Predictive Analytics for Students’ Quantitative Class Performance and Its Impact on Classroom Operations

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The application of predictive modeling in the field of education has steadily gained interest and acceptance in recent years. In this study, students’ course grade is predicted with variables controllable by instructors in the class setting. The best predictive model found is a stepwise regression model, and it accounts for 57% of the variability of a student’s course grade based on a sample size of 182 students. The results showed that a student’s clarity in career direction is most significant in predicting the semester grade, followed by his or her interest in the course. In addition, the results suggest that predictive models hold great promise for improving classroom operations in a way that will enhance students’ learning experience and, ultimately, their performance.

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I. INTRODUCTION

In any college or university, students constitute the main asset where the curriculum is specifically designed to maximize their academic growth and fulfill their potential as contributors to the society. The students’ in-class performance, therefore, plays a critical role in achieving such goals, and their performance is of interest not only to the higher educational institution but also to the companies looking for the right job candidates to compete successfully in the global market. The bulk of the responsibility for students’ performance falls onto the students themselves, for they ultimately have to manage their time effectively and motivate themselves to study hard. However, if instructors teaching and operating the classrooms’ learning environment can predict students’ performance early in the semester based on the measurements that are part of class operations and controllable by instructors, they may be able to make a positive difference in students’ learning experience and consequently their performance.

With the large amounts of data on students now collected by admissions offices, there has been a concerted effort to deploy data-mining techniques to discover useful and important patterns within the data that might otherwise be hidden (Mannila, 1996). These techniques also provide the ability to predict future outcomes based on a set of assumptions, for example, predicting students’ academic performance based on a set of cognitive measures, such as SAT or ACT, and noncognitive measures, such as personality traits. Data-mining techniques can discover useful information in the educational data sets and accurately predict future situations in a way that can improve knowledge-based decision-making processes by both administrators and faculty. These techniques can also map input variables to target variables, with the goal of understanding which input variables are the main drivers, comparing the several predictive models to determine the best model for the data, and finding value-adding associations between the inputs and target.

The main objective of this study is to develop predictive models based on data composed of noncognitive measures as input variables and use them to predict students’ semester performance in a core quantitative business class. This main goal
is directed at finding hidden patterns and rules that can improve understanding of the association and influence of specific inputs to the target. The second objective of this study is to assess potential for using its results to improve instructors’ management of their classroom operations in a way that enhances students’ learning experience and performance. Information about students’ self-perceived popularity, affinity of being part of a team, interest in the subject taught in the class, clarity of career direction, community service commitments, gender, and major are used as explanatory, or independent, variables to predict their final semester grade. By studying the influence of these variables on students’ in-class performance, instructors can improve their classroom operations to produce better qualified and happier students.

The remainder of the paper is organized as follows: Section II gives the background information and related work of data mining and its application to student performance. Section III explains the data used in the study. Section IV describes the methodology used in developing the predictive models, and Section V discusses the performance and results from the data-mining analysis. Section VI covers concluding remarks and the future direction of the study.

II. DATA MINING AND ITS APPLICATION TO STUDENT PERFORMANCE

Data mining, also known as knowledge discovery in databases, is the process of discovering meaningful insight and patterns by exploring and analyzing data. It is largely concerned with building models that use techniques such as regression, neural networks, and decision trees to understand the relationship between input variables and the target variable, and then using that relationship to make predictions about the target.

The data can be stored in many different formats and may reside in centralized data storage accessible by data-mining tools. The data-preparation step, perhaps the most time-consuming process, transforms the raw data into an appropriate format for data mining, identifying and defining independent, or explanatory, variables and the dependent, or target, variable. The model-development step uses training and validation data sets to develop a predictive model, and this process terminates when the error between the actual and predicted values of the target variable is minimized over a predetermined number of iterations or the training duration, measured by time (Shmueli, Patel, and Bruce, 2010).

Data-mining tasks are divided into two main categories, predictive and descriptive. The objective of a predictive task is to forecast the value of a target, or dependent, variable based on the values of independent, or explanatory, variables. The objective of a descriptive task is to derive patterns that summarize the underlying relationships in data.

In recent years, growing volumes of data to be analyzed, combined with the increase in computing power, have led more and more researchers to embrace the use of data-mining techniques in higher education. Many researchers have already used these techniques successfully to extract knowledge and bring value to students. Tam and Sukhatme (2004) evaluated students’ academic success based on high school percentile rank variable by collecting data from the enrolling freshmen cohort at the University of Illinois at Chicago for fall term 1994. The academic progress of the cohort was tracked over six years, with the definition of success being the earning of a degree or degrees within those years. The researchers used a high school’s average ACT score for all students as the means of defining its academic quality and found that better admissions decisions could have been made by using the high school academic quality indicator. The results led to the generation of a new variable called the modified student high school percentile rank, to be incorporated into the admissions decision criteria. Similarly, Johnson (2008) examined the effect of the type of high
school that students attended on their rates of success at a university. More specifically, the study incorporated the effects that high school–related variables and individual student variables have on academic success by developing a predictive model to determine the likelihood of a student’s graduation from the college within five years of entry. He also found that the type of high school attended does matter in predicting successful graduation of a student within the time window measured.

