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Board 422: Using Adaptive Learning Platform Metrics for Early Identification and Personalized Support of Low-Performing Students

Prof. Autar Kaw, University of South Florida

Autar Kaw is a professor of mechanical engineering at the University of South Florida. He is a recipient of the 2012 U.S. Professor of the Year Award (doctoral and research universities) from the Council for Advancement and Support of Education and the Carnegie Foundation for Advancement of Teaching. His primary scholarly interests are engineering education research, adaptive, blended, and flipped learning, open courseware development, composite materials mechanics, and higher education's state and future. His work in these areas has been funded by the National Science Foundation, Air Force Office of Scientific Research, Florida Department of Transportation, and Wright Patterson Air Force Base. Funded by National Science Foundation, under his leadership, he and his colleagues from around the nation have developed, implemented, refined, and assessed online resources for open courseware in Numerical Methods (http://nm.MathForCollege.com). This courseware annually receives 1M+ page views, 1.6M+ views of the YouTube lectures, and 90K+ visitors to the "numerical methods guy" blog. This body of work has also been used to measure the impact of the flipped, blended, and adaptive settings on how well engineering students learn content, develop group-work skills and perceive their learning environment. He has written more than 115 refereed technical papers, and his opinion editorials have appeared in the Tampa Bay Times, the Tampa Tribune, and the Chronicle Vitae.

Dr. Ali Yalcin, University of South Florida

Dr. Ali Yalcin received his B.S., M.S., and Ph.D. degrees in Industrial and Systems Engineering from Rutgers University, New Brunswick New Jersey in 1995, 1997 and 2000. He is currently an Associate Professor at the University of South Florida, Industrial and Management Systems Engineering Department, and an Associate Faculty member of the Center for Urban Transportation Research. His research interests include systems modeling, analysis and control, data analysis and decision support in healthcare, information systems and engineering education research. His work has been funded by federal organizations including National Science Foundation and Army Office of Research and medical device manufacturing industry. He has taught courses in the areas of systems modeling and performance analysis, information systems design, production planning, facilities design, and systems simulation. He co-authored the 2006 Joint Publishers Book-of-the-Year textbook, Design of Industrial Information Systems, Elsevier.

Dr. Renee M. Clark, University of Pittsburgh

Renee Clark serves as the Director of Assessment for the Swanson School of Engineering at the University of Pittsburgh. She received her PhD from the Department of Industrial Engineering, where she also completed her post-doctoral studies. Her research has primarily focused on the application of data analysis techniques to engineering education research studies as well as industrial accidents. She has over 20 years of experience in various engineering, IT, and data analysis positions within academia and industry, including ten years of manufacturing experience at Delphi Automotive.

Using Adaptive Platform Metrics for Early Identification and Support of Low-Performing Students

1. Introduction

In the last two decades, flipped learning has become one of the pedagogies for integrating active learning into a classroom [1,2]. Although flipped learning has tangible benefits for learning and engagement, student resistance remains challenging to such active learning strategies [3]. This struggle is most evident with the pre-class learning required for the flipped classroom. It leads to inadequate preparation for the in-class engagement exercises, including answering conceptual questions and solving procedural problems.

In a course in Numerical Methods taught in the mechanical engineering department at a large southeastern university, we aimed to alleviate this resistance [4] to pre-class preparation via adaptive learning platform (ALP) lessons. These ALP lessons replaced the one-size-fits-all pre-class learning approach of assigning short videos, specific textbook pages, and an online quiz administered using a learning management system (LMS). Instead, ALPs use machine learning algorithms to deliver content and learning activities (similar to an LMS) but in a personalized fashion with valuable feedback [5].

ALP lessons significantly improved the flipped classroom, as evidenced by an increased concept inventory average with a Cohen's effect size of $d = 0.14$ [4]. Limited-income groups like Pell Grant recipients experienced the most significant positive effect with $d = 0.30$. Additionally, all seven dimensions of the CUCEI classroom environment had desirable increases with the use of ALP, with the Innovation dimension seeing the most significant increase ($p = 0.007$ and $d = 0.54$).

One of the other benefits of using an ALP is the significant amount of data it collects about student behavior and engagement with the course material [6-8]. We used this data to identify and support potentially lower-performant students (C or lower students) during the first few weeks of the semester instead of waiting until the sixth week when the first unit test gets graded for the class. By the sixth week of the semester, it may be too late for the student to recover from low performance on the test due to feeling discouraged or unable to make significant adjustments in their approach to academics.

