AC 2011-1608: A MULTI-OUTCOME HYBRID MODEL FOR PREDICTING STUDENT SUCCESS IN ENGINEERING

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A Multi-Outcome Hybrid Model for Predicting Student Success in Engineering

Abstract

In this work, we propose a backpropagation neural network model to predict retention and college GPA of engineering students simultaneously. Unlike previous models, which can only predict single outcomes, this method is capable of modeling two outcomes in the same model. A multi-outcome model and two single-outcome models are developed and tested on 1470 first-year engineering students who enrolled in a large Midwestern university during the 2004-2005 academic year. The predictors of the models include seven affective measure factors and eleven high school history factors. The affective measure factors are leadership, deep learning, surface learning, motivation, meta-cognition, expectancy-value, and major decision. The high school history factors are high school GPAs, standardized test scores, and the grades and number of semesters in math, science, and English courses in high school. In the multi-outcome model, the overall accuracy of retention prediction is 71.3%. The mean error of GPA prediction is 16.5% of the full scale. High school grades and SAT scores are better predictors of college GPA, while the number of semesters of English, science, and math in high school and affective measure factors (motivation, leadership, etc.) are better predictors of first-year retention. This work lays a foundation for modeling multiple success outcomes in the future.

Introduction

Many statistical modeling methods have been studied to predict student success. These methods include linear regression, logistic regression, and discriminate analysis. These methods are principally used to predict single outcomes (e.g., retention in engineering). Recently, neural network models have been developed to predict student outcomes and they are shown to have better prediction performances over more traditional methods (e.g., logistic regression) [1,2]. One unique feature of neural network models is that they can predict multiple outcomes in the same models. However, such multi-outcome models have not yet been studied to predict student success outcomes.

Retention and college GPA are the two most widely studied success outcomes of engineering students [3-7]. A multi-outcome neural network model is capable of modeling these two outcomes in the same model and identifying factors that are important to the two outcomes individually. It is also valuable to see whether or not the important factors for the two outcomes identified in the same model align with each other.

Thus, the purpose of the study is to design multi-outcome neural network models predicting retention and GPA of first-year engineering students, to compare the prediction performances of the multi-outcome model with single-outcome models, and to identify the predictors that are important to these two outcomes.

Research Questions

The research questions in this study are:

1) How do prediction performances of multi-outcome model compare with those of individual single-outcome models?
2) Do the important predictors identified by the multi-outcome models align with those identified by single-outcome models?
3) Are the important predictors of first-year retention the same as those of first-year GPA?

Modeling Student Success in Engineering

Figure 1 shows the framework of our model of student success. The predictors, listed at the left in the figure, can be grouped into two categories: the affective measures and the high school history matrix. Affective measures include nine factors: expectancy, leadership, meta-cognition, major decision, deep learning, self efficacy, surface learning, team, and motivation. The high school history matrix includes SAT/ACT scores, high school core GPA, high school math, English, and science grades, and number of semesters taken. Outcomes of the model can be retention in engineering and academic performance through students' undergraduate study.

In this study, only seven of the affective measures were included. Also, as a starting point, we only focused on retention and GPA after one year. The results of this study will help determine the potential of using neural networks to model a larger list of outcomes in the future.

