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Predicting student success by modeling student interaction in asynchronous online courses

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Abstract

Early-warning intervention for students at risk of failing their online courses is increasingly important for higher education institutions. Students who show high levels of engagement appear less likely to be at risk of failing, and how engaged a student is in their online experience can be characterized as factors contributing to their social presence. Social presence begins with teacher-student and student- student interaction in online courses. Fortunately, student interaction data can be gleaned from learning management systems, used to model and predict at-risk students at an early stage. This research addresses an existing model for predicting at-risk students to test a previous hypothesis that a holiday effect is a contributor for failure. A new analysis then presents an alternative approach, one that tests the frequency of student interaction rather than amount of interaction as a preferable indicator.

Introduction

Sixty-five percent of higher education institutions report that online learning is a critical part of their long-term strategy (Allen & Seaman, 2013). A reoccurring concern for these institutions is that student attrition rates are frequently higher in online courses than in their campus-based counterparts (Bos & Shami, 2006; Heyman, 2010). In fact, student retention has been suggested as one of the greatest challenges facing online education (Herbert, 2006; Heyman, 2010). As online enrollments continue to grow, it is imperative for institutions to develop practices and interventions that can contribute to student retention in online programs. While online educators regularly highlight the limitations of learning management systems (LMSs) (Groom & Lamb, 2014; Lane, 2009; Lowenthal & Thomas, 2010), one of the affordances of LMSs is their capacity to collect student data, which can in turn be analyzed by institutions to decrease student retention and improve student learning (Dietz-Uhler & Hurn, 2013; Wolff, Zdrahal, Nikolov, & Pantucek, 2013). Despite advances in learner and aca- demic analytics, though, online educators and online program administrators remain unsure of the best kinds of data to collect, when to collect them throughout a given semester, and what to do with this data once collected in order to improve student success. Faced with this problem, researchers set forth to develop a model using real-time data that could help identify at-risk students before they fail (Shelton, Hung, & Baughman, 2015). The first model developed by Shelton et al. (2015) was able to identify up to 78.57% of at-risk students by week 10 of a semester. However, online educators need to identify at-risk students earlier in a semester to successfully apply intervention strategies. Refining the model to more accurately and more timely identify at-risk students in online courses was needed by considering a research lens of social presence. In this paper, further refinement is reported using newly collected real-time data. Implications for practice and areas where additional research is needed are presented.

Background

Enrollments in online courses continue to grow across all grade levels (Allen & Seaman, 2013; Ginder & Stearns, 2014). Despite this growth, online courses continue to have attrition rates that

are higher – which some estimate as 10–20% higher – than traditional face-to-face courses (Boston et al., 2009; Patterson & McFadden, 2009; Willging & Johnson, 2004). The factors surrounding the higher attrition rate are complex (Hagedorn, 2005), and research about attrition in online courses is still nascent (Shea & Bidjerano, 2008).

Research findings have suggested that a primary reason students drop out of online courses is due to feelings of isolation and loneliness (Angelino, Williams, & Natvig, 2007; Kanuka & Jugdev, 2006; Ludwig-Hardman & Dunlap, 2003). Online educators have found that one way to help students persist, and address feelings of isolation and loneliness, is through establishing and maintaining social presence (Boston, Ice, & Gibson, 2011; Dunlap & Lowenthal, 2010; Oztok & Brett, 2011; Reio & Crim, 2013). Social presence is the degree of salience (i.e. quality or state of being there) between two communicators using a communication medium (Short, Williams, & Christie, 1976). Online educators have leveraged the theory of social presence to better understand and explain how people communicate and socially interact in online learning environments. Researchers have found a relationship between social presence and student satisfaction (Dunlap & Lowenthal, 2014; Gunawardena & Zittle, 1997; Hostetter & Busch, 2006; Richardson & Swan, 2003; Swan & Shih, 2005), social presence and perceived learning (Caspi & Blau, 2008; Joksimović, Gašević, Kovanović, Riecke, & Hatala, 2015; Kang & Im, 2013; Richardson & Swan, 2003), social presence and the development of a community of learners (Rourke, Anderson, Garrison, & Archer, 1999; Rovai, 2002a, 2002b) and finally social presence and student retention (Liu, Gomez, & Yen, 2009; Reio & Crim, 2013).

