Optimizing Virtual Reality Solutions for Predicting English Online Network Performance Using the XGBoost Algorithm

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Abstract. In view of the current informatization needs of English learning and the advantages of deep learning algorithms, an English grade prediction based on the XGBoost algorithm is proposed. In order to verify the validity of the model in English score prediction, the principle of the XGBoost algorithm is firstly analyzed, and then the English test scores of a college from 2019 to 2021 are used as the basic data source, and the probability in the XGBoost algorithm model is used to compare the results under different attributes. Students' English grades are predicted, and the results show that the grades predicted by the XGBoost algorithm are basically consistent with the actual grades.

Keywords: XGBoost algorithm; grade prediction; data source; conversion; Virtual Reality Solutions
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1 INTRODUCTION

With the development of the current application of informatization in teaching, strengthening the application of informatization in teaching has become a current trend [15]. For example, [26] applied data mining algorithms to the evaluation of English teachers' abilities so as to obtain the necessary abilities in English teachers' teaching; others applied the data mining algorithm to the adult English test and obtained some rules for passing the adult English test. With the application of data mining, its drawbacks have also begun to be exposed, such as the amount of data to be mined is small and the mining accuracy is not high [28]. In this regard, people began to try to apply the XGBoost algorithm to the English subject field. For example, the real scene data of the large-scale unified test of spoken English as the basis, and used the XGBoost algorithm model to recognize the speech and then conduct the evaluation. The results show that the method has strong robustness in dealing with noise; [24] applied the XGBoost algorithm to English writing, processed the text by natural processing language, and used the XGBoost algorithm to mine, thereby improving English writing. ability. It can be seen from the above research that deep learning algorithms are widely used in English research [29].

Xgboost is the abbreviation of eXtreme Gradient Boosting [12]. On the basis of massively parallel boosted tree, Xgboost has played an important role as its extension tool, and has become the best speed in the current open source boosted tree toolkit. The fastest algorithm, which is more than 10 times faster than common toolkits [17]. It is widely used on the crowdsourcing platform Kaggle, and a large number of contestants use it in various data mining competitions. The Xgboost algorithm is used in the winning plan of several kaggle competitions. In the practical application of real business, Xgboost's portability is widely used, and still retains local In addition, there are other efficiency improvement methods, so that it can achieve good results under the huge scale of the industry [35]. Xgboost implements the general Tree Boosting algorithm by engineering, the Gradient Boosting Decision Tree (GBDT) is the representative of the Tree Boosting algorithm, and it is also called MART (Multiple Additive Regression Tree) [32].

After obtaining high-quality data, this paper analyzes the original attributes of the data, and combines relevant knowledge in the professional field to design and generate high-quality features, which will have a direct impact on the model prediction effect [14]. Therefore, the work of data preprocessing and feature construction will occupy 90% of all the time of the system. Next, use the Xgboost algorithm to model the data, adjust its parameters, and then fuse the above three models to generate a high-accuracy prediction model. The feasibility of predicting students' answering results using historical student answer data is obtained, and the feasibility of its prediction accuracy is extremely high [8]. From a scientific point of view, the ability to predict unknown data with low error has demonstrated that it enables students and teachers to discover the underlying factors of students' difficulty in answering questions. Understanding these reasons can be of great help in designing high-quality courses and lesson plans [11].

2 RELATED WORK

Educational data mining technology has been weak at the beginning, through years of research and innovation by researchers, this technology has made great progress and has been popularized and popularized in the field of foreign education [25]. In 2007, an article published by scholar described the broad application space of machine learning methods in the field of education, and this article was widely recognized by the academic community [31]. [10]in order to find the law of improving students' performance, used rough set theory to combine with problems in the field of education, and found a method that can dominate students' motivation.[13] analyzed the records of the log system of the education platform, and generated a model that can predict the students' performance through the students' behavior record, other scholars in order to infer the newly enrolled graduate students. The candidates' future academic performance was analyzed and modeled on their undergraduate grades, and their GGPA1 was successfully predicted]. From the above content, it can be seen that foreign countries have a profound background on the performance prediction system, and the development speed is very fast. Foreign scholars have effectively combined data mining technology with the field of education, and developed many excellent technologies and projects.

