Boosting Early Detection of Spring Semester Freshmen Attrition: A Preliminary Exploration

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Abstract: We explore the use of a two-stage classification framework to improve predictions of freshmen attrition at the beginning of the Spring semester. The proposed framework builds a Fall semester classifier using machine learning algorithms and freshmen student data, and subsequently attempts to improve the predictions of Spring attrition by including as predictor of the Spring classifier an error measure resulting from the discrepancy between Fall predictions of attrition and actual attrition. The paper describes the proposed method and shows how to organize the data for training and testing and demonstrate how it can be used for prediction. Experimental tests are carried out using several classification algorithms, to explore the validity and potential of the approach and gauge the increase in predictive power it introduces.

1 INTRODUCTION

Student dropout has long been one of the most critical problems in higher education. Weak student retention rates affect both the reputation and bottom line of higher education institutions, as well as the way they conduct their academic planning. In the current highly competitive environment, in which the value and high costs of undergraduate education are constantly being questioned by students and their families, colleges and universities have the need to monitor student attrition closely, and freshmen attrition in particular, which accounts for a large percentage of total student attrition (DeBerard et al., 2004). Achieving low student dropout rates has been, however, a difficult obstacle to overcome for many higher education institutions: according to The Chronicle of Higher Education College Completion website, in the United States the average six-year degree completion across all four-year institutions, of those students starting bachelor degree programs, stands at 58% for public institutions to 65% for private institutions, with percentages plummeting when considering black or Hispanic student populations. Four-year graduation rates are considerably more worrying (for more details, check https://collegecompletion.chronicle.com).

Transition to college is especially challenging for students (Lu, 1994). Freshman class attrition rates are typically greater than any other academic year. In the US, over fifty percent of the dropouts occur within the first/freshmen-year (Delen, 2010). This statistic of freshmen attrition does not differentiate between the students who may have dropped out for poor academic performance and students that transferred to other academic institutions universities to complete their studies. These statistics mirror retention levels at our institution, where attrition amounts to roughly 20% over 6 years, with 10% of attrition occurring during freshman year (approximately split in halves between Fall and Spring semesters).

Methods for modeling student dropout are not a new concept. Models like Tinto's Institutional Departure Model (Tinto, 1975), Bean's Student Attrition Model (Bean, 1982; Cabrera et al., 1993), and (Herzog, 2005) described retention as related to academic and social dimensions of a student's experience with an academic institution. The rise of machine learning and big data has allowed for new methods of retention analysis to be explored. Delen (2010) compared the performance of multiple machine learning algorithms to predict freshmen retention. A team from University of Arizona (Ram et al., 2015) enriched student data by deriving implicit social networks from students' university smart card transactions to develop freshman retention predictive models.

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Researchers in Australia (Seidel and Kutieleh, 2017) proposed the use of CHAID decision tree models aimed at predicting students' risk of attrition. Lately, Delen et al (2020), have implemented a Bayesian network to capture probabilistic interactions between freshmen attrition and related factors.

Making predictions of freshmen retention is especially challenging given the reduced amount of information available from the students, which is typically limited to the student's high school academic performance, financial support, student's and school's characteristics and general demographics. The end of the Fall semester adds Fall semester GPA as a valuable piece of information which should be included as a relevant predictor for models built to predict attrition in the Spring semester. In this work we explore the feasibility of using the information obtained from Fall attrition predictions to enhance the predictions of Spring attrition. The intuition behind this approach is that the Fall prediction errors -the mismatch between the actual attrition computed at the end of the Fall semester, and the predictions made on Fall attrition-should also inform Spring attrition predictions: if the Fall attrition models predicted false positives, there may be a good chance that those students will not leave the institution during the Spring either. If that premise stands, the Fall prediction error could be a relevant predictor of Spring retention.