Establishing social presence in online courses is dependent on instructor-student and student-student interaction. More specifically, research suggests that social presence is dependent on the frequency, type, and quality of interactions between instructors and students in online courses (Dennen, 2005, 2007, 2011; Swan, 2002; Swan & Shih, 2005). Social presence is strengthened when instructors and students interact with each other in meaningful and consistent ways throughout an online course. As these interactions progress, students are more likely to develop a sense of social presence – which some researchers specifically describe as a sense of belonging (Picciano, 2002), connectedness (Bolliger & Inan, 2012), or sense of community (Rovai, 2002a, 2002b; Whiteside, 2015; Whiteside, Garrett Dikkers, & Lewis, 2014).

For over 30 years, distance education and online learning researchers have been interested in student interaction (Bernard et al., 2009; Moore, 1989). Early on, this interest in interaction focused on adding conceptual clarity and specifically defining student interaction (see Moore, 1989; Wagner, 1994). These efforts, in turn, led to a number of studies on ways to analyze student interaction in online courses (see Gunawardena, Lowe, & Anderson, 1997). The methods, which often included a type of content analysis to code the overall frequency of certain interactions, did not investigate frequency of interaction on a weekly or semester basis. Bernard et al. (2009) later reported, in their meta-analysis on interaction, that research on interaction in distance education and online learning tends to focus more on interaction interventions (i.e. conditions or environments designed to elicit interaction) than on students' actual interactions (i.e. their behaviors). Given the importance of interaction when it comes to developing social presence and addressing feelings of isolation and loneliness, online educators need to spend more time analyzing how students interact online to see how this can better inform which students are more likely not to persist in online courses.

Method

In general, a student's performance is highly related to their engagement level in any given course (e.g. Hung & Crooks, 2009; Hung, Hsu, & Rice, 2012; Hung, Rice, & Saba, 2012; Macfadyen & Dawson, 2010; York & Richardson, 2012). A few predictive algorithms and early-warning systems aimed at identifying at-risk students for early interventions were developed prior to the one used in this research (e.g. Abdous, He, & Yen, 2012; Macfadyen & Dawson, 2010). Most of these predictive algorithms have been constructed using aggregated learning

behaviors, and in doing so, have limitations as to their effectiveness. First, an aggregation approach fails to consider variances in learning patterns. As such, that model will assume that two students with identical aggregated time-spent-per-week will result in similar performance outcomes. However, these two students might have completely different learning patterns. For example, some students might evenly allocate their learning time across weekdays, while other students might only interact on weekends.

Second, the aggregation approach fails to consider that more than one pattern might lead to success or failure (Cerezo, Sánchez-Santillán, Paule-Ruiz, & Núñez, 2016). This is especially true when learning patterns interact with student demographics. For example, male students' success patterns might be different from female students' successful patterns. Low grade point average (GPA) students might have different success patterns than high GPA students. Third, the aggregation approach does not consider variances in course activity requirements across different course modules (Hung & Crooks, 2009). While a course is in progress, students may be asked to participate in different course activities during any single week. At-risk situations may occur when a student fails to meet the changing requirements of a course at a specific point in time. Although certain aspects of previous algorithms and early-warning systems built by other researchers can inform the development of an institu- tion's own early-warning system, the unique context of each institution and program often requires institutions to custom build their own system to meet their own needs.

Given the focus and the common instructional strategies used throughout the courses in in this sampled graduate online program, the method chosen incorporates an analytic algorithm that focused on the variances generated by different learning patterns and course activity requirements (i.e. reading course content, reading discussion posts, posting and replying to discussion posts). Realizing that these four activities would cover the entire scope or means of social interactions, the assumption was made that they could be useful for

predictive purposes. The model was also based on the assumption that students with similar profiles (e.g. course load) and learning patterns (e.g. long gaps without logging into the course) should display similar performance in the courses they complete. In addition, if a student's shorter time-series (such as a pattern from weeks 1–8 in a 16-week semester) matches with one of the at-risk patterns, then the student can be regarded as at risk and identified before dropping out.

