A Prediction and Early Alert Model Using Learning Management System Data and Grounded in Learning Science Theory

Wonjoon Hong
University of Nevada, Las Vegas
4505 S Maryland Pkwy Las Vegas, NV 89154, USA
+001(702)895-3253
hongw1@unlv.nevada.edu

Matthew L. Bernacki
University of Nevada, Las Vegas
4505 S Maryland Pkwy Las Vegas, NV 89154, USA
+001(702)895-4013
matt.bernacki@unlv.edu

ABSTRACT

Students experience considerable challenge in STEM coursework and many struggle to earn the grades needed to move forward in their majors. Interventions informed by prediction models can support learners to ensure successful completion of STEM courses and entry into the STEM workforce. In order to accurately target intervention efforts, we developed a prediction model based on log data generated by student use of content hosted on a learning management system (LMS; Blackboard Learn) course site in the first weeks of the course. The prediction model employed a forward selection logistic regression algorithm (with 10-fold cross validation) trained on four semesters of data, and provided instructors the opportunity to message students and provide learning support before the first major exam, potentially intervening before onset of poor performance. The best fitting model was used to identify students unlikely to obtain the required grade (B or better) in the course. Among 106 students predicted to perform poorly, 63 received a message from the instructor's account that referenced an upcoming exam and linked students to supportive materials. Messaged students who accessed learning supports outperformed non-messaged but eligible students (n = 43) on each of five subsequent exams throughout the semester (ds = .64 - .88). Fifty-eight percent earned a B or better, compared to 25% of non-messaged peers predicted to earn a C or worse. This study affirms that data-driven early alert messages can provide targeted support and boost achievement in challenging STEM courses.

Keywords

Learning management system, Prediction modeling, Early warning system, STEM learning, learning sciences

1. INTRODUCTION

Learning management system (LMS) have become a central tool in higher education. Logs of learning events can be combined with achievement data in order to identify (un)productive patterns of events and predict the achievement of future students based on their behavioral match to prior students who achieved certain levels of performance [1].

2. METHODS

The university LMS, Blackboard Learn, captures and records student use of materials hosted on course sites. Student activity and achievement data (N=510) from 4 semesters of an undergraduate calculus course taught by two instructors (identical content, assessments) from fall 2014 to spring 2016 informed prediction modeling (Table 1).

Table 1. Training and testing data

Section	Training set	Testing set
Instructor A	Fa 2014 & Sp 2015 (n=167)	Fa 2015 (n=96)
Instructor B	Fa 2014 & 2015 (n=161)	Sp 2016 (n=86)
Both	Instructor A (Fa 2014 & Sp 2015) Instructor B (Fa 2014 & 2015) (n=328)	Instructor A (Fall 2015) Instructor B (Spring 2016) (n=182)

Developing the prediction model went through two main phases, training and testing process. In the training phase, logistic regression with forward selection was used to build the prediction model, and the problem of overfitting was examined through 10-fold cross-validation. In the testing phase, the most accurate prediction model developed in the training phase was applied to the testing data set to assess potential overfitting and ensure generalizability to future students' data [2].

Based on the Kappa (κ) and recall, the best 3-week prediction model developed through the training and testing phases was then applied to data from fall 2016 Calculus students to identify students in need of an early alert message that provides learning support.

In order to investigate the effect of messaging identified students, those identified as likely to perform poorly by the prediction model were randomly divided into two groups, a "Message" group who would receive a message that focused attention on an upcoming exam and some useful learning resources (Figure 1) and a "No Message" group who would not.

Hi [Name]!
Our first course exam is coming up on Friday…

1. The first is a one-page summary of advice from students who have completed the course with an excellent grade in the past….
2. A set of learning modules called "The Science of Learning to Learn." These modules describe learning strategies you can use with our course materials…

Figure 1. Message to students

3. RESULTS

Among three models, the prediction model based on Instructor B's students produced the best Kappa (κ = 0.26) and recall (73%) values. The model accurately identified ≥ 7 in 10 students who would ultimately earn less than 80% of points (i.e., a C or Worse). We thus moved forward to the testing phase using the Instructor B model (Table 2) and for the prediction and messaging phase.