In my country, the field of data mining entered the field of education relatively late, and it is still insufficient compared with foreign development. However, my country is catching up at this stage, and there are many excellent scientific research and engineering personnel who have made achievements in this field. [9] conducted data modeling for the training of students in this major, and finally used the C4.5 algorithm to successfully find the laws of student behavior hidden behind the data. [22] scholar used the K-mean algorithm in the analysis of students' test scores, and applied it to the computer grading module, so that educators could obtain the mastery of students' scores and reduce the difficulty of work. In order to find the influencing factors of students' English test, scholar used decision tree algorithm to analyze test data, and found rule sets in data mining, which provided method guidance for the improvement of teaching effect [27]. There are still many unsolved problems waiting for these outstanding talents in our country to study and solve.

3 IMPROVED ALGORITHM MODEL

XGBoost can efficiently construct augmented trees and run in parallel. There are two kinds of augmented trees in XGBoost, regression trees and classification trees [7]. Optimizing the value of the objective function is the core of XGBoost. Here, the objective function is used as an example to introduce the theory. The objective function is shown in Equation (1):

$$Obj^{(t)} = \sum_{i=1}^{n} l\left(\left(y_i, \hat{y}^{(t-1)}\right) + f_t(x_i)\right) + \Omega(f_i) + C \tag{1}$$

Where $\hat{y}^{(t-1)}$ denotes the retention of the model predictions from the previous t-1 round, As shown in Equation (2) :

$$g_i = \partial_{\hat{y}^{(t-1)}} l\left(y_i, \hat{y}^{(t-1)}\right) h_i = \partial^2_{\hat{y}^{(t-1)}} l\left(y_i, \hat{y}^{(t-1)}\right) \tag{2}$$

be changed to the form of equation (3) :

$$Obj^{(t)} \approx \sum_{i=1}^{n}\left[l\left(y_i, \hat{y}^{(t-1)}\right) + g_i f_t(x_i) + \frac{1}{2} h_i f_i^2(x_i)\right] + \Omega(f_i) + C \tag{3}$$

When the model is trained, the objective function can be expressed by Equation (4) :

$$Obj^{(t)} = \sum_{j=1}^{t}\left[\left(\sum_{i \in I_j} g_i\right) w_j + \frac{1}{2}\left(\sum_{i \in I_j} h_i + \lambda\right) w_j^2\right] + \gamma T \tag{4}$$

Defining Equation (5)

$$G_j = \sum_{i \in I_j} g_i \, , H_j = \sum_{i \in I_j} h_j \tag{5}$$

Bring equation 5 into equation 4 to get equation 6 :

$$Obj^{(t)} = \sum_{j=1}^{t}\left[G_j w_j + \frac{1}{2}\left(H_j + \lambda\right) w_j^2\right] + \gamma T = -\frac{1}{2}\sum_{j=1}^{T} \frac{G_j^2}{H_j + \lambda} + \gamma T \tag{6}$$

The optimal combination of parameters is finally substituted into the Xgboost algorithm to improve the prediction performance [33]. After constructing the GS-XGBoost model, multi-step prediction is performed, and the model is applied and then the prediction results are compared with the original XGBoost model, GBDT model and SVM model, and finally the model is validated according to the evaluation index. The specific experimental flow chart is shown in Figure 1.

The prediction performance evaluation indexes of the prediction model were compared with the experimental results using three evaluation indexes: mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE).

1. Mean square error is the average of the minimization of the sum of squared errors (SSE)[4],[1],[2] cost function in the process of fitting the linear regression model. The better the prediction effect, the closer the value is to 0, and vice versa, the farther the value is from 0. Its calculation formula is shown in Equation (7):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y^{(i)} - \hat{y}^{(i)}\right)^2 \tag{7}$$

Where,y is the predicted true value, $\hat{y}$ is the predicted value

2. The formula for calculating the root mean square error is shown in Equation (8):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y^{(i)} - \hat{y}^{(i)})^2} \tag{8}$$

3. The formula for calculating the average absolute error is shown in Equation (9)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y^{(i)} - \hat{y}^{(i)}\right| \tag{9}$$