Data from spring 2014 was originally used to test and validate a model that could predict students at risk of failing; more specifically, 60% of the data from spring 2014 was used for model training and 40% for model validation. Two types of data, static and dynamic, were included for analysis. Static data included student demographics and prior academic records; dynamic data consisted of students' behaviors within the LMS, specifically accessing course content, reading discussions, posting a discussion, and replying to a discussion. In total, the model consisted of 34 original or derived variables. The data collected for testing the model required data cleaning and processing, which included dimension consolidations, grouping final grades into categories of A, B or F, because in graduate programs students generally require a B or better to stay in good academic standing in their program of study. The spring 2014 data came from 12 courses, which consisted of 25 sections, 509 enrollments, for a total of 431,708 cleaned logs. Of the students, 84% were Caucasian. The distribution of female and male students was almost even (50.1 and 49.9%, respectively). Twenty-one percent of students took one course only, 70% of students took two courses, and 9% of students took three or more courses. Eighty-four percent of the students were Master's degree seeking, the remainder were pursuing a graduate certificate or doctoral degree. Fifty-eight percent of students had been admitted to the program for 1 year or less, 25% of students had been enrolled for 2 years, and the remaining students had been in the program for more than 2 years.

Two analysis approaches of traditional (aggregated data) and time-series clustering were used with six models for the nominal dependent variable: decision tree, boosting, logistic regression (forward, backward and stepwise), and rule induction (Figure 1). Overall, the time series clustering approaches outperformed the traditional aggregated approaches. The best model was selected by validation misclassification rate, resulting in a time series clustering approach for the decision tree.

In comparing the six models (Figure 2), the time series decision tree generated the most accurate prediction of student failure, but this model could only predict student failure after week 10 of the 16-week semester. The model also could not differentiate A and non-A students until that point in the semester. Before week 10, patterns of F students were similar to A or B students. But beginning in week 10, the data showed that F students became inactive (they still accessed course materials but did not read, add, or reply to discussions). As useful as the original model was with predicting student failure, it appeared as if students' inactivity could be related to a holiday effect. Week 10 in the spring 2014 semester was spring break. Did a similar holiday effect exist in other semesters? Using the existing validated model, the time-series decision tree model previously developed was used with newly collected student data from fall 2014. The fall 2014 data consisted of 546,965 logs with 661 enrollments in 18 courses of 31 total sections. The primary purpose was to deter- mine if there was indeed a holiday effect that moved (Thanksgiving holiday break in the United States not occurring at week 10) and to examine dynamic interval data.

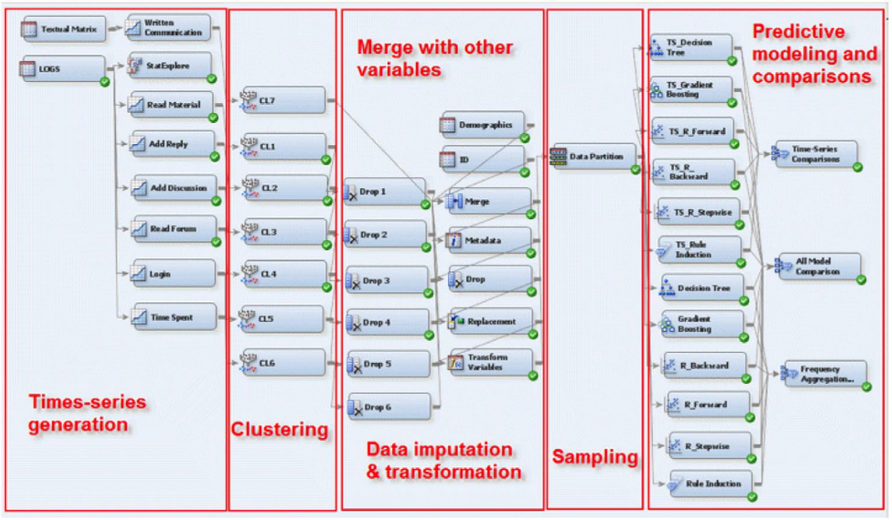

Figure 1. analytic flow of data analysis to derive best model selection.

