Based on the Weighted Naive Bayes Algorithm. In this section, the experiments are carried out on the Windows10 operating system and on the experimental platform, which is written in the Python3.5 programming language for algorithm development.

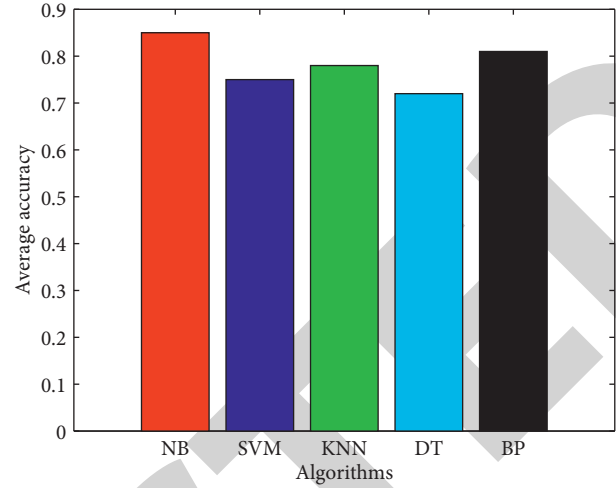


FIGURE 2: Comparison of classification accuracy of different algorithms.

4.2.1. Comparison of Classification Accuracy between NB and WNB Algorithm. Data from the teaching evaluation database is used for cross-validation studies, with 200 data records selected as the training set and 100 data records selected as the test set. The classification accuracy is evaluated in 10 cross-validation trials. It is shown in Table 2 how each experiment performed.

From Table 2, the classification accuracy comparison between NB algorithm and WNB algorithm is shown in Figure 4.

It was found through the experiments that the average classification accuracy of Naive Bayes technique is 0.81, whereas a similar result was found for the weighted Bayes algorithm, which had an average classification accuracy of 0.84. In general, the weighted naive Bayes algorithm outperforms the regular naive Bayes algorithm when it comes to classifying data from the instructional evaluation data.

4.2.2. Comparison of Classification Accuracy. Back propagation (BP) neural networks are the most commonly used methods in teaching evaluation research nowadays, but for better understanding the teaching evaluation research, this study employs a WNB classifier for the development of an assessment model and the comparison of its efficiency with traditional approaches. Normalization is used to transform a percentage into a decimal in the [0, 1] range when using the BP neural network technique to handle training data. In order to anticipate the evaluation level of fresh data samples, a model is constructed by specifying an error threshold.

For the BP algorithm experiment, 200 data records from the evaluation database are randomly chosen as the training set, and 100 data records from the evaluation database are randomly selected as the test set. According to the results of debugging tests, the most successful experimental parameter settings are as follows: tanh acts as the activation function, the learning rate is 0.005, and the number of cycles is 5000, all of which are depending on the number of characteristics. The input layer, hidden layer, and output layer nodes are set to 8, 6, and 1.

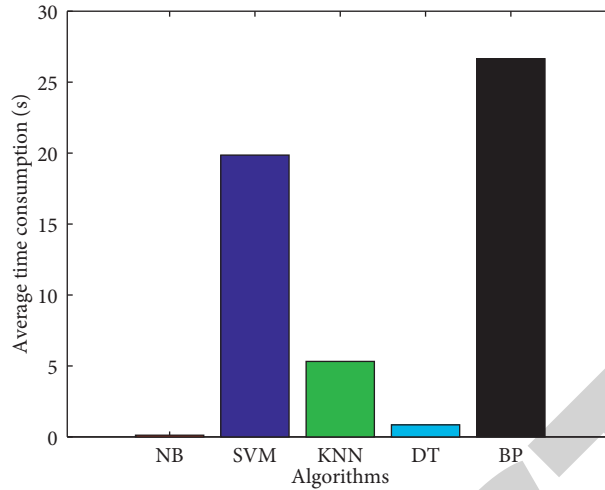


FIGURE 3: Average running time of different algorithms.

TABLE 2: Classification accuracy of NB algorithm and WNB algorithm.