Naik and Ragothaman (2004) used predictive models to better forecast performance of MBA students by comparing the results from neural network, logit, and probit models used to make MBA admission decisions, as well as to understand the capability of neural network model compared to more traditional statistical methods. They incorporated 10 explanatory variables into their research, including measurements on campus location, undergraduate major, GMAT scores, and undergraduate institution. The MBA applicants were divided into successful group for those with a graduate GPA of 3.3 or more, and marginal group for those students with a graduate GPA of less than 3.3; the researchers found that predictive models were effective in identifying successful MBA students and that they provided evidence that neural network models can outperform well-known traditional techniques in probit and logit models.

Allen and Robbins (2008) developed a predictive model to help students identify the right major based on their interests and abilities. The researchers followed 47,914 students in 25 colleges and found that students were more likely to excel in academic environments that fit their ability and personality. In addition, they found that the students’ interests affected both choice of entering major and the likelihood of staying in a major. Their finding provides useful insight in helping academic advisors to effectively guide students in choosing the right major early in their academic careers.

Tracey and Robbins (2006) followed 80,574 students in 87 colleges over a five-year span. They examined two different representations of interest-major congruence in Euclidean distance and angular agreement. The researchers found that making good grades is related to having a major close to one’s interests and personality. In addition, they highlighted their finding that congruence predicted cumulative GPA better than standardized academic skills tests (i.e., ACT scores).

Vandamme, Meskens, and Superby (2007) studied correlations of various parameters, including chance of success in college, study skills, attendance, and prior academic performance. They found that changing factors during a student’s stay at the university plays a large part in academic performance. In addition, they explored use of different data-mining tools to predict students’ performance and found that the tools’ predictive performance was not good due to the researchers’ difficulty in categorizing students into high-, medium-, and low-risk groups before their first university exam.

Lee, Harrison, Pell, and Robinson (2008) applied statistical techniques to predict students’ first-year performance in engineering courses. The study results found that a high level of preparation upon entering the university, a high level of motivation in seeking help with their studies, and willingness to use the university’s learning support center contribute to students’ success.

In summary, many researchers have undertaken prediction of academic performance by using various influencing factors to map students’ academic success. Many researchers have found success in applying data-mining techniques to gain useful insights and develop accurate predictive models; however, some have found traditional statistical methods to perform better than the newer predictive tools. With varying success, they used both cognitive and noncognitive measures to predict student performance.
This study predicts students’ performance early in the semester based on noncognitive and in-class measures that are controllable by the instructor. More specifically, the data are collected from students to gain insights into their performance and help the instructors provide a more customized learning environment to improve students’ competence. Moreover, the instructors can further leverage the study findings to improve operational aspects of their classrooms and to design the right intervention that can be implemented early in the semester to help students reach their academic potential. Finally, this study employs not only the newer predictive models but also the traditional statistical methods to predict students’ performance, and it compares the models.

III. DATA

The data set of 182 students used in this study was obtained from a core quantitative business course at the AACSB-accredited Haub School of Business, Saint Joseph’s University, Philadelphia. The data set was collected by a survey given to the students in the first week of each semester from fall 2009 through spring 2011. This date range was selected for analysis because all requirements for the course remained consistent during that period; taking the survey in the first week minimized anchoring and acquiescence bias (Hurd, 1999). This course is designed to be taken in the second year of the undergraduate business program. Hence, over 80% of students in the study are in their second year; 42% of them are female. The variables collected for this study included each student’s number of community service commitments participated in during the preceding year, level of clarity in career direction, interest in the course, comfort level with being part of a team, and self-perceived popularity. These measurements are all controllable by the way an instructor chooses to operate the class over the course of a semester. For example, the instructor can add more industry cases that are relevant to the topic covered, with the goal of increasing clarity in career direction for some students; other students, however, might find such content interesting and, as a consequence, find the entire course more interesting.

The students’ gender, major (Accounting, Business Intelligence, Finance, Management, Marketing, and Undecided), and final semester grade for the quantitative course were merged with the aforementioned data at the end of the semester to complete the data set for analysis; the final course grade is the target variable. Students’ grade point average (GPA) coming into the course was also collected to increase our understanding of its correlation with the target variable. Since GPA coming into the course is not controllable by the instructor, it is not used as part of predictive modeling. These variables are summarized in Table 1.