This paper explores the use of a two-stage classification framework to predict Fall and Spring freshmen attrition learnt from student data. The framework builds a Fall semester binary classifier, and subsequently attempts to improve the predictions of Spring attrition by including as a predictor in the Spring classifier the Fall prediction error produced by the Fall classifier. Hence, the paper makes two contributions: 1) it explores the use and relevance of previous prediction errors to improve subsequent predictions of freshmen attrition. 2) It presents a methodology to organize the data for training and testing and shows how it can be used for prediction of freshmen retention.

We first describe the methodology used to build a two-stage boosted framework. We follow with a description of the experiment, including the data, methods, results and analyses of this study. The paper ends with a summary of our conclusions, limitations of the study and pointers to future work.

2 BUILDING A TWO-STAGE BOOSTED CLASSIFIER OF FRESHMMEN ATTRITION

2.1 Methodology

Two independent datasets $\mathbf{D}_{trn}$ and $\mathbf{D}_{tst}$ are used for training and testing. The training dataset $\mathbf{D}_{trn}$ is made up of several years of freshmen data (i.e. data from accepted and registered freshmen students). One year of student data is used to populate test dataset $\mathbf{D}_{tst}$ (different from the years used for training). Dataset $\mathbf{D}_{trn}$ has a schema $[X_{trn}; y_{trn}^{Fall}; y_{trn}^{Spring}]$, made up of a vector of predictors X_{trn} and target variables y_{trn}^{Fall} y_{trn}^{Spring} representing freshmen attrition in Fall and Spring. The response variable is binary, indicating whether a student has attrited or not. Similarly, dataset $\mathbf{D}_{tst}$ has a schema $[X_{tst}; y_{tst}^{Fall}; y_{tst}^{Spring}]$, made up of a vector of predictors X_{tst} and response variables y_{tst}^{Fall} and y_{tst}^{Spring} (more details on the use of the data files follow).

In **Stage 1** (training and testing Fall semester, see Fig 1):

- **Step(i)** corresponds to Train Fall classifier, where a classifier M_{Fall} is trained using dataset $\mathbf{D}_{trn}[X_{trn}; y_{trn}^{Fall}]$ and classification algorithm C (a probabilistic classifier). The notation $\underline{\text{cv}}$ indicates model tuning using cross-validation.
- In **Step(ii)**, the trained classifier M_{Fall} is used to predict the outcome of attrition in Fall $\hat{y}_{trn}^{Fall}$ and its corresponding probability estimate $\hat{p}_{trn}^{Fall}$ (the probability that $y_{trn}^{Fall} = 1$), a measure of the confidence of the prediction.
- **Step(iii)** calculates the error measure e_{trn}^{Fall} by computing the absolute value of the difference between the target y_{trn}^{Fall} and probability estimate $\hat{p}_{trn}^{Fall}$. Error signal e_{trn}^{Fall} is a vector of length n_{trn}, where n_{trn} is the number of observations in data set $\mathbf{D}_{trn}$.
- In **Step (iv),** corresponding to Test Fall classifier, trained model M_{Fall} is applied to dataset

$\mathbf{D}_{tst}[X_{tst}; y_{tst}^{Fall}]$, to produce prediction vector $\hat{y}_{tst}^{Fall}$ and probability estimate $\hat{p}_{tst}^{Fall}$ (the probability that $y_{tst}^{Fall} = 1$).

- **Step(v)** <u>calculates the error measure e_{tst}^{Fall}</u> by computing the absolute value of the difference between the target y_{tst}^{Fall} and probability estimate $\hat{p}_{tst}^{Fall}$. Error measure e_{tst}^{Fall} is a vector of length n_{tst}, where n_{tst} is the number of observations in data set $\mathbf{D}_{tst}$.

