Predictive Student Modeling for Interventions in Online Classes

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ABSTRACT

As large-scale online classes become more prevalent there is great interest in finding ways to model students at scale in these classes in order to predict outcomes. Student models, if successful, would help determine strong predictors of student success, which would highlight potential causal factors for such success, allowing schools to focus on refinements and interventions that positively impact their student outcomes. In this research, TutorGen has partnered with Western Governors University (WGU), a large online university, and gathered data at scale in order to build exploratory models to predict student outcomes. This paper presents our results so far in successfully identifying students who will pass (or even take) the final exam. We have examined the order in which students take courses, as well as the timing of starting and completing work; our initial analysis reveals that these are strong predictors of course outcomes.

Keywords

Predictive modeling, online education, student interventions, cognitive models, student models, online courseware, feature selection, data visualization, mixed effects modeling, logistic regression.

1. INTRODUCTION

In collaboration with Western Governors University, a large online university, we have been examining large data sets of students' online interactions, which will help provide insight into the way students succeed in course completion. Our initial work has focused on building a set of predictive models looking at success within course and also between courses. Based on student in course data as well as post course assessment, we know learning is occurring within courses. We do know that some students do not pass the final assessment, and these are the students we were most interested in modeling. From our exploratory data analysis and initial models, three important and distinct factors emerged. First, there was a "basic dropout," students who did not pass simply because they stopped being active in the course – not completing assignments or taking tests. Second, was a group termed "late and out of time" that started very late in the semester and appeared to run out of time. And finally, there was group we termed "exam avoidance" that appeared to have mastered enough to pass the final assessment, but for unknown reasons did not attempt the test. We examined some of the properties of each of these types of students and suggest strategies that we plan to implement in order to intervene with each type appropriately.

2. BACKGROUND

Western Governors University (WGU) was founded in 1997 by nineteen governors as a non-profit, competency-based, 100% online university, which has graduated more than 100,000 students. WGU currently has more than 94,000 students across all 50 states. Offering 60 degrees in four colleges supporting high-demand fields such as business, K-12 teacher education, information technology, health professions, WGU's success is founded on their unique learning ecosystem that is student-centric, competency-based, and 100% technology enabled. This approach lowers tuition and provides faster time to graduation.

The WGU competency-based model enables students to leverage their existing knowledge and skills while seeking to improve their opportunities to advance their careers. Students earn college credit by demonstrating what they know and can do rather than basing the credit on seat-time in a course. The curriculum and assessments are defined by career-relevant competencies to accelerate learning according to a student's level of experience. WGU provides the curriculum, formative assessments, and summative evaluation. In addition, the WGU student-centric support services promote success in student learning through disaggregated faculty roles including: program mentors, course instructors, evaluators, and curriculum and assessment developers. This approach allows students to remain at the center of all activities such that the focus is on the learning of each student. The success of the online model that combines competency-based learning models with strong student support is demonstrated by their high student satisfaction ratings, contributing to a higher than average retention rate.

WGU is committed to continually evaluating all aspects of their educational experience in order to enhance their models, content, delivery methods, and student support through proven academic research. This approach helps them make strategic and impactful improvements to student learning outcomes while enhancing the overall student experience (reduced time to achievement, career advancement, learning support, completion/achievement etc.) This drive to measure and identify areas for improvement resulted in a deep data dive evaluating courses that have relatively lower completion rates than others within the same program.

2.1 WGU Course and Term Structure

WGU students begin their degree programs on the first of any month, which begins their first term. A term at WGU is six months in length. Tuition is billed at a flat-rate every term, so students pay for the time, not by credit hour or by course. Students are encouraged to complete as many courses as they can in those six months, resulting in cost savings for students. Students complete courses by passing assessments, demonstrating competency.

2.2 WGU Faculty

The faculty at WGU underpin WGU's unique, student-centric, competency-based approach that places the greatest emphasis on student learning. Learning at WGU is competency-based, the institution does not use typical online classes that are dependent upon fixed schedules or group pacing. Instead, each student is guided and assisted through a personalized learning experience by two primary roles: program mentors and course instructors.