IV. METHODOLOGY

SAS Enterprise Miner was used for the data-mining analysis. After identifying variable Team as having a strong negatively skewed distribution, with skewness (-0.859), the log transformation was applied to offset the skewness in the transform variable step. Then, 70% of the data set was partitioned, to be used to train the predictive models, with the other 30% held out for the purpose of validating the models’ performance; this step took place in the data-partition step. Three categories of models in decision tree, neural network and various regressions were developed for the data. This step was followed by comparing the models based on the average squared error (ASE), which is a measure of the model’s predictive accuracy. Finally, the model with the lowest ASE was selected, and its results were analyzed. The flow of this methodology is shown in Fig. 1.
TABLE 1: DATA SET DESCRIPTION

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Measurement (scale)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Male or Female</td>
<td>Binary: 0/1</td>
</tr>
<tr>
<td>Major</td>
<td>Business</td>
<td>Nominal: 1-6</td>
</tr>
<tr>
<td>Service</td>
<td>No. of service activities participated in</td>
<td>Interval: No. of events participated in</td>
</tr>
<tr>
<td>Direction</td>
<td>Career direction</td>
<td>Interval: 1-10</td>
</tr>
<tr>
<td>Interest</td>
<td>Interest level in the quantitative course</td>
<td>Interval: 1-10</td>
</tr>
<tr>
<td>Team</td>
<td>Comfort level as a team member</td>
<td>Interval: 1-10</td>
</tr>
<tr>
<td>Popularity</td>
<td>Self-perceived popularity level</td>
<td>Interval: 1-10</td>
</tr>
<tr>
<td>Grade (target)</td>
<td>End-of-semester course grade</td>
<td>Interval: 0-100</td>
</tr>
</tbody>
</table>

FIGURE 1: PROCESS FLOW OF THE PREDICTIVE MODEL.

The predictive models used are decision tree, neural networks, stepwise regression, polynomial regression, and partial least squares. These are all powerful and well-applied models in predictive analytics. Decision tree is a well-received and -applied prediction and classification technique. The appeal of this technique comes from its rule-based algorithm, which allows users to interpret the results easily. Decision tree is also heavily used for data exploration, making it a popular choice among professionals in the predictive analytics domain. The algorithm for the decision trees is based on a splitting rule that increases purity in the target variable. Using the rule, the data set is repeatedly split to find smaller groups that can provide useful insights. In this study, the split point is based on the highest logworth value in an input variable in relation to the target. The neural networks model is a powerful pattern-recognition tool that works by...
simulating a large number of interconnected simple processing units that mimic the human brain. These processing units are typically arranged in three layers: an input layer, with units representing the input fields; one or more hidden layers; and an output layer, with a unit or units representing the output field. The units are connected with varying connection strengths, also known as weights. Although the reputation of this technique is often hampered by the “black box” nature of the algorithm, when it is used in well-defined domains, its ability to generalize and learn from data makes it a very powerful tool. As a result, it is not surprising that neural networks have a proven track record of successful application in a wide variety of industry problems in spite of the black box label (e.g., Hopfield and Tank, 1985; Jain and Vemuri, 1999).

Regression models applied in this study are stepwise, polynomial, and partial least squares. Regression is a classical statistical approach that has the objective of fitting the best model to the data in an attempt to learn about the underlying relationship of the variables. In data mining, however, the focus is typically on predicting new observations. The coefficients for the independent variables are determined using the training data, and the performance of the model is validated using the validation data. The derivation of these coefficients is based on minimizing the sum of squared deviations between the actual and the predicted values.

Stepwise regression is an iterative search algorithm where the model starts with no independent variable and then independent variables are added one at a time. Each independent variable added is the one that has the largest contribution to $R^2$ on top of the independent variables that are already significant to the model. Moreover, the algorithm considers dropping independent variables that are not statistically significant in each step. The algorithm stops when the contribution of an additional independent variable is not statistically significant (Shmueli et al., 2010).

Polynomial regression is a special case of multiple linear regression in which the relationship between the independent variables and the dependent variable is modeled as an $n^{th}$-order polynomial. It is mainly used to describe a nonlinear relationship between the variables. The partial least squares method is a newer predictive model that was developed to remedy some weak points in other regression methods. Specifically, the method is powerful in cases where the independent variables are highly collinear; this method is also effective when there are many independent variables without having many observations. The emphasis is on predicting the target and not necessarily on trying to understand the underlying theory and relationship between the variables (Geladi and Kowalski, 1986).