Note that both error signals e_{trn}^{Fall} and e_{tst}^{Fall} are computed during Stage 1, but are used in Stage 2.

$$\mathbf{D}_{trn} \rightarrow \overbrace{\mathbf{D}_{trn}[X_{trn}; y_{trn}^{Fall}]\ \underline{cv}\ \mathrm{C}}^{\text{Train}}$$

$$\downarrow$$

(i) Train Fall classifier M_{Fall}

$$\mathbf{D}_{trn} \rightarrow \overbrace{\mathbf{D}_{trn}[X_{trn}; y_{trn}^{Fall}] \leftarrow \mathrm{M}_{Fall}}^{\text{Predict}}$$

(ii) Predict on training data $\downarrow$

Compute: $\hat{y}_{trn}^{Fall}, \hat{p}_{trn}^{Fall}$

(iii) Compute $e_{trn}^{Fall} = \mathrm{abs}\left(y_{trn}^{Fall} - \hat{p}_{trn}^{Fall}\right)$

$$\mathbf{D}_{tst} \rightarrow \overbrace{\mathbf{D}_{tst}[X_{tst}; y_{tst}^{Fall}] \leftarrow \mathrm{M}_{Fall}}^{\text{Predict}}$$

(iv) Predict on test data $\downarrow$

Compute: $\hat{y}_{tst}^{Fall}, \hat{p}_{tst}^{Fall}$

v) Compute $e_{tst}^{Fall} = \mathrm{abs}\left(y_{tst}^{Fall} - \hat{p}_{tst}^{Fall}\right)$

Figure 1: Training and testing the first stage (Fall semester) classifier.

In **Stage 2** (training and testing Spring semester, see Fig 2):

- **Step(i)** augments the list of predictors X_{trn} with error measure e_{trn}^{Fall}, resulting in $\mathbf{D}_{trn}^{(aug)}[X_{trn}^{(aug)}; y_{trn}^{Fall}; y_{trn}^{Spring}]$ dataset. Other features are added in this step to $X_{trn}^{(aug)}$; in particular Fall semester GPA which is computed for each student at the end of the Fall semester, and is typically a relevant predictor of Spring attrition.

i) Augment X_{trn} with $e_{trn}^{Fall} = \mathrm{abs}\left(y_{trn}^{Fall} - \hat{p}_{trn}^{Fall}\right)$

$X_{trn}^{(aug)} \leftarrow concatenate(X_{trn}, e_{trn}^{Fall})$

Therefore, $\mathbf{D}_{trn}^{(aug)}[X_{trn}^{(aug)}; y_{trn}^{Spring}; y_{trn}^{Spring}]$

ii) Subset $\mathbf{D}_{trn}^{(aug)}$, deleting strudents attrited in Fall

$\mathbf{D}_{trn_S}^{(aug)} \leftarrow \mathbf{D}_{trn}^{(aug)}\left[\mathbf{D}_{trn}^{(aug)}[AttritedFall]! = 1\right]$

$$\mathbf{D}_{trn_S}^{(aug)} \rightarrow \overbrace{\mathbf{D}_{trn_S}^{(aug)}[X_{trn_S}; y_{trn_S}^{Spring}]\ \underline{cv}\ \mathrm{C}}^{\text{Train}}$$

$$\downarrow$$

(iii) Train (boosted) Spring classifier M_{Spring}

iv) Augment X_{tst} with $e_{tst}^{Fall} = \mathrm{abs}\left(y_{tst}^{Fall} - \hat{p}_{tst}^{Fall}\right)$

$X_{tst}^{(aug)} \leftarrow concatenate(X_{tst}, e_{tst}^{Fall})$

Therefore, $\mathbf{D}_{tst}^{(aug)}[X_{tst}^{(aug)}; y_{tst}^{Fall}; y_{tst}^{Spring}]$

v) Subset $\mathbf{D}_{tst}^{(aug)}$, deleting strudents attrited in Fall

$\mathbf{D}_{tst_S}^{(aug)} \leftarrow \mathbf{D}_{tst}^{(aug)}\left[\mathbf{D}_{tst}^{(aug)}[AttritedFall]! = 1\right]$

$$\mathbf{D}_{tst_S}^{(aug)} \rightarrow \overbrace{\mathbf{D}_{tst_S}^{(aug)}[X_{tst_S}; y_{tst_S}^{Spring}] \leftarrow \mathrm{M}_{Spring}}^{\text{Predict}}$$

(vi) Test (boosted) Spring classifier $\downarrow$

Compute: $\hat{y}_{tst_S}^{Spring}, \hat{p}_{tst_S}^{Spring}$

Figure 2: Training and testing the second stage (Fall semester) classifier, boosted by adding the error measure generated at the end of the Fall semester.

