IIAI Open Conference Publication Series
IIAI Letters on Informatics and Interdisciplinary Research
Vol.006, LIIR369
DOI: https://doi.org/10.52731/liir.v006.369

The Prediction Modeling System for Monitoring Elementary Students' Mathematics Progress in Online Curriculum-Based Measurement

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Abstract

The curriculum-based measurement (CBM) is a data-based individualization method that monitors students' performance and improvement over time. The purposes of this research were to develop prediction models—including ordinary least squares linear regression (OLS), Gaussian Naive Bayes, Bayesian Networks, and Random Forest—within a web-based CBM system, and to investigate their effectiveness in predicting elementary students' mathematics performance. A total of 92 fourth-grade students participated in the study. They used mobile devices to complete CBM probes over an eight-week period. Performance metrics were analyzed to evaluate the error rate between predicted and observed scores. Overall, the results showed that OLS and Bayesian-based models were effective in predicting elementary students' mathematics performance. Moreover, the findings indicated that distinct growth patterns still existed across different classes.

Keywords: Curriculum-based measurement, prediction modeling system, mathematics education, elementary students

1 Introduction

Curriculum-Based Measurement [1] are brief assessments used to assist in screening for students at risk for academic difficulties and subsequently monitoring specific skills in subject areas such as reading, mathematics and social science. CBM used the simple indicators of academic competence, which represent a student's level of performance, can be used to model the trajectory of the student's score over time [2]. The CBM process is data-based individualization (DBI) which is signature or high-leverage special education practice [3]. This DBI process requires progress-monitoring tools that index performance level and improvement [4]. It also requires methods to help teachers use the results students' performance data to meaningful connecting their instructional decisions. Decisions about student response to intervention are particularly important as continuing an ineffective intervention or effective intervention for individual students, especially for low-achieving students.

CBM research focused on longitudinal modeling of progress, has increased over the decades [3]. Currently, ordinary least squares (OLS) linear regression is the most common method used by researchers to estimate students' CBM progress [5]. In CBM oral reading [6] found that, compared to OLS, Bayesian regression produced more reasonable growth estimates when only a small number of observations were available. However, few studies have focused on comparing the prediction models of students' CBM performance. Ethan et al. [7] compared six types of

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slope estimation methods on students' CBM scores in reading: OLS, Theil-Sen, Huber M, Tukey Bi-Square, Bayesian Uniformed, and Bayesian Informed. OLS intercepts and slopes. The results showed OLS tended to perform better than the majority of other trend estimation methods as with residual outcomes. When data collection schedules were short, the Informed Bayesian method outperformed the OLS method. However, research of modeling students' performance on CBM mathematics (CBM-M) was scarce. Therefore, the purpose of this research was to investigate the prediction models (Gaussian Naive Bayes, Bayesian Networks. Random Forest), relative to OLS, on elementary students' CBM-M time-series data.

2 Methods

2.1 Participants

A total of 92 fourth-grade students from five classes at an elementary school in New Taipei City participated in the study. Curriculum-Based Measurement (CBM) assessments were administered weekly over an eight-week period to measure longitudinal academic growth. Baseline data were collected in the first week to evaluate students' initial mathematics performance

2.2 Procedures

Each CBM probes were administers weekly. Every student was provided a iPad. Students have to complete a CBM probe in 25 minutes. Each CBM probe was alternative form which generated from the ECBM item bank database. The testing item of the ECBM database was derived from students' mathematics curriculum of the current semester [8]. Each CBM probe was dynamically generate CBM probes through module selection. In this study we adopted the mixed type CBM probes. Tsuei [8] developed the EBCM system which is a web-based curriculum-based measurement system for class-wide ongoing assessment. The ECBM randomly selected five concepts, three computations and two application questions from the item bank. Every CBM probe was alternative test which repented the same mathematics concepts in the same curriculum.

Tsuei [9] developed the iCBM application for elementary students online tests on mobile tablet device. While students completed the test, the iCBM will automatically send the results to the iCBM sever system for grading and saving the related learning logs. Students also get their scores on the iPad. The digital scoring process (DS) was implemented in the CBM tests [9]. The digital scoring process was based on aggregating the correct digits (the right numeral at the right place) for each question. The correct digit was defined as the right numeral at the right place including the numeral written in reversed form [8].