2.2.1 Program Mentors

For each student, the primary faculty support is a personally assigned Program Mentor. The role of the Program Mentor is to provide program instruction, coaching, and support from the moment an individual becomes a student to the time he or she graduates. More specifically, Program Mentors:

- Provide instruction and guidance at the program level.
- Provide information on programs, policies, and procedures.
- Assess students' strengths and development areas to help them develop a plan of study.
- Provide feedback on assessments and recommend learning resources.
- Help students to sustain motivation and maintain on-time progress to their degree.
- Recommend appropriate student services.

This support involves regularly scheduled academic progress conversations weekly and active involvement in other aspects of the student's academic career. While not an expert in all subjects, the Program Mentor guides the student through the overall program and offers coaching, direction, and practical advice.

While there is a default order to degree paths, mentors and students are empowered to personalize the course order. During enrollment each term, the student and program mentor agree upon a set of courses to meet the credit requirement for that term. They set an order, taking any prerequisites into account. Estimated start/end dates are populated for each course assuming the student works on 1 course at a time. (The student may, however, opt to work on multiple courses consecutively.) The program mentor helps guide students' academic activities.

2.2.2 Course Instructors

WGU's Course Instructors are subject matter experts who instruct and support students as they engage specific sections of the WGU curriculum. Their experience and advanced training is specific to the courses they support. They are knowledgeable and can address any issue that might arise related to a course, a learning resource, or an assessment. Specifically, Course Instructors:

- Bring WGU courses of study to life with students via one-to-many or one-to-one forums.
- Provide instructional help (proactively and reactively) and facilitate learning communities.
- Provide content expertise for students who are struggling with course material.

The type and intensity of instructional support varies based on the needs of each student in a particular course, from help with specific questions that arise to more fully engaged tutorial support.

2.3 Assessments at WGU

WGU has developed assessments for each course based on the competencies identified for each course subject. Assessments can take several forms at WGU but follow two main categories: performance assessments and objective assessments.

Performance assessments are embedded throughout the course, such as tests, quizzes, and other assignments, as a way to track progress as students complete the course material. Performance assessments receive qualitative feedback from an assessment team using a standard rubric. Objective assessments are timed and proctored summative exams. Question types may include short answer responses, fill-in-the-blank questions, or multiple choice. With a high-speed Internet connection, a block of uninterrupted time, and a dedicated room with no distractions, students can take these exams at home. During the exam, students are monitored by a live proctor through a webcam provided by WGU. The course evaluated here was of the objective assessment variety.

For objective assessment courses, pre-assessments (also called pre-tests or practice tests) help students and faculty gauge student readiness to take an objective assessment. Pre-assessments measure the same content as the objective assessment, with the same question types, and the same time limit. However, the questions that appear on the pre-assessment will be different from those that appear on the objective assessment.

Both pre-assessment and objective assessment results are provided using four categories: unsatisfactory, approaching competence, competent, and exemplary. A score of "competent" or "exemplary" is required to pass a pre-assessment and/or objective assessment. Exactly what constitutes competence for a given assessment is carefully determined by WGU's Assessment department in concert with a group of experts in the subject matter being assessed.

A student's first attempt on their objective assessment is approved by the program mentor. Mentors can require the completion and pass of a pre-assessment before approval to schedule the objective assessment. Second and subsequent attempts are approved by a course instructor. Course instructors will require the student to complete certain tasks to gauge success on the next attempt before an approval is granted. Students are permitted four attempts for each objective assessment requirement. Any attempt thereafter will need to be approved through the program mentor and course instructor senior leadership.

A WGU course is considered complete when the assessment is passed. For courses with objective assessments, a student with extensive prior knowledge can forgo any interaction with the course materials and move directly to the assessment (typically passing the pre-assessment first). This is true for first and subsequent attempts—so if a student is very close to passing during their first attempt, their second attempt might require very little time and/or effort.

3. RELATED LITERATURE

As large-scale online classes become more prevalent there is great interest in finding ways to model students at scale in these classes in order to predict outcomes. This has been a major area of work in the fields of Educational Data Mining (EDM) and Learning Analytics (LAK) [2] and is leading to methods of executing large scale data experiments in near real-time [9]. Student models, if successful, would help determine strong predictors of student success, which would highlight potential causal factors for such success, allowing schools to focus on refinements and interventions that positively impact their student outcomes. For example, early research at Purdue University presented "academic analytics" tools for predicting at-risk students [4,1]. In [12] the authors develop a "survival model" of student dropouts in a MOOC, determining several significant predictors of dropout behavior. MOOCs, however, present a special case of online courseware, and tend to show quantitatively different outcomes than online courseware with a fixed enrollment, monetary costs to students, and offering course credit and accreditation. In this vein some researchers have looked at similar online environments. In [7] the authors not only developed models to predict student outcomes, but also showed how metrics and visual data provided to instructors can help improve outreach and positive interventions.