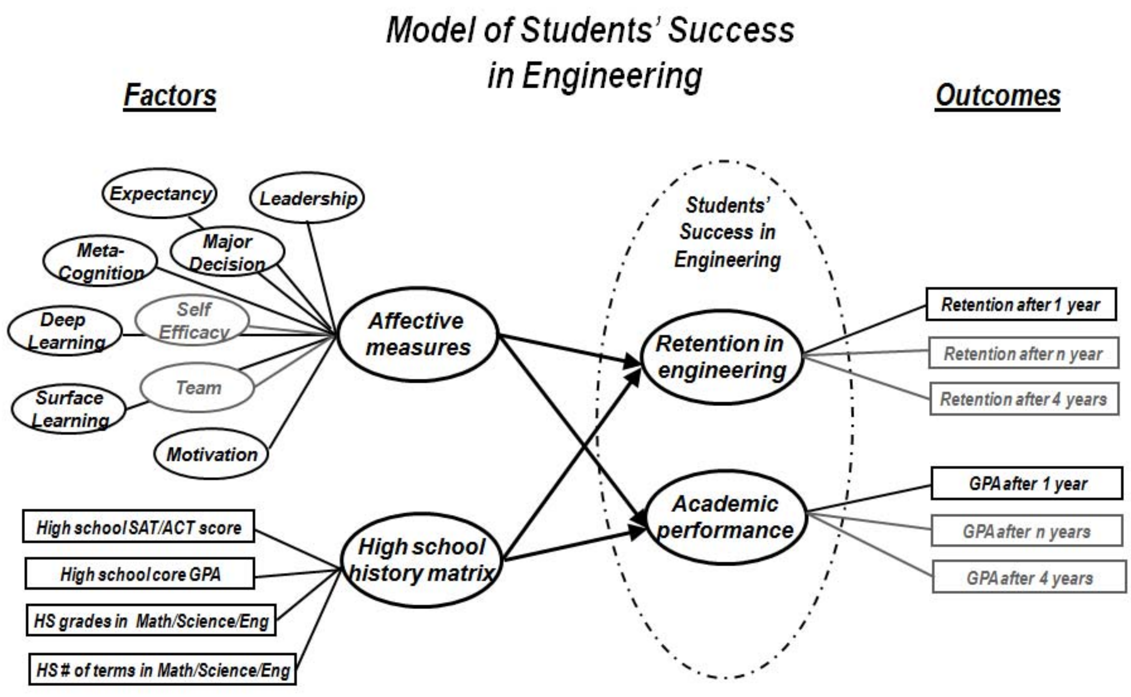


Figure 1. The Model of Student Success

Literatures

College GPA and retention have been widely studied as student success outcomes in previous works. Nicholls et al. identified variables that were significant to STEM retention using a set of statistical tests [4]. They found that the SAT math score, high school GPA, self-rated math ability, computer skills, and academic ability were good predictors of retention. Other studies reported SAT/ACT scores and high school GPA as predictors of first-year GPA [8-10].

Prediction of both GPA and retention has been performed in separate statistic models. French et al. used hierarchical multiple linear regression to model college GPAs over six and eight semesters, and used hierarchical logistic regression to model university and engineering retention [3]. They found that the pre-college variables, SAT math, and high school rank were significant predictors of GPA, while participation in the first-year engineering seminar, academic motivation, and institutional integration had the potential to impact university and engineering retention. Veenstra et al. modeled first-year GPA and retention for engineering students using a linear regression model and a logistic regression model, respectively [5]. They found that high school academic achievement, quantitative skills, commitment to career and educational goals, and confidence in those quantitative skills were significant predictors of first-year GPA. Allen et al. modeled first-year GPA using hierarchical linear regression and modeled third-year retention using hierarchical logistic regression [6]. They found that high school GPA and ACT scores were important predictors to first-year GPA, while social connectedness and motivation constructs had important effects on third-year retention. Generally speaking, pre-college academic variables were good predictors of college GPAs, while students' engagement in college studies and their own characteristics were good predictors of retention. These findings were consistent with Tinto's models, which emphasized that students' goals, individual characteristics, and institutional commitments are crucial to students' retention decisions [11,12].

Research Methods

A. Participants

The participants of this study were 1470 first-year engineering students who enrolled in a large Midwestern university during the 2004-2005 academic year. 80.5% of these participants were male students and 19.5% were female students. By the beginning of the third semester, 17.62% of the participants (259 students) left the engineering college, and the rest of the participants were retained. The average cumulative GPA for non-retained and retained students was 2.46 and 2.79, respectively.