For teachers, students' performance were analysed in the ECBM system. In this study, individual students' prediction models including OLS, Gaussian Naive Bayes, Bayesian Networks, Random Forest were calculated and presented as Figure 1.

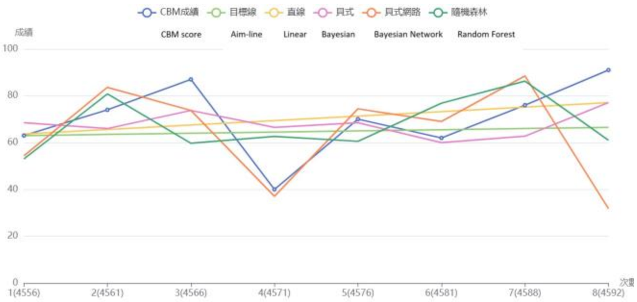

Figure 1: The Predication Models of Students' CBM Mathematics Progress in ECBM system

2.3 Evaluation Criteria for Prediction Models

Numerous machine learning (ML)-based predictive modeling techniques have been applied to educational predictions. Therefore, it is essential to evaluate the performance and predictive accuracy of each model. Previous research has commonly adopted four performance metrics to assess prediction accuracy: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2) [10].

MAE measures the average absolute difference between the predicted and actual scores. MSE calculates the average of the squared differences, reflecting the overall error magnitude. RMSE is the square root of the MSE and represents the average magnitude of the prediction error. It is particularly useful for interpreting prediction accuracy in the same units as the target variable. R^2 measures the proportion of variance in the dependent variable explained by the model and serves as an indicator of the model's goodness of fit.

3 Results

3.1 The Performance Metric Values for Prediction Models by All Students

The performance metric values were compared, and the best results for each metric are highlighted in bold in the table. The Ordinary Least Squares (OLS) prediction model achieved the lowest MAE (11.82), MSE (206.77), and RMSE (14.38), as well as the highest R-squared value (0.57), indicating the best overall predictive performance. The second most accurate model was Gaussian Naive Bayes. In contrast, the Random Forest model produced the highest error rates, with an MAE of 19.54, MSE of 599.94, RMSE of 24.49, and a negative R-squared value of -0.236, reflecting poor predictive fit.

Figure 2 illustrates all participating students' CBM-M scores alongside the predictions from each model. The mean of each student's actual CBM-M scores and the corresponding predicted values from each model are shown in Figure 3. These results further confirm that OLS and Gaussian Naive Bayes were the most suitable models for predicting student performance.

Table1: The performance metric values for prediction models for all students

Models	**MAE**	**MSE**	**RMSE**	**R^2**
OLS	**11.82**	**206.77**	**14.38**	**0.574**
Gaussian Naive Bayes	11.46	226.86	15.06	0.532

Bayesian Network	16.27	579.21	24.07	-0.194
Random forest	19.54	599.94	24.49	-0.236