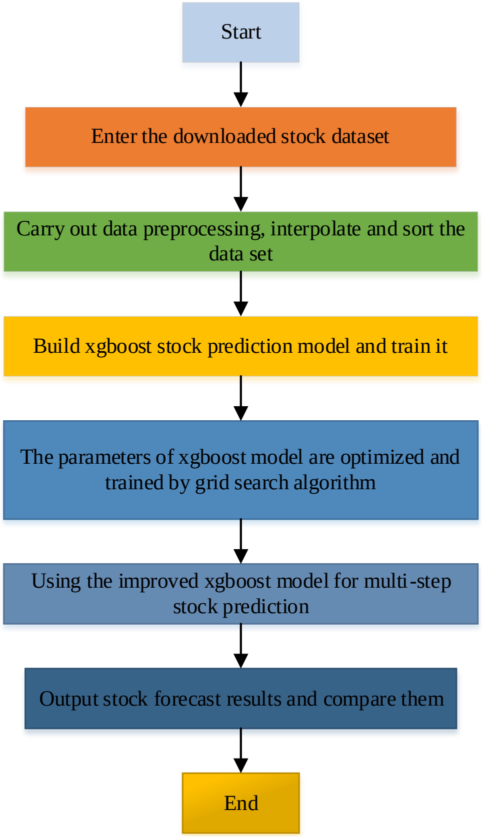

Figure 1: Experimental flow chart.

The main steps of the improved PrefixSpan algorithm (called Im_Prefixspan algorithm in this paper) are as follows: Step 1 Scan the sequence database S once, find all the 1st order sequences, and count them. If the support of a sequence of order 1 is less than the broad value, the sequence is divided into two, and its left and right subsequences are put back into the sequence database, and the original sequence is deleted from the sequence database. For each L(L>1) prefix, only the first item of the sequence in the suffix database is scanned for counting. If the support count is lower than the queue value, the sequence corresponding to the first item is removed from the suffix database and the expansion of the first item is stopped. Step 4 Combine the first items that satisfy the support count and the current prefixes to obtain some new prefixes. Step 5 Make L=L+1, scan the current suffix database, and construct the corresponding suffix database with the new prefixes. Return to step 3 until the suffix database is empty.

In this genetic algorithm, the genetic operators use constant crossover probabilities as well as variation probabilities. This is more effective for simple optimal problems, but has disadvantages for complex problems. The disadvantage is that it can lead to early "premature" and slow convergence, and the final result can easily fall into local optimum. The crossover probability and variation probability can be changed in time, and the linear function is used for adaptive change adjustment, which can effectively solve the problems of premature maturity. In Srinvas' improved algorithm, the equations of crossover rate and variation rate are shown in 10 and 11:

$$P_c = \begin{cases} \frac{k_1(f_{max} - f')}{f_{max} - f_{\text{avg}}} & f' \geq f_{\text{avg}} \\ k_2 & \text{other} \end{cases} \tag{10}$$

$$P_m = \begin{cases} \frac{k_3(f_{max} - f)}{f_{max} - f_{\text{avg}}} & f \geq f_{\text{avg}} \\ k_4 & \text{other} \end{cases} \tag{11}$$

Where f_{max} and $f_{avg}$are the maximum fitness of the individuals in the population and the average fitness of all individuals, respectively, and f is the fitness of the individuals in the population that are about to mutate. From the intuition of Eqs. 10 and 11, the variation rate and crossover rate are adjusted for linear processing and are no longer fixed. When the fitness of an individual calculated from the fitness function is lower than the average fitness, it means that the solution represented by the individual is less effective, and then a larger evolution is performed according to the idea of genetic algorithm, i.e., a larger crossover rate and variation rate is used. If the fitness of the individuals in the population is higher, then linear adjustment is performed according to Equations 11 and 12[5],[6],[18],[3].

The above improvements to the variance and crossover rates can significantly improve the ability of the model to find the best. However, there is a problem that when f is equal to f_{max}, at this time, according to Eqs. 1 and 2, bothP_m and P_c are 0, resulting in the genetic algorithm.