B. Neural Network Models

Three neural network models were trained and tested in this study: a multi-outcome model predicting first-year retention and first-year college GPA, a single-outcome model predicting first-year retention only, and a single-outcome model predicting first-year college GPA only. These three models were built with the same input variables and the same number of neurons in the hidden layer.

Outcomes (dependent variables)

The outcomes of the multi-outcome neural network models were students' retention and cumulative GPA by the beginning of the third semester. Single-outcome models with only retention or GPA as outcomes were developed for comparison with the multi-outcome models. The scales of retention and cumulative GPA were binary and interval, respectively. On the scale of retention, zero represents that a student left engineering college and one represents that a student was retained. Students' cumulative GPA was transferred into a range of [0.1, 0.9].

Inputs (independent variables)

Two groups of factors performed as inputs (predictors) in the neural network models, as shown in Figure 1. Seven affective measure factors were included in this study: leadership (LM), deep learning (LL21-30), surface learning (LL31-40), motivation (MV), meta-cognition (LL1-20), expectancy-value (EV), and major decision (MD). The affective measure factors were collected through a self-reported online survey completed prior to the freshman year. The items in the online survey were measured through a five-point Likert-scale. Table 1 summarizes the number of items that were included in this study in each of the affective measure factors. The total number of items of affective measure factors was 61. The collected data were transferred into a range of [0.1, 0.9]. More details of this instrument can be found in previous study [13,14].

Affective Measure Factors	Number of Items Included
Leadership	11
Deep Learning	8
Surface Learning	7
Motivation	11
Meta-Cognition	2
Expectancy-Value	9
Major Decision	13
Total	61

Table 1. Number of items included in the affective measure factors

Another group of factors was the high school history matrix, which included students' SAT/ACT scores; high school core GPA; high school math, English, and science grades; and semesters taken in high school math, English, and science. Students' ACT scores were transferred into SAT equivalence according to the table provided by Schneider and Dorans [15]. High school history matrix data were also transferred into the range of [0.1, 0.9]. The total number of high school history matrix items was ten.

Settings of the Neural Networks

The three neural network models had an input layer, a hidden layer with 50 neurons, and an output layer. The activation function of the hidden and the output layer was a log-sigmoid (logsig) transfer function, which is a most commonly used nonlinear activation function in neural network modeling [16]. A log-sigmoid transfer function is shown in the following equation:

$$\log\text{sig}(x) = \frac{1}{1+e^{-x}} \tag{1}$$

The backpropagation models were trained using the Levenberg-Marquardt training algorithm, which was considered to have the strength of converging quickly [17]. All models were trained and tested using Matlab (R2010a) from Math Works Inc.

C. Prediction Performances

The prediction performances of the models were evaluated for the two outputs. The classification threshold for the three models was set to allow 25% of students be predicted as at risk. Prediction of retention was evaluated based on overall prediction accuracy, probability of detection (POD) for retained students, and probability of detection (POD) for non-retained students. Prediction of GPA was evaluated based on sum of squared errors (SSE) [18]. The following table and equations define these terms:

		Predicted	
		Retained	Non-Retained
Actual	Retained	a	b
	Non-Retained	c	d

Table 2. Classification of Students' Retention Outcomes

$$\text{Overall accuracy} = \frac{a+d}{a+b+c+d} \tag{2}$$

$$\text{Probability of detection } (\text{POD}) \text{ for retained students} = \frac{a}{a+c} \tag{3}$$

$$\text{Probability of detection } (\text{POD}) \text{ for non}-\text{retained students} = \frac{d}{b+d} \tag{4}$$

$$\text{Sum of Squared Errors } (\text{SSE}) = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5}$$

The data were randomly split into ten equally-sized partitions for a ten-fold cross-validation[19]. Neural network models were independently trained, validated, and tested using the ten parts of data. In each turn, seven parts (1029 students) served as training data, two parts (294 students) served as validation data, and one part (147 students) served as testing data. For each turn, the models were initiated, trained, and simulated four times. Thus, the overall accuracy, POD for retained students, POD for non-retained students, and SSE were averaged first on the four runs and then on the ten-folds. Average standard deviations (SD) of prediction performance indices were the average of the ten standard deviations, which were calculated based on four runs.