Table 2. Prediction models in the training and testing phase

	True: Predicted				K	Accuracy (%)	Precision (%)	Recall (%)
	1;1	1;0	0;1	0;0				
Training set								
Instructor A (Fall 2014 & Sp 2015)	79	12	46	27	.25	65	87	37
Instructor B (Fa 2014 & 2015)	**39**	**36**	**23**	**63**	**.26**	**63**	**52**	**73**
Both	97	69	63	96	.19	59	59	60
Testing set								
Instructor A (Fa 2015)	16	25	9	46	.24	65	65	84
Instructor B (Sp 2016)	19	23	11	33	.20	61	59	75
Both	35	48	20	79	.21	63	62	80

In the testing phase, attributes and their weights achieved from the training phase were applied to the testing data to examine risk of overfitting. The prediction model resulted in the Kappa value of .20 or more for all testing sets. In addition, values of recall were 84, 75, and 80 respectively, all of which were greater than result in the training phase. We thus retain the Instructor B model for the prediction and messaging phase.

Upon sending the message four days prior to the first exam, student access of recommended resources and performance on exams were tracked throughout the remainder of the semester. For all exams throughout the semester, the students in treatment group (i.e., Message & Access) performed better than those without any treatment (No Message, No Access; p <.05). In addition, effect sizes for all exams were more than "medium" (d > .5) (Table 3).

Table 4. Contingency Table

		Predicted C or Worse		Total
		Messaged	Control	
True	B or Better	11 (58%)	7 (25%)	18
	C or Worse	8 (42%)	21 (75%)	29
Total		19	28	47

Table 4 shows the proportion of students who performed better than (i.e., B or Better) vs. as projected (i.e., C or Worse). A Chi-square analysis indicated that a significantly greater proportion of students (58%) in the Message and Access group earned a final grade of B or better, χ^2 (47) = 5.18, p = .02. Only 25% of students predicted to earn a C or worse outperformed their prediction in the No Message, No Access control group.

4. DISCUSSION

In this study, those who received a brief email message from a course instructor and accessed a learning resource outperformed non-messaged students on all exams. Results thus indicate that data-driven interventions can be provided relatively early in the semester – six weeks earlier than the typical data-driven indicator of poor future outcome: a week 9 response to midterm grades. The >200-word message required only a minute or two of a typical student's time, and a visit to the advice page – the common material accessed – required only slightly more time investment from messaged students (~900 words).

The benefits of receiving a message and accessing the resources it recommends were substantial: 12% on all exams, or a full letter grade. Surprisingly, few students heeded the early alert as intended; 30% of messaged students accessed supportive materials, confirming that obtaining students' attention is a clear challenge to realization of the benefits messaging can provide. Messaging efforts thus clearly require improvement. We must also consider how to provide more adaptive message contents based on students' likelihoods of poor performance, or different supports based on the maladaptive practices summarized by features present in students' prediction models. More specific feedback about the kinds of learning behaviors that require adjustment may further increase messages' effects.

5. ACKNOWLEDGMENTS

This project was supported by National Science Foundation Award number #1420491 and Office of Information Technology.

6. REFERENCES

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Table 3. Result of t-test of scores for all exams

	No Message & No Access			Message & Access			t	df	Sig.	Mean difference	Cohen's d
	N	Mean	SD	N	Mean	SD					
Exam 1	24	77.0	11.0	17	85.5	8.3	2.701	39	0.010	8.51	0.877
Exam 2	23	73.7	19.0	17	85.7	10.4	2.349	38	0.024	12.01	0.783
Exam 3	22	59.5	14.8	18	71.5	22.2	2.047	38	0.048	12.00	0.637
Exam 4	22	58.9	15.9	19	71.0	20.3	2.136	39	0.039	12.09	0.663
Final	22	55.7	23.8	19	70.9	23.6	2.043	39	0.048	15.17	0.640