- **Step(ii)** subsets dataset $\mathbf{D}_{trn}^{(aug)}$, removing instances corresponding to students attrited in the Fall. The resulting dataset, named $\mathbf{D}_{trn_S}^{(aug)}[X_{trn_S}; y_{trn_S}^{Spring}]$, is subsequently used for training, using $y_{trn_S}^{Spring}$ as target.
- **Step(iii)** corresponds to <u>Train (boosted) Spring classifier</u>, where a classifier M_{Spring} is trained and tuned through cross-validation using

augmented and subsetted dataset $\mathbf{D}_{trn_S}^{(aug)}[X_{trn_S};y_{trn_S}^{Spring}]$ and classification algorithm C.

- **Step(iv)** augments the list of predictors X_{tst} with error measure e_{tst}^{Fall}, resulting in dataset $\mathbf{D}_{tst}^{(aug)}[X_{tst}^{(aug)};y_{tst}^{Fall};y_{tst}^{Spring}]$. If features such as Fall semester GPA were added to the augmented training dataset $\mathbf{D}_{trn}^{(aug)}$, those same features must be added to augmented test dataset $\mathbf{D}_{tst}^{(aug)}$
- **Step(v)** subsets dataset $\mathbf{D}_{tst}^{(aug)}$, removing instances corresponding to students attrited in the Fall. The resulting dataset, named $\mathbf{D}_{tst_S}^{(aug)}[X_{tst_S};y_{tst_S}^{Spring}]$, is subsequently used for testing, using $y_{tst_S}^{Spring}$ as target.
- In **Step (vi),** corresponding to <u>Test (boosted) Spring classifier</u>, trained model M_{Spring} is applied to dataset $\mathbf{D}_{tst_S}^{(aug)}[X_{tst_S};y_{tst_S}^{Spring}]$, to finally produce prediction vector $\hat{y}_{tst}^{Spring}$ and probability estimate $\hat{p}_{tst}^{Spring}$.

After classifiers M_{Fall} and M_{Spring} are trained, tuned and tested, they can be used to make predictions on new data $\mathbf{D}_{new}$. Figure 3 depicts the classifiers making predictions on new, incoming (and therefore unlabeled) data $\mathbf{D}_{new}$ at the beginning of the Fall semester and Spring semester respectively**:**

- In **Step (i),** corresponding to <u>Predict on new (upcoming year) data</u>, trained model M_{Fall} is applied to dataset to produce prediction vector $\hat{y}_{new}^{Fall}$ and probability estimate $\hat{p}_{new}^{Fall}$ (the probability that $y_{new}^{Fall}=1$)
- **Step(ii)** <u>calculate the error measure</u> e_{new}^{Fall} by computing the absolute value of the difference between the target y_{new}^{Fall} and probability estimate $\hat{p}_{new}^{Fall}$ (the probability that $y_{new}^{Fall}=1$).
- **Step(iii)** augments the list of predictors X_{new} with error signal e_{new}^{Fall}, resulting in dataset $\mathbf{D}_{new}^{(aug)}[X_{new}^{(aug)};y_{new}^{Fall}]$. As before, if other features (e.g. Fall semester GPA) were added to the augmented dataset $\mathbf{D}_{trn_S}$ used to train M_{Spring}, those same features must be added to augmented test dataset $\mathbf{D}_{new}^{(aug)}$.