Num	1	2	3	4	5	6	7	8	9	10	Average
NB	0.79	0.83	0.78	0.82	0.84	0.81	0.81	0.83	0.79	0.80	0.81
WNB	0.83	0.85	0.87	0.85	0.85	0.81	0.82	0.84	0.86	0.82	0.84

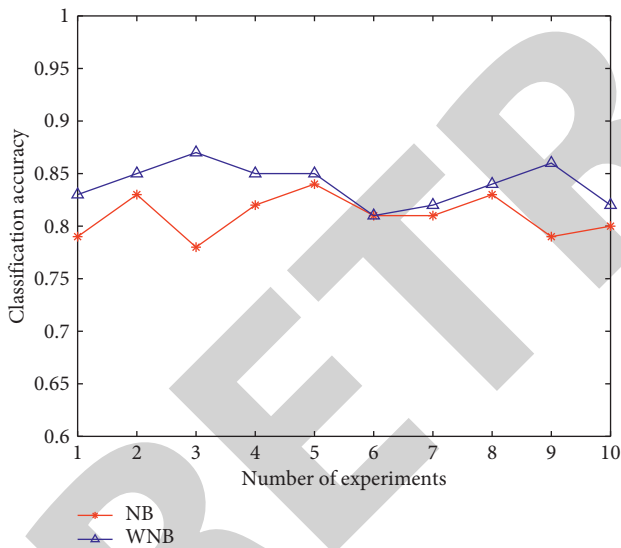


FIGURE 4: Comparison of classification accuracy between NB and WNB algorithm.

Following the training of the neural network method, the following Table 3 shows the results of the tests that were conducted:

From Table 3, the classification accuracy comparison between NB algorithm and WNB algorithm is graphically depicted in Figure 5.

As a result of the high number of outstanding ratings in the genuine teaching evaluation data set, there are few additional grades available. As a result, when training the classification model with hierarchical data, if the extracted training data sets are different, the experimental findings will have a certain degree of influence. The WNB algorithm had

an average classification accuracy of 0.85, whereas the BP method had an average classification accuracy of 0.75. The WNB algorithm has a greater classification effect than the BP method, according to the testing data. This experiment also found that the WNB algorithm consumes less time on average than the BP method, with an average time consumption of 0.15 s compared to 0.63 s. The WNB algorithm, on the other hand, is faster and more accurate. There are many advantages to teaching evaluation using the WNB method.

4.3. *Incremental Learning Experiment Results.* Create an incremental classification model based on weighted naive Bayes and finish the construction of it. Set the initial training data set at 200 and the test data set to 100 and gradually increase the training sample set. In the accompanying Table 4, the exact computation results of a piece of test data at each stage of the increment are selected at random from a pool of possible outcomes:

As shown in Table 5, when the incremental classifier is used to perform classification, the calculation result is more inclined to the correct category, suggesting that the probability value of belonging to the correct category is increasing. The probability value of other categories is reduced. As the training data gradually increases, the average classification accuracy rate changes as shown in Table 5:

The WNB algorithm with incremental learning uses the same experimental data set to compare the time consumption of the WNB algorithm and the “Add_WNB” algorithm. The running time comparison chart is shown in Figure 6.

Experiments have shown that using an incremental approach improves the classification model. To avoid retraining and calculating a previously trained data set, all that is required of an incremental model is to categorize and

TABLE 3: Classification accuracy of BP algorithm and WNB algorithm.

Num	1	2	3	4	5	6	7	8	9	10	Average
BP	0.75	0.72	0.73	0.77	0.79	0.74	0.73	0.74	0.78	0.75	0.75
WNB	0.85	0.86	0.88	0.87	0.85	0.83	0.85	0.84	0.82	0.85	0.85

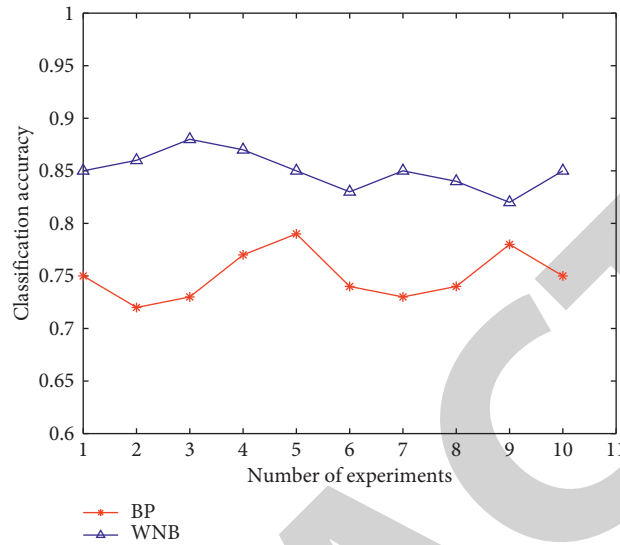


FIGURE 5: Comparison of classification accuracy between BP and WNB algorithm.