In this research, TutorGen has partnered with Western Governors University (WGU), a large, fully accredited online university that offers course credit and an online degree program, and gathered data at scale in order to build exploratory models to predict student outcomes. This paper presents our results so far in successfully identifying students who will pass (or even take) the final exam. We have further examined the order of the courses that students complete and the timing of the course work completed to subsequently show that this order of completion and timing of the work within the semester is a strong predictor of student success.

4. DATA AND METHODS

Our research focused on a single course in the Business school dealing with Finance. The dataset spanning 2016 contained data from over 1,000 students and had low level interaction data of nearly 1 million transactions that was imported into DataShop [8]. In addition to the transaction data, we had practice test data, final summative evaluation data (in the form of Pass, Not Pass, Other), student interactions with the LMS (both with the finance course and other courses), and student summative data from previous courses attempted.

5. ANALYSIS AND DISCUSSION

In order to derive insight about student behavior in the online courses, we used several approaches including: visualization, predictive modeling, and knowledge tracing.

Questions:

1. Are students learning within the course?
2. How are students interacting with the course materials?
3. What are the key differences between the passing and non-passing students?
4. What behaviors describe non-passing students?
5. Can these be used to build an intervention?

To explore question 1, we performed a learning curve analysis on the data in DataShop based on previously defined methods [10]. From these methods, we can visually inspect the learning curves created from low level interaction data tagged at a Knowledge Component (KC) level. From these visualizations we would expect a declining learning curve to emerge as seen in Figure 1. Looking at combined learning curves of all 97 tag KCs in our dataset, we visually saw a declining curve suggesting learning is occurring within the course. Drilling down to individual skills the majority were also classified as "good" in the DataShop learning curve interface suggesting learning is occurring.

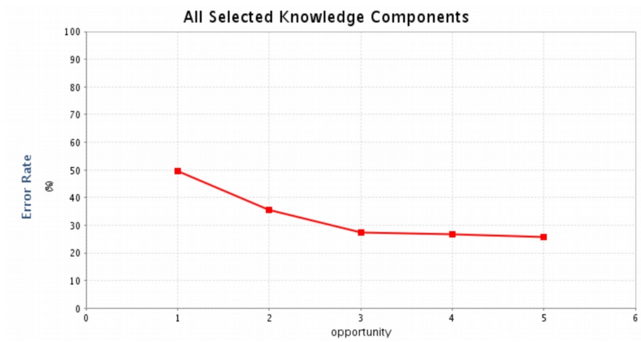

Figure 1. A sample learning curve of all KCs. The y-axis represents error rate and the x-axis represents all student opportunities to apply each skill. If learning is occurring we expect to see a declining curve as seen.

To examine question 2, we did an exploration of the activities that students did within their course. We did note that the particular course we were exploring was one of the most difficult and had lower than average completion rates. We used the finest-grained level of data available. This data included the student's step by step actions in the online system. We constructed a visualization to represent student behavior across time, as well as how they performed on practice tests and final assessments.

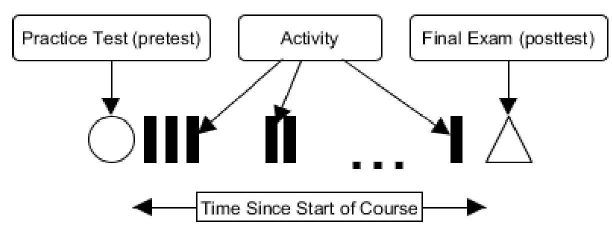

Figure 2. Timeline for an individual student. Vertical bars represent a course activity session, and circles and triangles represent the practice test and final exam attempts.

Figure 2 shows a timeline for an individual student, vertical bars represent a course activity session (reading, practice problems, etc. performed within the same time online session) Circles and Triangles represent the practice test and final exam attempts. This provides a high-level view of student work across time, as well as visually representing the student testing behaviors. We used color (blue and orange) to encode passing and non-passing students, figure 4 shows typical behavior of passing students while figure 5 shows typical behavior of some non-passing students.