Model Name	Validation: Misclassification	Training: Misclassification
TS_Decision Tree	0.101942	0.092409
TS_Gradient Boosting	0.106796	0.09571
TS_Rule Induction	0.11165	0.082508
TS_R_Stepwise	0.135922	0.108911
TS_R_Forward	0.135922	0.108911
R_Foward	0.150485	0.138614

R_Stepwise	0.150485	0.138614
Decision Tree	0.150485	0.138614
Gradient Boosting	0.150485	0.138614
TS R_Backward	0.160194	0.092409
R_Backward	0. 174757	0.132013
Rule Induction	0.203883	0.151815

Figure 2. Model comparison results for training and validation.

Results

The accuracy rate of the model, using data from fall 2014, was 89.26%, with the model capturing up to 85.45% of at-risk students in total. Once again, by week 10, the frequency of student interactions within the dynamic data revealed students to be at-risk for failure, further validating the time series decision tree model developed in spring.

To model interval data, we used the time difference in login data with the same outcome categories as before (i.e. grades of A, B and F). The amount of time between activity for A, B, and F students varies considerably, beginning in earnest by week 6, which observably is sooner than week 10 results when comparing frequency of interaction data noted previously (see Figure 3).

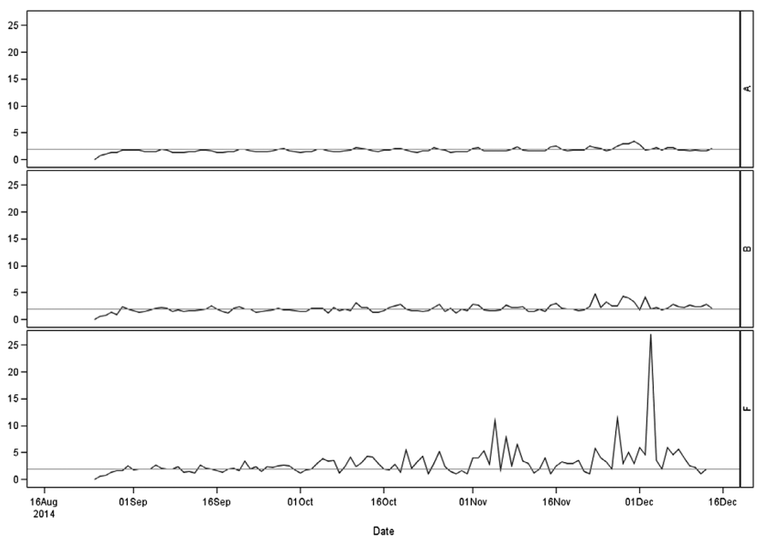

Figure 3. Model comparison results for training and validation, separated into a, B, and F categories for student activity intervals.

