Machine Learning-Based Prediction of the Course Assessment

Weimin Geng[1][a], Qiuling Li[2,*] and Dian Zhang[2]
[1]Shanghai Urban Construction Vocational College, 2360 Jungong Road, Shanghai 201999, China
[2]Clinbrain Co., Ltd., Shanghai Putian Information Industry Park B2 Building, Shanghai 200233, China
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Abstract: In order to keep track of the students' learning status and make early warning, the model of predicting the final course assessment was proposed based on machine learning. Take the course of water supply and drainage engineering cost as an example, the students' related information and the historical assessment data (such as the teaching activities and the stage assessment scores etc.) collection and cleaning were carried out firstly. Then the features were filtered out by Light Gradient Boosting Machine (LightGBM), and the prediction model of the final score was built on the basis of Least Absolute Shrinkage and Selection Operator (Lasso) regression. Phases 1 and 2 forecast were completed and the error statistics were analysed. The predicted results at different stages of the semester help the teachers and students get the learning situation and take timely adjustment measures.

1 INTRODUCTION

For the applied colleges, the assessment and evaluation of the specialized courses usually adopt a process-based and comprehensive mode and are distributed throughout the semester. In recent years, researchers have done various studies on teaching assessment and evaluation. The processing-assessment mechanism and reasonable curriculum assessment method were introduced by Zhou et al. (2023). Zhou and Liu (2023) studied the evaluation framework building based on Context, Input, Process, Product (CIPP). The evaluation index system of online and offline blended curriculum was constructed by Huang (2023). And Kou analysed the problem of a course evaluation based on Outcome Based Education (OBE) and proposed the implementation scheme of the diversified course evaluation system (Kou, 2023). With the development of Artificial Intelligence (AI), the researchers began to apply it in the course evaluation, and AI has formed a discipline system with neural networks, machine learning, and expert systems etc. as core algorithms. Maestrales et al. (2021) trained human raters and compiled a robust training set to develop machine algorithmic models and cross-validate the machine scores in chemistry and physics. Gao et al. (2023) summarized the advantages of machine learning in the fields of scoring strategies, learning assessment and educational intervention. In addition, Cao et al. (2023) studied the method of student learning situation early warning.

During the semester, to know the learning situation of students timely and take measures when there is an abnormality are very important for the teachers. The paper suggested the method to forecast the total final grade of the course according to the various assessments that have been completed during the semester. The prediction helps the teachers to keep track of the learning situation of each student in a timely manner and make solutions for some students who have difficulties in passing the final assessment.

[a] https://orcid.org/0009-0004-8404-5114

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2 BUILDING THE PREDICTION MODEL OF THE COURSE ASSESSMENT

The course assessment is an important teaching evaluation and feedback. Taking the course of water supply and drainage engineering cost as an example, the process assessment includes writing articles, course comprehensive assignments, course practice, explanation and presentation, and quality behaviours (such as attendance, engagement, teamwork) etc. Therefore, based on the phased assessment results during the semester, the prediction of the final course score is possible. The related student's information items and the course assessment's components are listed in Table 1. And the prediction model is based on the data in Table 1 except Score 4, with the Final Score as the target variable and the rest of the information as the characteristic variables.

Table 1: The related students' information items and the course assessment's components.

Number	Data Name	Meaning	Types of variables
1	Attribute 1	In high school, the student has learned the basic knowledge of science or not.	Categorical variables
2	Attribute 2	Gender	Categorical variables
3	Activity 1	Credits of view online e-resource.	Continuity variables
4	Activity 2	Frequency of answering questions in class.	Continuity variables
5	Score 1	Quality behaviours (such as attendance, course participation, teamwork etc.)	Continuity variables
6	Score 2	Test of basic concept understanding.	Continuity variables
7	Score 3	Integrated homework.	Continuity variables
8	Score 4	Explanation and presentation.	Continuity variables
9	Final Score	Final course assessment.	Continuity variables

Since the linear correlation between the input features (number3-7 in Table 1) and the target variables was very strong, the prediction model adopted the combination of LightGBM and Lasso regression. LightGBM is a type of decision tree, and it could directly use the characteristics of categorical features, calculate the importance of features. So, the features that are meaningful to the target variables are filtered out. Tree models belong to machine learning algorithms, which are non-parametric supervised learning methods. The decision-making process is represented through a tree structure, where each node of the tree represents a feature or attribute, and each leaf node represents a category or numeric value, and the decision-making rules of the data are presented through the tree-like structure. LightGBM is an algorithm that combines Gradient Boosting Decision Tree and Random Forest to improve prediction performance by building multiple weak learners (decision trees) (Meng et al., 2016). Lasso is a linear model and proposed by Tibshirani for estimation based on Ridge Regression Theory in 1996 (Tibshirani, 1996). This method minimizes the residual sum of squares subject to the sum of the absolute value of the coefficients being less than a constant. The building of the prediction model mainly includes the following 3 steps.