At the early stage of the calculation, individuals with high fitness in the population can only undergo smaller changes and are easily trapped in a local optimum. Therefore, the To address this problem, this paper establishes an improved linear adaptive genetic algorithm (Improved Linear Adaptive Genetic Algorithm (ILAGA), which further optimizes the crossover rate and variation rate in the genetic operator.

The following optimization is done for P_c and P_m, and the crossover rate and variation rate are calculated as shown in 13 and 14.

$$P_c = \begin{cases} cI - \frac{(c1 - c2)(f' - f_{avg})}{f\text{ar}_{max}} & f' \geq f_{avg}\{ \\ cI & \text{other} \end{cases} \tag{13}$$

$$P_m = \begin{cases} mI - \frac{(mI - m2)(f - f_{av})}{favg_{max}} & f \geq f_{avg}\{ \\ mI & \text{other} \end{cases} \tag{14}$$

The flow chart of the improved linear adaptive genetic algorithm is shown in Figure 2. The detailed steps of the improved linear adaptive genetic algorithm based on crossover rate and variation rate are as follows:

Step1: Encoding. After determining the set of parameters of the actual problem, some form of encoding is performed for the variables to be solved, and the encoding should reflect the solution space of the problem.

Step2: Initial population generation. The GA starts the selection of generations with these N string structure data as the initial point.

Step3: According to the optimization objective of the actual problem, determine the objective function and fitness function of the problem, such as in regression, you can use RMSE as the objective function, and the inverse of RMSE as the function to calculate the fitness,

Step4: Adaptation calculation. Substitute the individuals in the population into the objective function and fitness function of the optimization problem, and calculate the fitness value of each individual. If the optimization index of the problem is satisfied or the maximum number of selected generations is reached, the solution of the problem is output, otherwise, the genetic operation of the chromosome (step5-step6) is continued and the population is upgraded[20],[21],[16].

Step5: Crossover operation. The better individuals selected in the fifth step are crossed over in a certain way to produce new individuals to make the population more diverse.

Step6: Mutation operation. Mutation is performed on some of the chromosomes after the crossover operation, i.e., some gene values of individual strings in the population are changed to further expand the diversity of the population.

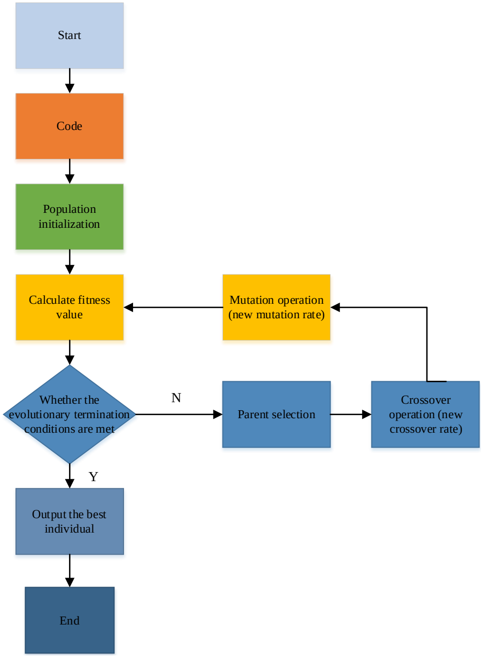

Figure 2: Flow chart of the improved linear adaptive genetic algorithm.

4 REALIZATION OF ENGLISH TEST SCORE PREDICTION

The XGBoost algorithm to predict the grades of middle school students in the college English skills training system, as shown in Figure 3.

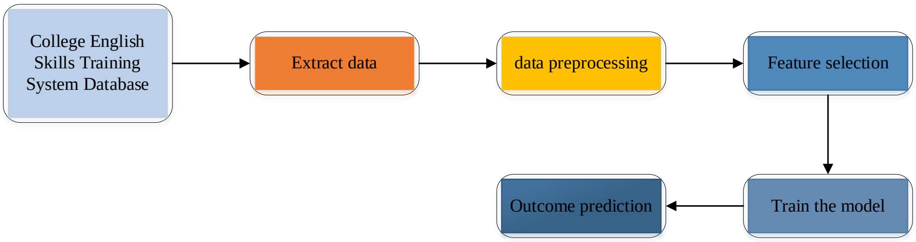

Figure 3: The performance prediction process.