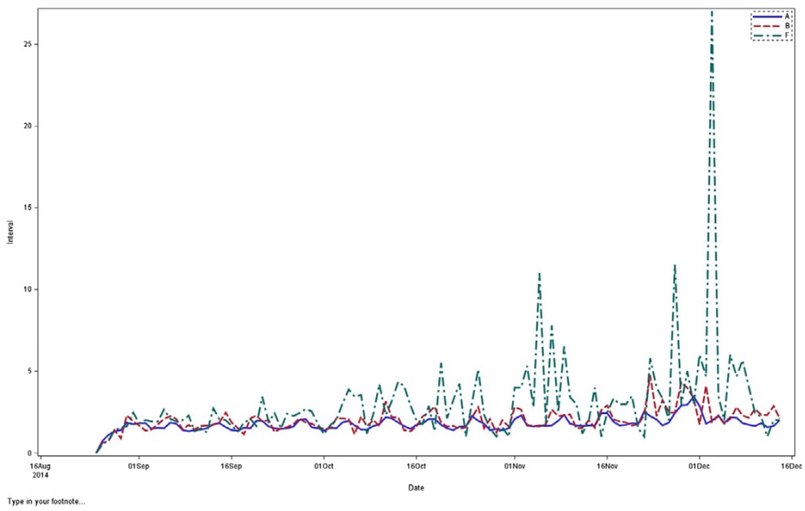

Figure 4. training and validation overlaid model comparison results. Predictive accuracy occurs by week 6.

When this interval data is overlaid (see Figure 4), the differences between A and B students combined is distinctly less variable than the F students. Week 6 does not correspond to any holiday effect as the distinctive break for these students (known as Thanksgiving break) occurs in week 11, much after the noticeable pattern differentiates.

Conclusions

Students in this data-set who could not sustain and make consistent interaction throughout the semester were the most at risk of failure. However, unlike Shelton et al.'s (2015) previous model, this model demonstrates that this consistency is not necessarily due to a holiday effect during the semester. Rather, this model demonstrates that it is the frequency of inter- action that serves as a better indicator of student success and persistence in a given course, not simply the total amount of interaction in a course. The benefit of this result is to identify students who are not interacting consistently in their online course earlier in the semester. In other words, while more interaction is important, it is not as important as consistent interaction over time.

This finding is supported by earlier research on interaction. For instance, York and Richardson (2012) found that a number factors'influence interaction in online courses, such as group work, course environment, model use, community, discussion question type and assessment, feedback type and medium, immediacy behaviors, discourse guidelines, and instructor participation' (pp. 91, 92). Further, Dennen, Darabi, and Smith (2007) found that students want instructors to maintain frequency of contact, have a regular presence in class discussions, and make expectations clear to students. Students also reported that the content of the interactions is just as important as the frequency of the interactions. Bernard et al. (2009) reported support for this idea in their meta-analysis and concluded that 'increasing the quantity of interaction may lead to enhanced learning and satisfaction, but increasing the quality of such interactions, especially in terms of cognitive engagement and meaning- fulness, may be of greater importance' (p. 1266). Research like this suggests a need to con- tinue to study how and when students interact with each other during online courses to get a better sense of the antecedents of social presence and connectedness to increase student satisfaction and decrease student attrition. Questions remain on the best ways for instructors and students to interact in online courses (Bernard et al., 2009). However, instructors should still strive not only for regular and frequent interaction in online courses – which can include weekly announcements, taking part in or summarizing weekly discussions, and giving detailed individual feedback on course assignments and projects when appropriate – but also to identify certain periods in the semester (e.g. after the first week, before the drop/add deadline, and after the first main assignment) to interact intentionally with each student.

Although there are a number of studies on attrition in online courses and programs, there is comparatively very little research on specific strategies to improve online retention at the course or institution level (Tung, 2012). Some research has looked at using student orientation programs (Hill, 2006; Lynch, 2001), student support services (Ludwig-Hardman & Dunlap, 2003; Yoder, 2005), peer mentoring (Boyle, Kwon, Ross, & Simpson, 2010), and peer tutoring (Hill, 2006) to improve student retention. Other research has focused at interventions at the course level. But before one can decide what intervention to use, a program or institution must identify the pattern of withdrawal (Simpson, 2004). As with this research, the need to identify a pattern of withdrawal has led to the rise of research on using learning analytics

and data mining to create early-warning systems to identify students at risk (Macfadyen & Dawson, 2010). The future of online learning depends on the continued success of students, which in turn depends on students persisting through their online courses and ultimately graduating from their online programs. Next steps for this line of research is to adopt different distance measures and clustering algorithms to further improve the model, add discussion contents (text mining and semantic analysis) to generate more meaningful analytic results regarding levels of learning, and refine the work on dropout prediction.

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