V. RESULTS

Correlation analysis for the independent variables shows statistical linear relationships between the variables. There are a couple of moderately negative correlations; most of these correlations are paired with Popularity: Interest (-0.349) and Direction (-0.338). There is one moderately positive correlation between Direction and Interest (0.358). The correlation between GPA and Grade is 0.709, which is consistent with previous research that used GPA as a predictor of student performance (e.g., Braunstein, 2002; Danko-McGhee and Duke, 1984). Other correlations between independent variables are summarized in Table 2.
Of the five predictive models developed, stepwise regression returned the lowest ASE value, 13.01. It is closely followed by partial least squares, with an ASE of 13.47, and then polynomial regression, with an ASE value of 14.67. Table 3 summarizes this model performance and predictive accuracy comparison.

### TABLE 3: MODEL COMPARISON

<table>
<thead>
<tr>
<th>Model</th>
<th>Average Squared Error (ASE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stepwise regression</td>
<td>13.01</td>
</tr>
<tr>
<td>Partial least squares</td>
<td>13.47</td>
</tr>
<tr>
<td>Polynomial regression</td>
<td>14.67</td>
</tr>
<tr>
<td>Decision tree</td>
<td>19.86</td>
</tr>
<tr>
<td>Neural networks</td>
<td>23.92</td>
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</table>

The stepwise regression analysis indicated that four variables explained significant proportions of the variance in students’ performance in the core quantitative course. Specifically, the significant variables in predicting the target variable are Direction, Interest, Popularity, and Team (all variables with $p < .01$). The adjusted $R^2$ for the model is 0.57, which means 57% of variability in the target is explained by the model. Table 4 summarizes the stepwise regression analysis. The decision tree analysis output also generated a ranking of variable importance. This ranking is based on the number of occasions on which a variable was used in splits within the model. Popularity is the most important variable, with a value of 1.00. Team is second, at 0.71, and Interest is next, at 0.65, followed by Direction, at 0.49. The variables found important in the decision tree analysis are the same variables that are statistically significant in the stepwise regression method. The decision tree shown in Fig. 2 attests to ease in interpreting the analysis result. The rules that were found reveal the negative impact of the level of popularity on the course. Following the branches reveals that a team player who is less popular has a significantly higher chance of performing well in the course, with an average semester score of 92. However, a less popular student who happens to be uncomfortable in a team setting is predicted to receive a C for the course. Another tree path reveals that a popular student who has little to no interest in the course is predicted to do poorly in it. On the other hand, a popular...
student who has at least a moderate interest in the course and has a very clear vision of career direction is predicted to do well in the course.

**VI. CONCLUSION AND FUTURE DIRECTION**

Universities and colleges need to find new ways to help students perform at their optimal level by managing their classrooms and operating them with end products in mind, just as do firms producing their goods with the utmost quality. Moreover, the focus now is to consistently produce high-performing and high-potential students who can successfully find their place in society and contribute to its greater good. By design, the variables studied in this research are those that can be controlled by instructors in operating their classes. For example, instructors can control the number of
team-oriented tasks in the classroom as well as invest time in invigorating students’ interest in the course. Instructors can also make the class relevant to the real world, providing legitimacy to the course and its link to achievement of their vision. By doing these effectively, this study shows, instructors can influence students’ class performance.

The predictive performance of the stepwise regression outperformed other models and demonstrated that it is strong enough to accurately predict students’ end-of-semester grade based on variables collected in the first week of the semester. Therefore, the faculty can help identify possibly struggling students very early in the semester and help them make a better connection with the course content and the instructor. Faculty can also partner with the school’s counseling professionals to design a customized intervention process to help students get much-needed individual-level support.

A limitation of this study is that the total sample consists of 182 students’ performances from a business quantitative class offered by a single university from 2008 to 2011. Therefore, results may not be generalized to other courses and to universities that have a different student makeup; however, this study provides a framework for other researchers interested in developing similar predictive models for their courses in their universities.

For the future direction of the research, the increasing use of predictive models and improved accuracy can lead to an increase in knowledge-management activities. The data set needed for developing a predictive model can act as a repository of knowledge and can...
enable knowledge to be more effectively managed. The repository of knowledge will then provide an opportunity for integration of domain knowledge by the instructors and administrators to allow it to be developed into a more powerful tool in helping students achieve their academic goals (Davenport and Prusak, 1998; Yi, 2008). Also, with more instructors involved in using predictive models to enhance the learning environment and with the integration of knowledge among courses, instructors, and even universities, the achievement of better understanding of the longitudinal effect of student development becomes a natural next step for researchers. Such knowledge of integrative environments holds great promise and opportunity to improve decision-making quality, the caliber of students going into the workforce, and overall organizational performance (Cai, 2006; Liebowitz, 2008).

VII. REFERENCES


Liebowitz, J., “Think of others’ in Knowledge Management: Making Culture Work for You”, Knowledge Management Research and Practice, 6, 2008, 47-51.