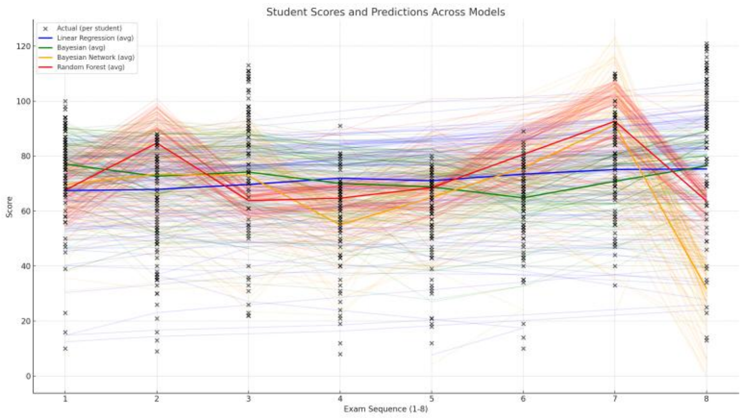

Figure 2: Students' CBM-M scores and prediction models

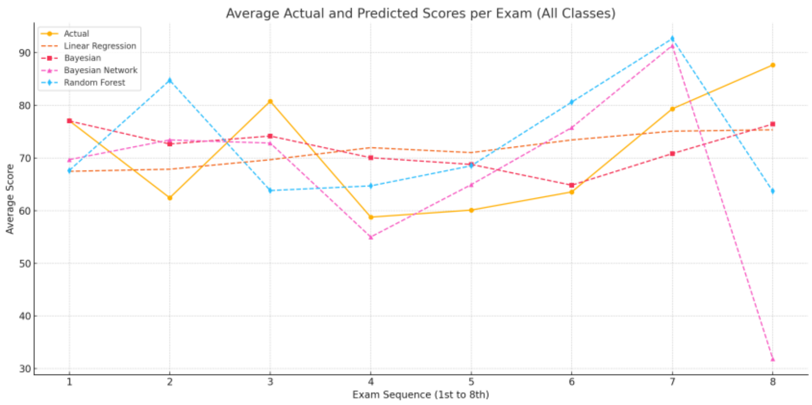

Figure 3: Students' CBM-M mean scores and prediction models

3.2 The Performance Metric Values for Prediction Models by Different Classes

To explore the differences in prediction model performance across classes, performance metric values were calculated separately for each class. The results are presented in Table 1, with the best values for each metric highlighted in bold. The findings indicated that the best prediction model for Class A was Gaussian Naive Bayes.

For Class D, the Ordinary Least Squares (OLS) model yielded the best performance. In Classes B, C, and E, MAE results suggested that Gaussian Naive Bayes was the most accurate model. However, for these same classes, the MSE, RMSE, and R^2 values showed that OLS slightly outperformed Gaussian Naive Bayes, indicating a marginal advantage in overall predictive accuracy.

Table 2: The performance metric values for prediction models by each class

Classes	**Models**	**MAE**	**MSE**	**RMSE**	**R^2**
A	OLS	11.79	196.48	14.02	0.26

	Gaussian Naive Bayes	**9.87**	**177.21**	**13.31**	**0.33**
	Bayesian Network	16.57	681.50	26.11	-1.56
	Random forest	16.82	477.96	21.86	-0.79
B	OLS	11.66	**199.51**	**14.12**	**0.54**
	Gaussian Naive Bayes	**11.06**	205.86	14.35	0.53
	Bayesian Network	17.51	671.18	25.91	-0.55
	Random forest	20.07	657.01	25.63	-0.52
C	OLS	12.68	**237.41**	**15.41**	**0.60**
	Gaussian Naive Bayes	**12.52**	255.35	15.98	0.57
	Bayesian Network	14.79	453.69	21.30	0.24
	Random forest	19.45	559.13	23.65	0.07
D	OLS	**11.18**	**188.52**	**13.73**	**0.62**
	Gaussian Naive Bayes	13.30	297.72	17.25	0.40
	Bayesian Network	17.07	584.32	24.17	-0.18
	Random forest	21.61	730.17	27.02	-0.48
E	OLS	11.60	**204.26**	**14.29**	**0.52**
	Gaussian Naive Bayes	**10.92**	214.30	14.64	0.50
	Bayesian Network	15.74	526.80	22.95	-0.24
	Random forest	19.89	594.31	24.38	-0.40

4 Discussion and Conclusions

This study extends previous findings by confirming that the optimal models for predicting the growth of elementary school students' mathematics learning are linear regression (OLS) and Bayesian prediction. These results are consistent with prior research on CBM reading [6][7]. However, our findings also indicate that differences in growth patterns persist across different classes. Therefore, it is recommended that the online CBM system automatically provide teachers with the most suitable prediction model based on the mathematical learning performance of students in their class. This would allow teachers to better forecast students' future learning goals and adjust their instructional strategies accordingly.

Based on the findings of this study, future research could apply these predictive models to larger-scale samples to further validate the accuracy of CBM-M growth prediction patterns and to investigate the impact of continuous monitoring on teachers' instructional practices and students' learning outcomes.

Acknowledgement

The author thanks the National Science and Technology Council of the Republic of China for financially supporting this research under Contract No. NSTC 112-2410-H-152 -001 -MY2.2413-H-133-006.

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