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# Models for early prediction of at-risk students in a course using standards-based grading

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Using predictive modeling methods, it is possible to identify at-risk students early and inform both the instructors and the students. While some universities have started to use standards-based grading, which has educational advantages over common score-based grading, at–risk prediction models have not been adapted to reap the benefits of standards-based grading in courses that utilize this grading. In this paper, we compare predictive methods to identify at-risk students in a course that used standards-based grading. Only in-semester performance data that were available to the course instructors were used in the prediction methods. When identifying at-risk students, it is important to minimize false negative (i.e., type II) error while not increasing false positive (i.e., type I) error significantly. To increase the generalizability of the models and accuracy of the predictions, we used a feature selection method to reduce the number of variables used in each model. The Naive Bayes Classifier model and an Ensemble model using a sequence of models (i.e., Support Vector Machine, K-Nearest Neighbors, and Naive Bayes Classifier) had the best results among the seven tested modeling methods.


## 1. Introduction

Despite numerous efforts to improve student retention and success in higher education institutions over the past 30 years, retention rates remain low (Gardner & Koch, 2012). According to the *National Collegiate Retention and Persistence to Degree Rates* report in 2012, the first to second year retention rate on average was 66.5% (ACT, 2012). Almost one third of students leave college after experiencing just their first year. The attrition continues through the next years of school - only 45% of students who enter college graduate after 5 years (ACT, 2012). Academic success is the most important factor in students' retention and the best predictor of students persistence (DesJardins, Ahlburg, & McCall, 1999; Pascarella & Terenzini, 2005). Risk of attrition decreases with an increase in academic achievement (Murtaugh, Burns, & Schuster, 1999). Thus, one way to increase retention is to increase academic success.

The first step to increasing academic success is the identification of at-risk students early in the semester. Through the use of predictive modeling techniques, it is possible to forecast students' success in a course and identify those that are at-risk (Jin, Imbrie, Lin, & Chen, 2011; Lackey, Lackey, Grady, & Davis, 2003; Olani, 2009). A predictive model can be used as an early warning system to identify at-risk students in a course and inform both the instructor and the students. Instructors can then

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use a variety of strategies to communicate with the at-risk students and provide them pathways for improving their performance in the course. Use of an early warning system in a course, along with intervention guidelines, can increase students' success in a course (Arnold & Pistilli, 2012; Essa & Ayad, 2012; Macfadyen & Dawson, 2010).

Despite the promise of academic early warning systems (e.g., Course Signals, Pistilli & Arnold, 2010), the existing ones have some shortcomings. First, one common and major problem is that they typically employ a general prediction model that cannot address the complexity of all courses. Employing a general prediction model can result in low accuracy predictions of students' success in a course because the course learning objectives, activities, and assessments can vary a great deal. For instance, being successful in a course that employs active learning strategies can be very different than a course that only employs lecture. Second, most early warning systems have been designed for online courses or rely heavily on Course Management System (CMS) access data (e.g., OU Analyze (Kuzilek, Hlosta, Herrmannova, Zdrahal, & Wolff, 2015)) and not performance data, which may not be a suitable data source for many face-to-face courses because many learning activities happen outside of the CMS. Third, early warning systems do not employ models optimized to identify at-risk students who need accurate predictions the most. Because grades are usually negatively skewed (i.e., the number of students who fail a course is fewer than number of students who pass the course), the models accuracy is higher for the students who pass the course and lower for those who fail. Fourth, all early warning systems have been developed based on summative score-based grading, which is typically norm-referenced. Some universities have started to change their grading from summative score-based to standards-based systems, which has educational advantages described below. Thus, academic early warning systems should adapt their models to this new grading system.

Standards-based grading is based on "the measurement of the quality of students proficiency towards achieving well defined course objectives" (Heywood, 2014, p. 1514) and grades "represent how well students achieve the course objectives" (Sadler, 2005, p. 179). Standards-based grading is criterion-referenced not norm-referenced. In other words, students are graded based on their achievements or what they can do, regardless of how other students in the course perform on the same assigned task (Carberry, Siniawski, & Dionisio, 2012; Heywood, 2014; Sadler, 2005). In this grading system, the course assessments are directly connected to the course learning objectives and are not a series of separate course assignments (Carberry et al., 2012).

Standards-based grading provides educational advantages for students. Because standard-based grading assesses students' achievement of the course learning objectives, it provides clear, meaningful, and personalized feedback for students related to achievement of the course learning objectives and helps them identify their weaknesses in the course (Atwood & Siniawski, 2014). In addition, because the students are aware of course learning objectives and a student's grade is independent of other students' performance, it provides "fairness and transparency" (Sadler, 2005). Because of its educational advantages, it is expected that more universities and courses will employ standards-based grading in the near future and it is important that early warning systems change their models accordingly.

Extensive research has been conducted to determine the factors that correlate to and/or predict students' academic success in a course. The majority of these studies focused on predicting students' grade in a course at the end of the semester using academic factors available before the start of the semester (e.g., cumulative GPA, grade in a pre-requisite course) and non-academic factors (e.g., gender, age). Neither course instructors nor students can influence past performance indicators (e.g., student GPA, previous grades) or many non-academic factors (e.g., gender, race, socio-economic status). If students are made aware of that these factors are used in the prediction models, it may discourage them because they may think their past behavior or circumstances have set them up for failure and there is nothing they can do to achieve positive future outcomes. Thus these models, despite their intention to help students, may negatively affect students' performance. More research is needed to investigate the positive and negative effects of using and sharing the basis for prediction models for students learning.

A few studies have utilized the academic performance data available during the semester, which logically can be the best predictor of the course grade. One such study compared four different methods to predict students' grades in an engineering Dynamics course using 323 students' data from four semesters (Huang & Fang, 2012). In this study, three midterm exam grades were used as indicators of students' performance during the semester. In addition, students' cumulative GPA and grades in four pre-requisite and Dynamics-related courses (i.e., Statics, Calculus I and II, and Physics) were used as indicators of students' performance before starting the course. Students' grades at the end of the semester were predicted using four different prediction methods, which in the best case predicted 64% of the students course grades. A comparison of different models revealed that adding grades from pre-requisite courses to GPA does not result in a significant increase in the accuracy of the model. Furthermore, using only the first mid-term exam with an accurate prediction method yields an overall 52.5% accuracy, which is similar to using pre-course performance data such as GPA or previous course grades. These results clearly demonstrate the value of using performance data gathered during the semester for predictive purposes. Adding other performance data such as homework and quiz grades could increase the accuracy of the models. Also unlike mid-term exams, homeworks and quizzes start earlier in the semester and using them as predictors of success may result in accurate predictions early in the semester.

In a previous study, we built three logistic regression-based models to identify at-risk students (defined as getting a D or F grade in the course) in a large first-year engineering course at three important times in the semester according to the academic calendar: at weeks 2, 4, and 9 (Marbouti, Diefes-Dux, & Strobel, 2015). For the weeks 2 and 4 models, we only used attendance records, homework, and quiz grades. For the week 9 model, mid-term exam grades were also used. The models were optimized for identifying at-risk students and were able to identify at-risk and successful students with overall accuracy