4.1 Data Extraction and Preprocessing

This research mainly extracts student information from the college English skill training system, and selects the data of first- and second-grade students in the four academic years from 2019 to 2021 in the spring and autumn, respectively. The final data file type selects the CSV format that stores tabular data in plain text [34] [30].

4.2 Feature Selection

Through feature processing, this experiment identified 18 important features for mining students' grade prediction, such as student number, name, gender, answering time, question type, and other 18 dimensions. Table 1 below lists some of the characteristics and data.

serial number	*gender*	*class*	*Question type*	*Answer time*	*self-rating*	*Question Score*	*Passing Score*
1	*male*	*1*	*SAQ*	*301*	*8.6*	*7*	*6*
2	*Female*	*2*	*TF1*	*286*	*9.1*	*8*	*6*
3	*male*	*1*	*SC*	*254*	*7.8*	*8*	*6*
4	*Female*	*3*	*SAQ*	*311*	*8.3*	*7.5*	*6*
5	*89.76*	*2*	*SW*	*292*	*6.6*	*6.5*	*6*
6	*Female*	*3*	*TF2*	*288*	*8.1*	*7*	*6*
7	*male*	*4*	*SC*	*276*	*7.9*	*7.0*	*6*
8	*Female*	*4*	*SW*	*272*	*7.3*	*6.0*	*6*

Table 1: Some characteristics of performance prediction.

4.3 Prediction Results and Analysis

In this study, the data mining regression method Xgboost algorithm model is used, and the relevant data of students' English exams in two academic years in the English skills training system are used as training data. After streamlining, the prediction model of students' grades in college English test is finally constructed, and the prediction of students' grades is realized, so that the scores that are close to the real grades of students are obtained. The model uses 18 features as the final forming factors of Xgboost, and constructs a decision tree with 6 lessons, the minimum sample leaf node is 6, and the maximum depth is 5. Table 2 shows actual and predicted scores of the data, of which the full score is 50 points.

serial number	*real grade*	*predicted grades*
1	*41*	*43*
2	*40.5*	*44*
3	*33*	*35.5*
4	*37*	*35*
5	*32*	*33*
6	*41*	*41*
7	*36*	*36*
8	*43*	*38*
9	*38*	*38*
10	*41.5*	*39*

Table 2: Comparison of actual grades and predicted grades.

The experimental results are evaluated by MAE. The smaller the value, the better. Finally, the MAE of all data sets is 0.7, and 79.86% of the data errors are 0. That is, the prediction accuracy is 79.86%. Comparing the actual score and the predicted score curve, it is found that the two curves are very similar, indicating that the predicted score is very close to the real score.

According to the English test scores of 120 samples predicted by the established prediction model equation, the predicted scores of these 120 students in the English test are compared with their actual scores. The predicted scores of some samples are almost exactly the same as the actual scores, which further shows that the predicted scores are basically reasonable and reliable, and also shows the accuracy of the prediction model. Of course, there may be deviations in the predictions of individual students, and there may be many reasons for this, but basically, they are all caused by objective reasons or very special subjective reasons. See Figure 4 for details.

Figure 5 shows that the average total English score of students in 2019-2021 is between 366.43 and 434.74. Except for the 2019 students, the total scores of the students in other grades are lower, indicating that the students' overall English level is not high. Considering that students with scores below 220 did not participate in the statistics, the actual average grade for all students was lower. However, in the past two years, the total score has shown a rapid upward trend. Over three years, the overall score has improved by 18%. The average annual increase was 4.4%. There are many reasons for this. In addition to the continuous improvement of the cultural quality of the school's students in recent years, the students pay more attention to English learning, gradually adapt to new topics, and the conditions have improved significantly after the school welcomes evaluation and promotes construction. At the same time, it also shows that the level of college English teaching has continued to improve in the past two years.