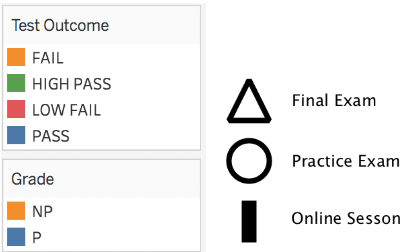

Figure 3. Key for the work timeline visualization.

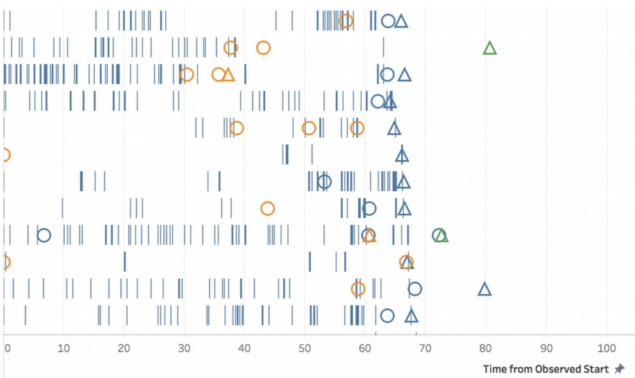

Figure 4. Typically, students engage with the course for a while before taking the practice test, depending on the results of that test they take and pass the final exam. It is rare for students to take the practice test before starting some of the coursework.

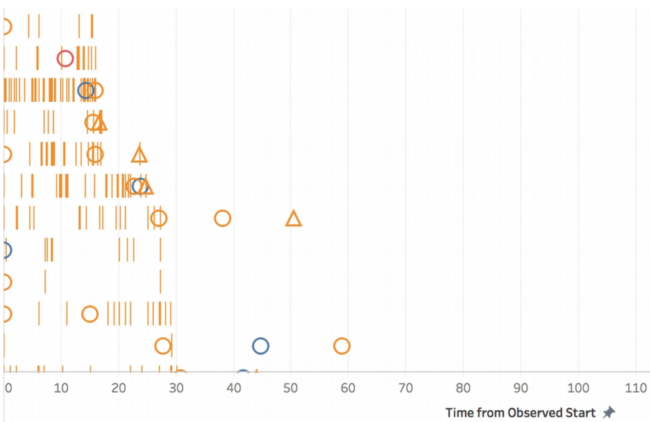

Figure 5. A common behavior for non-passing students is to dropout fairly soon after starting the course. Students have multiple opportunities to take the final exam, however many of the non-passing students do not take the final multiple times.

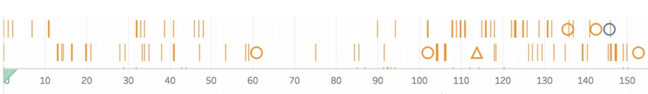

Figure 6. Long fail behavior, note the late pass on the practice exam with no attempt on the final exam. Not all failing students dropout quickly after starting, some students do work throughout a term. Interestingly, some students pass the practice exam but sim

These exploratory visualizations helped to highlight three important predictive features of this data: deviation from planned course start, action density once started, and the course order. For example, some students would quickly work through the material while others would spread it out.

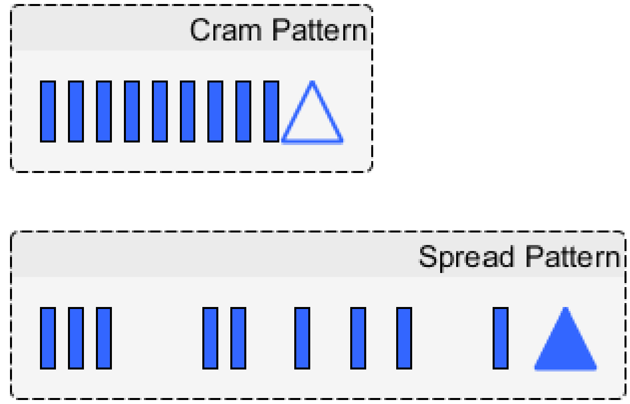

Figure 7. Cram pattern of activity vs. a spread pattern of activity. How students planned and executed their coursework proved to be predictive of success.

Students can choose when to schedule courses throughout a 180-day long term. We found that both planned start time, as well as deviation from that start time to be an important factor between passing and non-passing students. This information would help us to build a predictive model, and allow for more targeted interventions, as discussed in the next section.