TABLE 4: The calculation results of certain test data.

Number of increments	Add 50		Add 100		Add 200	
	Before	After	Before	After	Before	After
Level	Excellent		Excellent		Good	
Excellent	$1.2e-08$	$2.0e-08$	$4.0e-07$	$1.8e-07$	$1.5e-06$	$1.4e-06$
Good	$1.6e-10$	$4.5e-15$	$6.4e-13$	$4.8e-12$	$1.6e-07$	$4.2e-07$
Medium	0	0	0	0	$2.4e-08$	$3.2e-08$
Pass	0	0	0	0	0	0
Failed	0	0	0	0	0	0
Judgement	Excellent	Excellent	Excellent	Excellent	Good	Excellent

TABLE 5: Classification accuracy before and after increment.

Increment value	Before	Add 50	Add 100	Add 200
Average accuracy	0.75	0.77	0.79	0.82

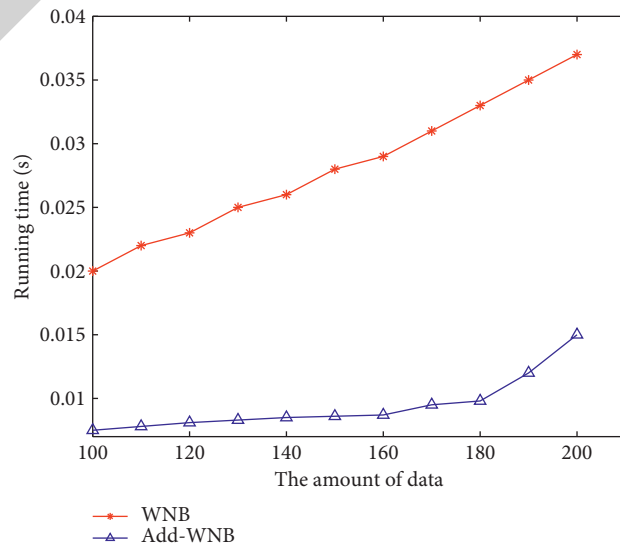


FIGURE 6: Algorithm runtime comparison.

calculate the new data, integrate it with the past training value, and update the model parameters that are required. As a result, the categorization model gains in terms of time savings and increased productivity.

5. Conclusion

Despite the merits of classical classification algorithms in teaching evaluation models, they also have their drawbacks. In order to assess the educational impact, the weighted Naive Bayes (WNB) method has been incorporated into the evaluation process. We can see that the technique is realistic and feasible for teaching assessment based on the outcomes of the experiments. Lastly, the notion of incremental learning is presented, the classifier is improved, and the experiment is compared to the nonincremental classifier's results. The experiments demonstrated that an incremental learning method increased the performance of a classifier while decreasing the time required for the procedure.

In order to explain the use of data mining and machine learning methods for the analysis and modelling data in the context of teacher assessment, this paper deeply described the classification algorithms and incremental learning methods. The classification method in machine learning is employed in the assessment model development to further increase the scientificity and feasibility of teaching evaluation. The following are the key findings of this study: (1) create a teaching assessment model based on machine learning's classification technique by introducing the weighted Bayes algorithm and proposing the design classifier. As a consequence of extensive data training, each evaluation index is assigned a specific weighting, and the evaluation result value is automatically calculated based on the evaluation data. Running time and classification accuracy show that the weighted naive Bayes method is superior than the classic BP neural network technique for evaluating instructional effectiveness. (2) The weighted Bayesian incremental learning method is used to address the issue of rapidly expanding data sets. The model parameters are constantly modified based on newly added sample data, which enhances the algorithm's effectiveness and reduces the amount of time it takes to process data. Through performing experiments and analyzing the outcomes, we confirmed that the incremental learning method can increase both the time efficiency and the evaluation model when the evaluation data is larger.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The author declares no conflicts of interest.

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