2. Model for Identifying Lower-Performant Students

To develop the model for identifying lower-performant students, we collected data from the ALP and conducted a descriptive analysis during Fall 2021 and Spring 2022 semesters. The course was taught face-to-face during both semesters. The data was collected for 30 topics called objectives, each of which had individual lessons called nodes. The data was collected under three categories, namely activity type, participation type, and performance type.
1) *Activity Type*: These activities are related to ALP interactions for instruction, practice, and review. Instruction involves covering a lesson before the due date, review involves doing a lesson without any changes to the grading criteria, and practice involves redoing the assessment. The data collected includes the number of times each activity was accessed, the amount of time

spent on instructional content, the number of times the lessons were reviewed after the deadline, and the amount of time spent practicing the assessment questions after the deadline.
2) *Participation Type*: These are related to which part of the lesson is interacted with, that is, introduction/learning objectives, videos/textbook content, and assessment. The data collected includes time spent on participation, number of participations completed, time spent on introduction/learning objectives sections, time spent on videos/textbook sections, and time spent on the assessment section.
3) *Performance Type*: These are related to student performance per instructor expectations for a lesson, including the number of times objectives were submitted late and by how much, number of times submitted early and by how much time, percentage grade, and number of incompletions.

Using this ALP data, we applied a combination of aggregate statistics, frequency analysis, Principal Component Analysis, and Partitioning Around Medoids (PAM) clustering to understand the engagement behaviors of students and the variables which presented significant variability [9, 10]. The analysis showed clear and considerable evidence of distinct behaviors between higher-performant and lower-performant students. The higher-performant students were associated with fewer attempts at the questions, more prolonged interactions with the content, more time spent learning, better performance on the assessments, and lesson completion, even if late.
We wanted to identify and support students who may be lower performant, that is, earn a C or lower, by the end of the course. To this end, we primarily used Decision Trees [11] as they are simpler to understand, visualize, and actionable.

We created a binary classification tree model (low- and high-performant students) using the Fall 2021 and Spring 2022 ALP data (Figure 1). This training data set included 116 students, 33 of whom are low-performant, obtaining a grade of C or below (classified as True). The two numbers shown in each leaf in Figure 1 correspond to the number of high and low-performant students. Three variables are used to classify, namely, Average ALP Grade (AvgALPGrade), number of Instructional Activities completed by the student (InstructionalCount), and total time (in hours) objectives completed prior to the due date (EarlyTime). The first node of the tree (shown by the number "1" in a small box) is based on the AvgALPGrade variable. Twenty-three students obtained an Average ALP grade of less than 70%, and 19 were low-performant, as shown in Node 3 of the tree. Similarly, in Node 2, the InstructionalCount variable is used to classify students. As shown in Node 4, 64 of the 65 those who completed less than 172 instructional activities were highly performant. Node 4, representing students with high AvgALPGrade and low InstructionalCount is the most accurate node in classifying high-performant students.

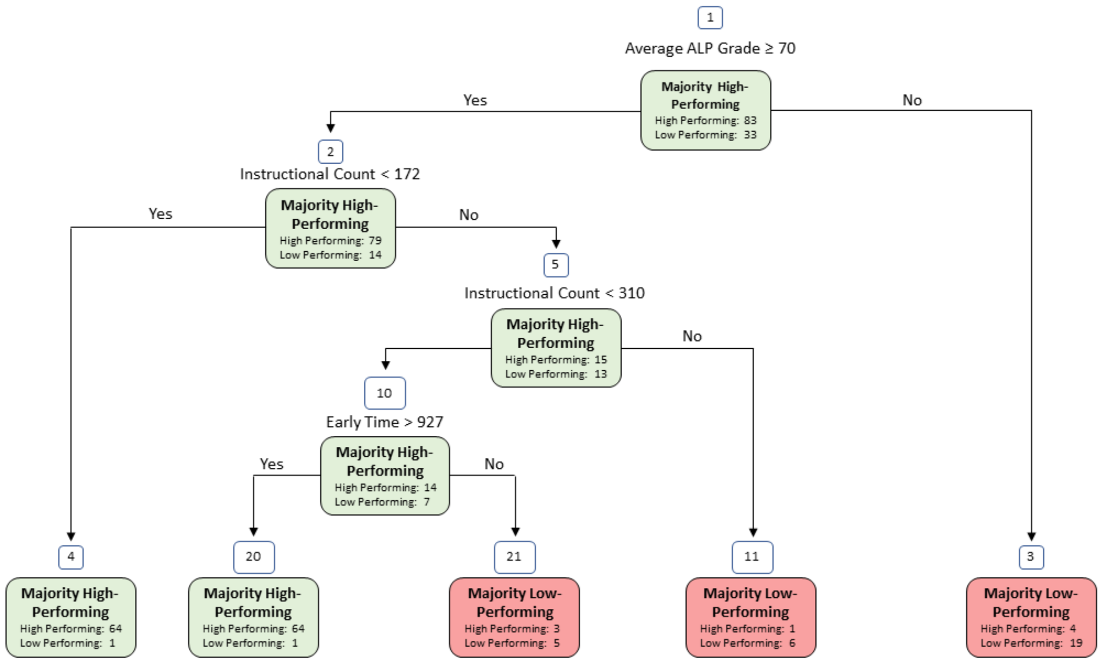

Figure 1. Decision tree model of the training data set.