D. Importance of the Inputs

A sensitivity analysis was used to find the importance of the inputs to the outcomes [20,21]. One input at a time, a 25% increase was introduced to that single input for the 1470 students to form a new input matrix. This new input matrix was then simulated in a trained and fixed neural network model. At the same time, the original input matrix was also simulated in the same model. The average change of the outputs from these two simulations, also called the sensitivity coefficient, represented how important this input was to the outcomes.

Results and Discussion

A. Prediction Performances

Table 3 summarizes prediction performances of the three different models based on ten-fold validation. The overall accuracy of the multi-outcome model was 71.3%, which meant that, on average, the multi-outcome model was able to correctly predict 71.3% of the students. POD of non-retained students and POD of retained students was 39.6% and 78.0%, respectively. The SSE of GPA prediction in multi-outcome model was 2.56. This meant that the mean error of prediction took about 16.5% of the full scale of GPA. The single-outcome retention model had an overall accuracy of 70.7%, a POD of non-retained students of 39.6%, and a POD of retained students of 77.7%. The single-outcome GPA model had an SSE of 2.81. The mean error of prediction took about 17.2% of the full-scale GPA.

		Multi-Outcome Model	Single-Outcome Model of Retention	Single-Outcome Model of GPA
Overall Accuracy	Mean	71.3%	70.7%	--
	Average SD*	2.0%	1.8%	--
POD of Non-Retained Students	Mean	39.6%	37.6%	--
	Average SD*	5.4%	5.1%	--
POD of Retained Students	Mean	78.0%	77.7%	--
	Average SD*	1.2%	1.1%	--
SSE of GPA	Mean	2.56	--	2.81
	Average SD*	0.21	--	0.24

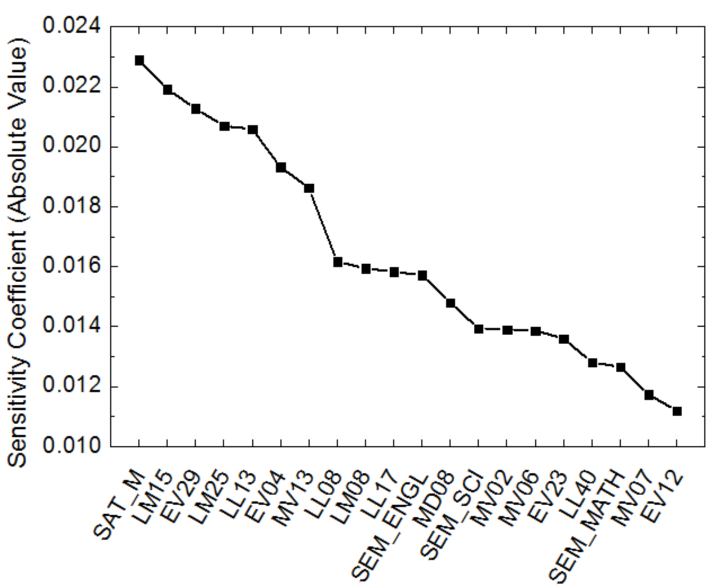
*Average SD is the average of ten standard deviations, which were calculated based on four runs.

Table 3. Prediction performances of multi-outcome and single outcome models for first-year retention and GPA.

The multi-outcome model performed better than the single-outcome models on both retention and GPA predictions, although the improvement was limited. Since the design of the input and hidden layers of the three neural network models were the same, this suggested that the multi-outcome model was able to process more information than the single-outcome models. This demonstrated the plasticity of neural network models [21].