2.1 Data Processing

The categorical variables were processed firstly. Attribute 1 and Attribute 2 generally couldn't be directly input into the model, so they need to be numerically encoded. The data were encoded according to 0 and 1 respectively. Then the two variables were converted into category type and passed to the LightGBM model for screening features. Secondly, for the continuous variables in the characteristics, the test score range was 0~100, the maximum value of activity 1 and activity 2 was not clear, and the numerical dimensions were different. So, they were mapped and scaled to the same interval range. Use maximum-minimum normalization to scale the data between the intervals [0,1].

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x' is the normalized data, and x_{max} and x_{min} represent the maximum and minimum values of the data respectively (https://scikit-learn.org).

2.2 Feature Selection

LightGBM uses fewer feature fragments, allows for faster model training, and has better generalization capabilities (Meng et al., 2016). In addition, LightGBM can directly use categorical features, and its high efficiency is mainly reflected in the processing of multi-sample and multi-features (Ke et al., 2017). LightGBM uses the characteristics of categorical features, calculates the importance of features, and filter out features that are meaningful to the target variable.

2.3 Predicting the Final Score

The training samples were cross validated with 5 folds, and 85% of the data was selected as the training set and 15% as the test set for each fold. Mean Absolute Error (MAE), Coefficient of Determination (R2, the closer the value is to 1, the better the model is trained.), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were adopted to evaluate the model effect to ensure it was balanced, and the average score of the model was used as the final model evaluation result. The error calculation formulas are as follows (Zhou, 2016).

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \tag{3}$$

$$R^2 = 1 - \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \Big/ \sum_{i=1}^{n} (\bar{y}_i - y_i)^2 \tag{4}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|\hat{y}_i - y_i|}{y_i} \times 100\% \tag{5}$$

where y_i is the measured value, $\hat{y}_i$ is the predicted value, $\bar{y}_i$ is the measured mean, and n is the number of samples.

3 CASE STUDY

Taking the course of water supply and drainage engineering cost assessment as an example, and there are a total of 79 students. The Final Score is the object variable, and number1- number 7 are the feature variables. Firstly, the features were screened. Through the ranking, the importance of Attribute 1 and Attribute 2 to the target in the input features is almost 0, so these two were not applied as input features in the prediction model (see Figure 1). Secondly, the correlation was analysed, and their linear correlation to the target was calculated. The correlation heat map is shown in Figure 2.

The prediction of the Final Score was carried out by Lasso regression. After the Score 2 and Score 3 were obtained during the semester, the Final Score was predicted respectively and named Phase 1 and Phase 2 (shown in Figure 3). The coincidence of Phase 2 prediction is higher than that of phase 1, and it can also coincide well for some uneven cases. Figure 4 is the scatter plots of the forecasting results, and it indicates that the prediction is better when it falls on the diagonal.

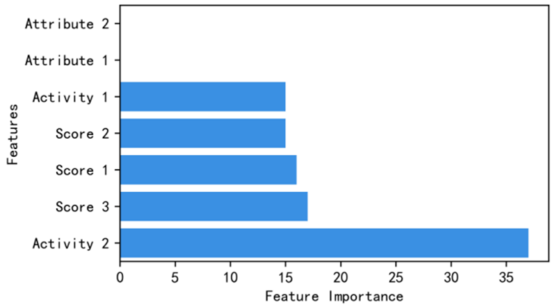


Figure 1: The feature importance ranking graph.