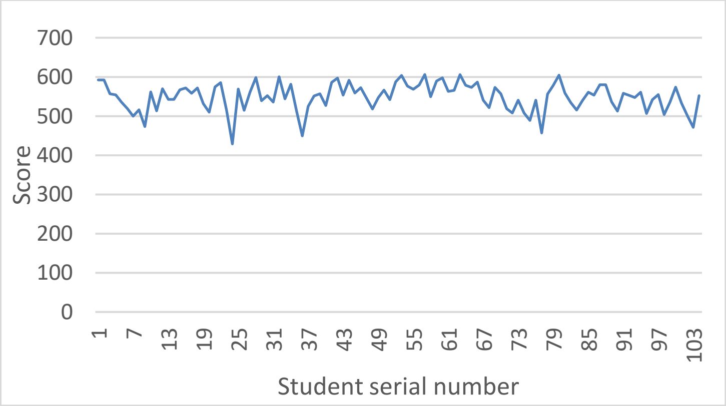

Figure 4: Comparison of English scores and predicted scores.

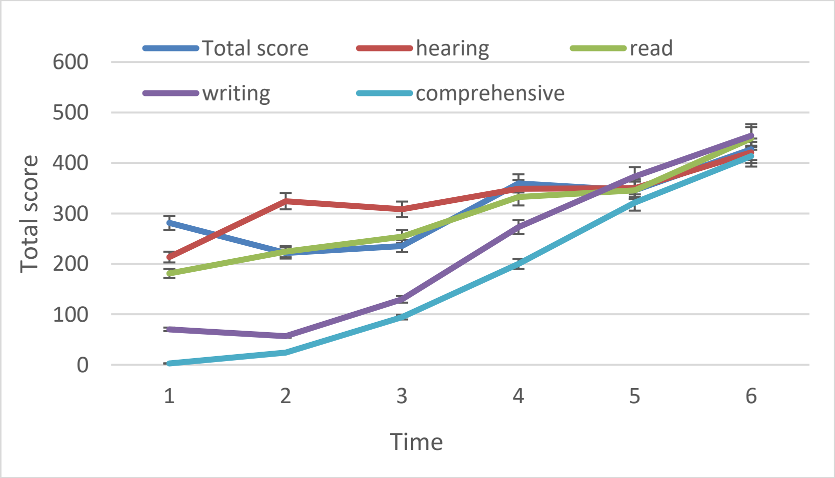

Figure 5: The English percentile score of the second-grade students in 2019~2021.

The scores of listening and writing are steadily improving every year, and the listening of the 2021 students is 40% higher than that of the 2019 students. This may be related to the obvious improvement of school pronunciation facilities in recent years, and the establishment of bilingual courses in some courses of various majors. Writing results may be abnormal due to changes in assessment objectives and other reasons.

Students' reading scores have improved in recent years, especially for the Class of 2021, but not yet. This is related to the high proportion of English reading and the importance that students attach to it, and it is more likely to be related to the improvement of students' reading ability due to the bilingual courses offered by schools in the past two years. The results of the comprehensive test showed a slow upward trend. This question type includes translation questions, cloze, grammar and vocabulary. Due to the variety of question types and low proportions, teachers and students have neglected the question types.

Judging from the predicted results of the results, in the next two to three years, under the condition that the examination mode, teaching form and the quality of students remain unchanged, the total score of the candidates will have a significant improvement. The performance of the single test will also improve, but there are still some unstable factors, which should attract the attention of teachers and strengthen some targeted training for students.

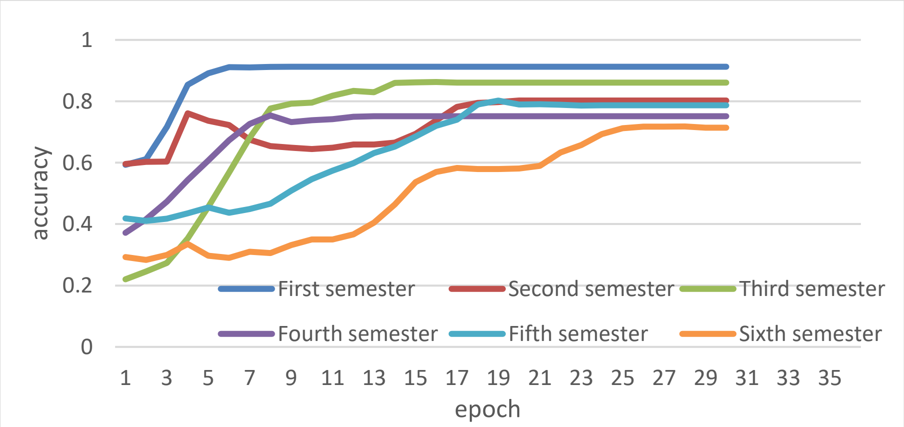

Figure 6: Student achievement prediction.