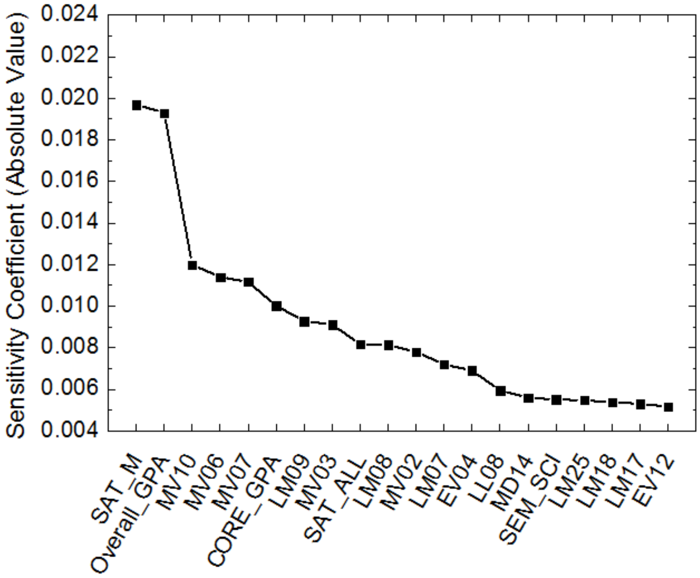
B. Importance of the Inputs

For the multi-outcome model, the sensitivity coefficients (in absolute value) of top 20 important inputs to retention and to GPA were plotted on Figures 2 and 3. Although in the same model, retention and GPA did not have the same important inputs due to the different weights connecting the neurons. When looking at the high school history matrix factors, number of semesters of English, science, and math taken in high school appeared in the top 20 most important inputs for retention. Conversely, the top 20 most important inputs for GPA included more of high school grades and GPAs. These results were consistent with our expectations. High school grades and GPAs were reported to have impacts on college GPA, but were not that closely related to retention in engineering. Students who got higher GPAs and grades in high school may take their studies more seriously, may be better at studying, or may be more motivated to get higher grades. However, all of these do not necessarily indicate that they would stay in the engineering programs. On the other hand, students' characteristics from affective measures and number of semesters of English, science, and math taken in high school could better predict whether they stay or leave engineering programs.



LM: Leadership
LL1-20: Meta-Cognition
LL21-30: Deep Learning
LL31-40: Surface Learning
MV: Motivation
EV: Expectancy-Value
MD: Major Decision

Figure 2. Top 20 Important Inputs to Retention in the Multi-Outcome Model



LM: Leadership
LL1-20: Meta-Cognition
LL21-30: Deep Learning
LL31-40: Surface Learning
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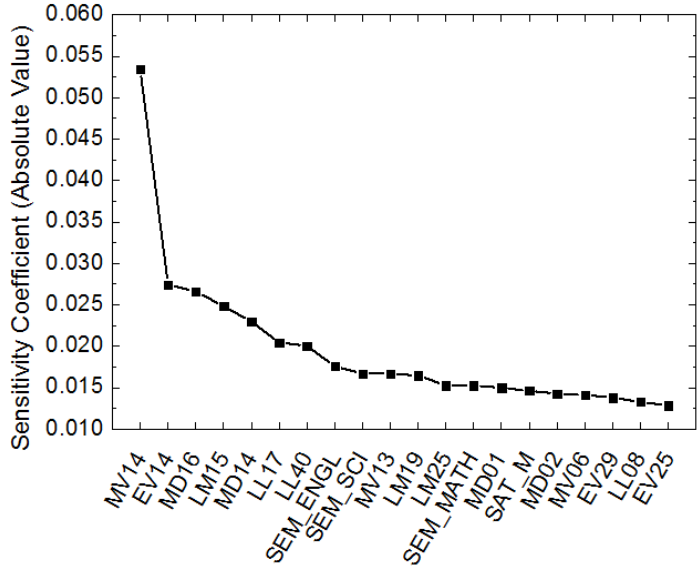
MD: Major Decision

Figure 3. Top 20 Important Inputs to GPA in the Multi-Outcome Model

Similar trends were observed in the single-outcome models, as shown in Figures 4 and 5. SAT math scores, and number of semesters of English, science, and math were in the top 20 list in the retention model. SAT scores, overall and core GPAs, math and English grades, and number of semesters of math and science were all in the top 20 list in the GPA model.