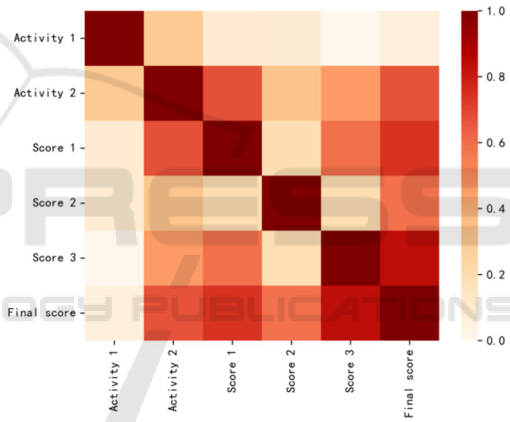


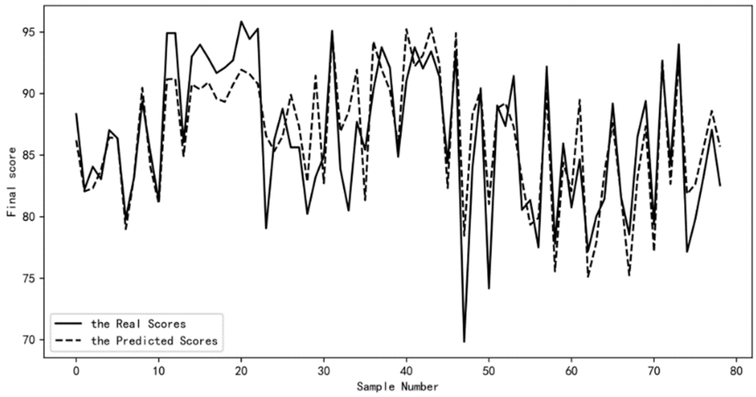
Figure 2: The correlation heat map.

The error statistics of the forecasting model is listed in Table 2. In addition, the residuals of the results were calculated. For Phase 1 period, the residuals of the mean value, the standard deviation, the minimum value, and the maximum value are -0.2026, 3.1173, -8.6150, 4.4774 respectively. In Phase 2, the above values are -0.0842, 1.0752, -2.7227, 1.8601.

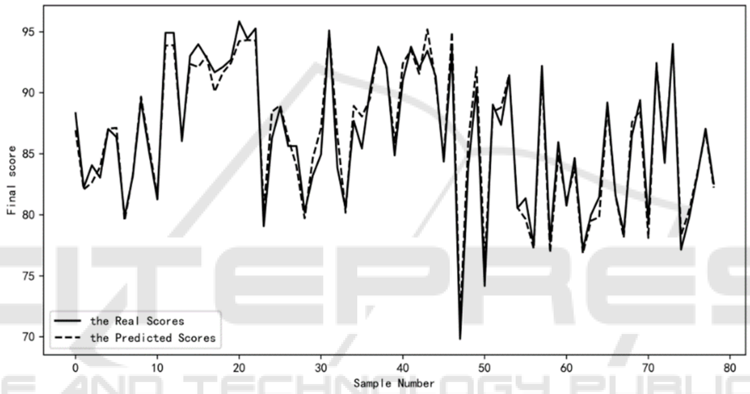
The prediction values of Phase 2 are better than Phase 1 and could meet the demand to assist the teaching and at the same time notify the students who have possibilities not to pass the final course assessment.

Table 2: The error statistics.

Phase	MAE	R^2	RMSE	MAPE
1	2.48	0.71	3.1	2.93
2	0.83	0.97	1.07	0.97

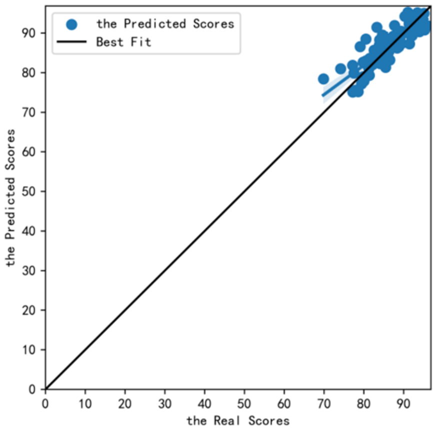


(a) Phase 1

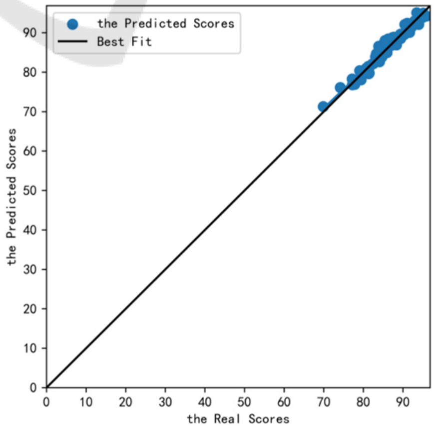


(b) Phase 2

Figure 3: Comparison of the predicted and actual values.



(a) Phase 1



(b) Phase 2

Figure 4: The fitted scatter plot of the prediction results.

4 CONCLUSION

Based on LightGBM and Lasso regression algorithms, the prediction model of the course final assessment was built. The final scores were predicted by filtering the features and learning the historical data rules. The course assessment prediction values can be obtained during the semester, and they remind some students to adjust their learning status avoid failing the final assessment. At the same time, it plays a role in helping the teachers take timely adjustment measures. Then in the future, with the increasing use of smart classrooms, their statistics number can also be included in the prediction model.

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