5.1 Predictive Model

In order to explore potential interventions, we aimed to create predictive models for test performance and course grade. We developed a predictive model for student test performance and overall course performance. In order to be useful in a live environment, we needed an updating model that makes a prediction based on the continuously updating activity data. We also needed to address the fact that students are able to choose when to take the assessment tasks.

For each session, we want to make a prediction about the student performance on the next test. We refer to the sessions between (or in the case of the first test taken, all sessions before) testing opportunities as assessment windows. Our model will use the previously observed data to predict the performance on the next testing opportunity.

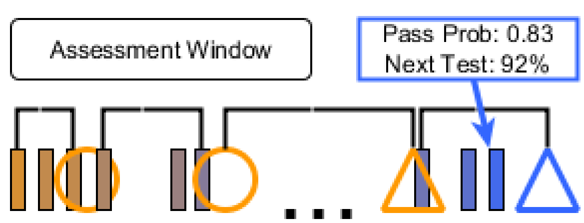

Figure 8. Next test performance is predicted using information from assessment windows proceeding testing opportunities.

We integrate the results of these models into our visualization, which takes the form of an orange to blue gradient on colorization with extra information available in tool tips.

We predict for each session the probability that the student will ultimately pass the course, as well as their predicted score on the next testing opportunity. We use a logistic regression for the pass prediction and a mixed effects model for the next test prediction. The overall performance of the pass prediction model was fair with 69% accuracy; when using an 80% cutoff value on the pass prediction we had a positive prediction value (Recall) of about .7 and a negative prediction value (Precision) of .66. The most important features include observed test performance, total number of observed actions, total time engaged in the materials, the accuracy the lesson activities, the total number of sessions, and the amount of time from the planned start of the course.

The next test prediction model also had fair performance with an overall RMSE of 6.92, which improves slightly as more data is added to a value of 6.6 until around the 20th session, after which the RMSE gradually moves to 6.95. The primary predictive features were previous test performance, total observed transactions, accuracy on lesson activities, time between sessions, and the amount of time between the planned start of the course.

Exploration of the model predictions and the visualization revealed that a number of students who are expected to pass the next assessment, simply never attempt the final. For students that ultimately do not pass the course, roughly 32% never attempt the final assessment (19% of failing students take neither the pretest or final.) Our model indicates that 35% of failing students would have been likely to receive a passing grade on their next test (30% if we only include students with at least one final exam attempt.) This is evidence of potential test anxiety [5] or avoidance of demonstrating a lack of ability [6]. Avoiding tests is not an uncommon occurrence in low-stakes tests [11]. See Table 1 for the complete breakdown of unsuccessful course explanations.

Table 1. Explanations or potential explanations, for students who did not pass the examined courses

Reason	Proportion
Quit Early, low use of resources	13%
Has Activity, Complete Testing Avoidance	4%
Has Activity, Predicted Pass w/o Test	35%
Ran out of time in term (Started very late)	8%
Low Activity	22%
Not Explained	18%

5.2 Intervention Opportunities

There are several opportunities for developing interventions that can improve student outcomes. There are three primary targets: Instructors, Mentors, and Students. Rather than target the students directly, we will focus on providing information to the Program Mentors. By providing visualizations like the ones above, we can allow the mentors to create unique advice to the students. For example, a mentor can provide encouragement to take an attempt on the final due to the next test prediction metric. Targeting the students who seem to be avoiding the final assessment is an area that could provide great impact to student outcomes. The challenge here is to balance flexibility for students - a key attribute of competency-based education [3] - with enough structure and support, in order to optimize student performance. For example, while a flexible timeframe for completing coursework is a hallmark of competency-based learning, it may prove that many students need some structure and prompting in order to compel completion rates.

6. CONCLUSIONS AND FUTURE WORK

WGU has a unique structure for online educational programs. Exploration of student data revealed that students generally make use of the course resources and learning materials, but will sometimes fail courses due to course scheduling and failing to adhere to their planned start dates. More importantly, a significant proportion of failing students would likely pass if they would attempt to take the final assessment. We propose interventions targeting the program mentors, rather than students, in order to explore methods of addressing the scheduling, activity, and test avoidance issues that make up the majority of the reasons students fail to pass courses. The end goal is to proactively advise students, course instructors, and student mentors with relevant just-in-time information in order to insert and test appropriate interventions.

7. ACKNOWLEDGMENTS

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