The prediction accuracy obtained after 100 iterations is shown in Figure 6. It can be seen that the prediction accuracy rate of each semester fluctuates from 70% to 100%. Among them, due to the small number of samples in the eighth semester, the prediction accuracy rate reaches 100% after 10 iterations. The sixth semester, which had the lowest accuracy rate, also reached 70%.

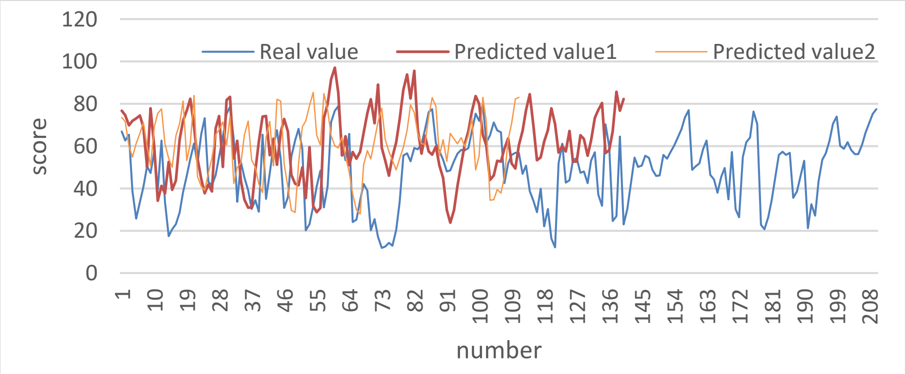

Figure 7: Results of grade prediction.

In this experiment, 320 random records are randomly generated as the training set, and the remaining 80 records are used as the verification set. The Xgboost algorithm adopts a dynamic learning rate, and the predicted value is obtained by inverse normalization. Figure 7 shows the comparison between the actual grades and the predicted values. The red dots represent the actual grades and predicted values of the students. 1 (black dots) represents the predicted grades using only the student's grades as the dependent variable. The predicted value is 2 (green, Color dots) represent the predicted value of students' grades and behaviors as dependent variables. It can be seen from the figure that the predicted value of students' grades and behavioral information as dependent variables is closer to the real grades, indicating that the students' performance Behavioral information is reasonable considering the factors that affect student performance and is in line with previous expectations.

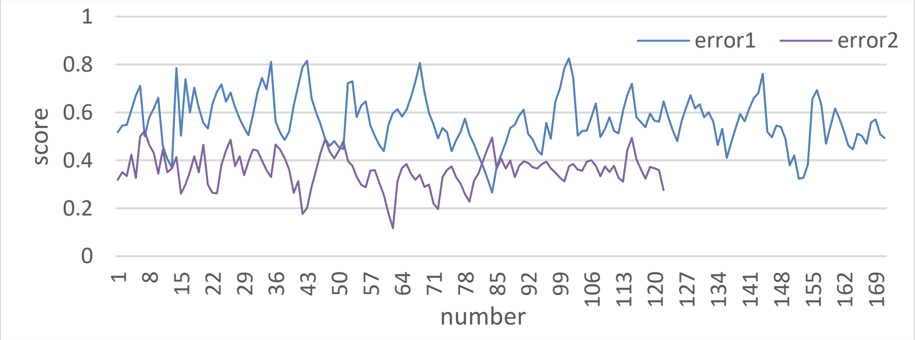

Figure 8: Relative error.