The confusion matrix [11] of the classification of the training data set is shown in Table 1. "True" denotes low-performant students presenting as candidates for support. The overall accuracy of the model is 90.5%. Note that only three low-performant students (out of 33) are misclassified.

Table 1. Confusion matrix for the binary classification of the training data set.

	False	True
False	75	3
True	8	30

Taught face-to-face, we used the model in Fall 2022 semester in Weeks 2, 3, and 4 to identify students who would benefit from advising and tutoring support. Since the decision tree model was constructed using ALP data from the whole semester data, we scaled the classification rules at some nodes based on the completion percentage of ALP lessons when the decision tree is used to make performance predictions. For example, in the end of Week 4 of the Fall 2022 semester, we used the criteria numbers of AvgALPGrade>=70%, InstructionalCount <68, InstructionalCount <122, and EarlyTime >=365, since only 40% of the nodes were expected to be completed by then.

Using the testing data from the Fall 2022 semester, we classified students in the second, third, and fourth weeks of the semester.

3. Advising and Tutoring Students

During the week students were identified, we extended an official invitation for one-on-one support and advice. Students were asked to give their weekly availability of one-hour slots to meet with the instructor or teaching assistants until the last day of class. We were flexible to meet after 5 pm and gave them a choice of meeting face-to-face (preferred) or online. Mandatory attendance was not required upon acceptance of our offer, but students were asked to provide a heads-up for not showing up.

By the end of the 4th week of the semester, 18 students were identified, and only 6 (33%) accepted the invitation. Two of the six students met with instructor A, two with teaching assistant B, and two with teaching assistant C. The assignment was dictated mainly by the time availability of the involved parties.

Table 21 shows a summary of some descriptive statistics from these advising sessions. The table shows who the student met with, how many weeks they could have sought help, and the number of sessions they attended. Students showed up for most sessions, but sometimes they would cancel or not show up. Reasons for missing sessions included a delayed response to the initial instructor support email, not showing up without cause, cancelations, and sessions falling on a holiday or during a hurricane closure.

Table 2: Summary of Advising Sessions Statistics

	Student 1	Student 2	Student 3	Student 4	Student 5	Student 6
Assigned Advisor/Tutor	Instructor, A	Instructor, A	TA, B	TA, B	TA, C	TA, C
Number Of Weeks Left After Support Email First Sent	13	12	12	13	13	13
Percentage of Times Met	38%	92%	83%	23%	31%	69%
Grade Expected Without Intervention	C or less	C or less	C or less	C or less	C or less	C or less
Grade Received	A	A-	B+	A-	D+	B-

Each session started with questions to the students about progress and challenges with the ALP lessons, in-class attendance, active learning activities, and ungraded end-of-chapter problem sets in the textbook. After these questions, most time was spent answering student questions related to the course. In one case, the student had taken a Research Experience for Undergraduates course that used Numerical Methods, and we spent our spare time in several sessions on the research topic.

Of the 12 students who did *not* opt for one-on-one support in Fall 2022, we can report only on ten students who chose to participate in the study. Their expected grades here were also C or less; their letter grades received were 1 A, 4 Bs, 4 Cs, 1 D, and 0 Fs (an average GPA of 2.5/4.0). The six advised and tutored students received 3 As, 2 Bs, 0 Cs, 1 D, and 0 Fs (an average GPA of 3.16/4.0). These results may indicate that the weekly support worked despite several no-shows and cancellations.

Students invited to the one-on-one support were requested to join a focus group conducted by the project's assessment analyst at the end of the semester. Five students participated in the focus group, three of whom had received support. Those who received support mentioned that the sessions helped them with their learning, including a better conceptual understanding of the course content and enhanced problem-solving skills. Those who did not avail themselves of the support said they did not need help or had to focus on other courses.

4. Future Advising and Tutoring of Students

Since this was the first time we had advised and tutored students based on the ALP data, we plan to formalize further the advising questions and the method of scheduling and running the tutoring sessions. Developing the framework will take time and requires meetings with the internal and external evaluators to sift through the data and create an improved plan. In Fall of 2022, our classification model could not identify four out of 11 low-performant students. We are looking for ways to improve the accuracy of the decision tree model. These reasons are why we are delaying the second implementation of the one-on-one support to Fall 2023.

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