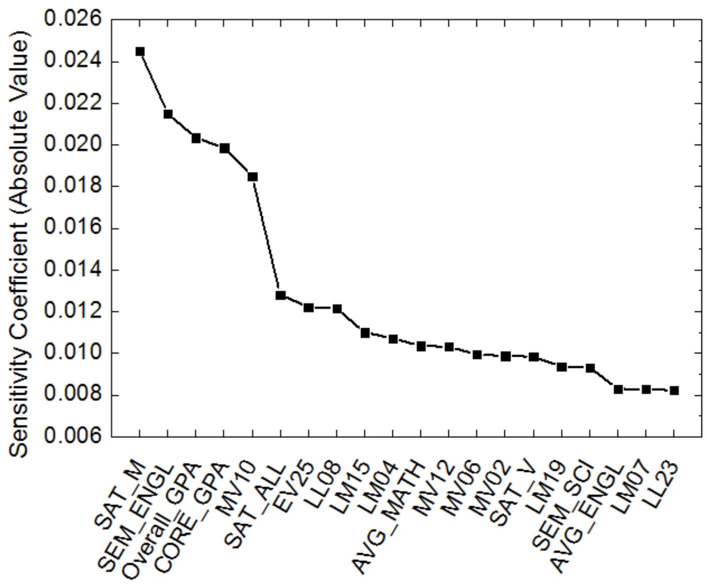
For affective measures, the most frequently appeared factors were motivation and leadership for both retention and GPA in all three models. Other factors that appeared on the top 20 list for retention were expectancy-value, meta-cognition, major decision, and surface learning. Other factors that appeared on the top 20 list for GPA were meta-cognition, expectancy-value, and deep learning. SAT math score was the most important input to both retention and GPA. These findings were consistent with Tinto's models [11,12].

Comparing the important inputs identified from the multi-outcome model with those from single-outcome models, the patterns were very similar, although the ranks and the items were not exactly the same. The importance of the factors may better be interpreted on the pattern level, because of the nature of neural networks [14].



LM: Leadership
LL1-20: Meta-Cognition
LL21-30: Deep Learning
LL31-40: Surface Learning
MV: Motivation
EV: Expectancy-Value
MD: Major Decision

Figure 4. Top 20 Important Inputs to Retention in Single-Outcome Model



LM: Leadership
LL1-20: Meta-Cognition
LL21-30: Deep Learning
LL31-40: Surface Learning
MV: Motivation
EV: Expectancy-Value
MD: Major Decision

Figure 5. Top 20 Important Inputs to GPA in Single-Outcome Model

Conclusions

In this study, we developed multi-outcome and single-outcome backpropagation neural network models to predict first-year retention and first-year college GPA of engineering students. The multi-outcome model was able to model first-year retention and first-year college GPA in the same model. The prediction accuracies of the multi-outcome model were higher than the two single-outcome models. The multi-outcome model was able to correctly predict 71.3% of the retention status of the students. The mean error of GPA prediction was 16.5% of the full scale of GPA. Different patterns of important predictors were observed for first-year retention and first-year college GPA. High school grades and SAT scores are better predictors of first-year college GPA, while the number of semesters of English, science, and math attended in high school and affective measure factors were better predictors of first-year retention. Findings of the importance of the factors supported Tinto's models.

Although the multi-outcome models do not greatly improve the prediction accuracies, this work lays a foundation for modeling multiple success outcomes in future work. These outcomes may include students' first-year placement decisions, retention and GPAs through their undergraduate study, and students' graduation time. Future integrated multi-outcome neural network models may provide a more systematic way of predicting students' performances and assisting educational decisions.

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