Figure 8 shows the relative errors of the comparative experiments. The red line (error1) represents the relative error that only takes the student's grades into account, and the black line (error2) represents the relative error of the prediction that takes both the student's grades and behavioral information into account. As can be seen from the figure, most of the black lines are below the red line, and only a small amount is above the red line, which indicates that the relative error of prediction considering both students' grades and behavioral information is lower than Only considering the relative error of students' grades, the experimental results show that students' behavior has a certain influence on grades. Schools should not only pay attention to students' previous grades, but also pay attention to students' daily behavior, encourage students to go to the library more, and get up early on time, It is significance to cultivate good study and living habits.

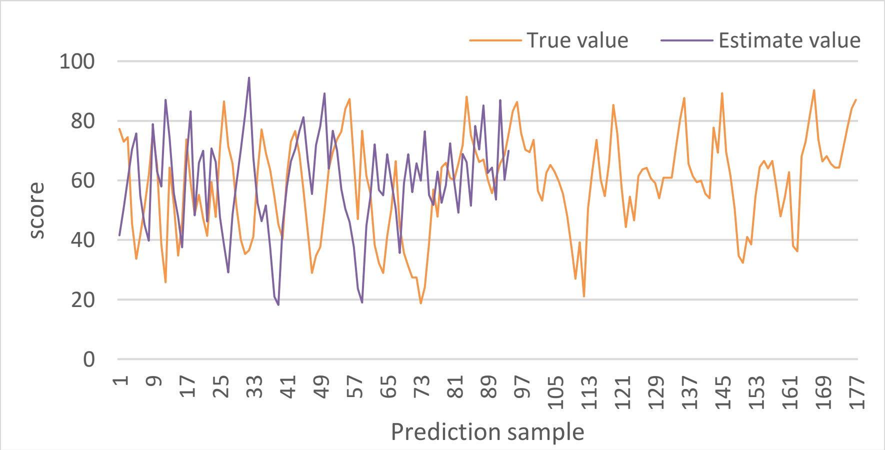

Figure 9: Determination coefficient 1.

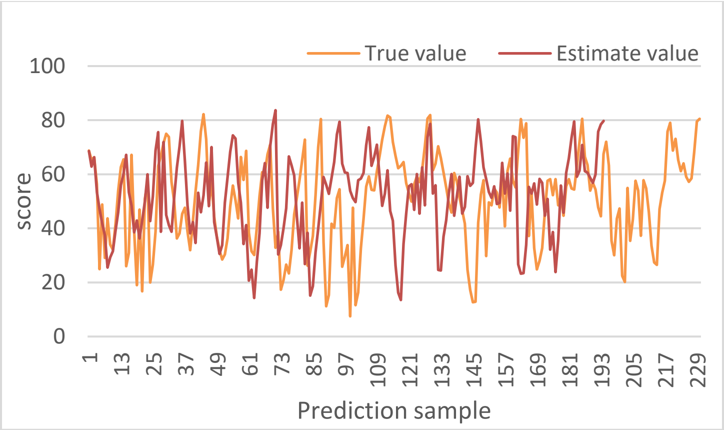

Figure 10: Determination coefficient 2.

From Figure 10, it can be seen that the coefficient of determination is 0.79424; Figure 8 shows the students' grades and the determination coefficient is considered for all behavioral information. The blue line and the red line represent the actual value and the predicted value respectively, and the determination coefficient is 0.99843. It can be seen that adding the student's behavioral information to the factors affecting the student's performance greatly improves the determination coefficient. It shows that the behavioral information of students has a significant effect on the final grades of students.

The above results show that the Xgboost algorithm model can predict college English test scores. Through data mining technology, it analyzes and evaluates students' test scores, and extracts the degree of students' mastery of English knowledge in teaching process. targeted teaching.

5 CONCLUSION

This paper uses data related to grades in the English skill training system, and uses the Xgboost model to predict students' grades. The experiment proves the accuracy and feasibility of data mining technology in English grade prediction. Data mining technology has been well applied in the education industry. In the data, the use of data mining technology will definitely change the traditional face of education. Prediction of college English grades in this study is helpful for students' English learning and teachers' in-depth understanding of test results. Additionally, the study explores VR-enhanced English online learning platforms. The findings contribute not only to the field of language education but also to the broader discourse on the intersection of immersive technologies and predictive analytics in educational contexts.

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