$\mathbf{D}_{new} \quad \rightarrow \quad \overbrace{\mathbf{D}_{new}[X_{new}] \leftarrow \mathrm{M}_{Fall}}^{\text{Predict}}$

(i) Predict on new Fall data $\downarrow$

Compute: $\hat{y}_{trn}^{Fall}, \hat{p}_{trn}^{Fall}$

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ii) At the end of the Fall we obtain the

Compute $e_{new}^{Fall} = \mathrm{abs}\left(y_{new}^{Fall} - \hat{p}_{new}^{Fall}\right)$

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iii) Augment X_{new} with $e_{new}^{Fall} = \mathrm{abs}\left(y_{new}^{Fall} - \hat{p}_{new}^{Fall}\right)$

$X_{new}^{(aug)} \leftarrow concatenate(X_{new}, e_{new}^{Fall})$

Therefore, $\mathbf{D}_{new}^{(aug)}[X_{new}^{(aug)}]$

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iv) Subset $\mathbf{D}_{new}^{(aug)}$, deleting strudents attrited in Fall

$\mathbf{D}_{news_S}^{(aug)} \leftarrow \mathbf{D}_{new}^{(aug)}\left[\mathbf{D}_{new}^{(aug)}\left[AttritedFall\right]!=1\right]$

$\mathbf{D}_{news_S}^{(aug)} \quad \rightarrow \quad \overbrace{\mathbf{D}_{news_S}^{(aug)}[X_{news_S}] \leftarrow \mathrm{M}_{Spring}}^{\text{Predict}}$

(v) Predict on new Spring data $\downarrow$

Compute: $\hat{y}_{news_S};\hat{p}_{news_S}$

Figure 3: Using the two-stage classification framework for prediction on new data.

- **Step(iv)** subsets dataset $\mathbf{D}_{new}^{(aug)}$, removing instances corresponding to students attrited in the Fall, resulting in dataset $\mathbf{D}_{news_S}^{(aug)}$.
- In **Step (v),** corresponding to <u>Predict on new (upcoming) Spring data</u>, model M_{Spring} is applied to dataset $\mathbf{D}_{news_S}^{(aug)}[X_{news_S}]$, to produce prediction vector $\hat{y}_{news_S}^{Spring}$ and probability vector $\hat{p}_{news_S}^{Spring}$ associated with the prediction (a measure of the confidence of the prediction).

2.2 Considerations and Best Practices

- The proposed classification framework is used to make predictions at two specific times throughout the academic year, Fall and Spring, but the focus is placed on the Spring semester, as the additional predictors available in the Spring semester (Fall semester GPA, and error measure) should provide enhanced predictions.
- At the beginning of the Fall semester, predictions are made about freshmen attrition by the end of the Fall semester using classifier M_{Fall}. The quality of those predictions is limited by the predictive performance of M_{Fall} and directly related to the contribution to the classifier of the features included as predictors.
- At the end of the Fall semester the list of Fall semester attritions becomes available and with it, the error measure calculated between predictions made at the beginning of the Fall semester, and actual attritions at the end of the Fall.
- The inclusion of the error measure in the Spring dataset attempts to boost the predictions made by classifier M_{Spring} at the beginning of the Spring semester, with the purpose of enhancing its predictive performance.
- As such, we have two rounds of predictions at early stages of each semester, with increasing predictive performance.
- In our proposed algorithm we chose to use the error measure computed as the absolute value of the difference between the target y^{Fall} and probability estimate $\hat{p}^{Fall}$ instead of computing the mismatch between target y^{Fall} and the predicted value $\hat{y}^{Fall}$: (mistmatch=1 if $\hat{y}^{Fall} \neq y^{Fall}$; else mismatch=0). The mismatch measure is binary and too crisp, whereas the formulation we propose yields a continuous variable bounded between 0 and 1, and a measure of the strength of the prediction error.
- Also, we chose to include the error measure as an additional feature of the Spring training dataset, instead of using it to identify instances of misclassification and placing weights on those instances, as in the case of traditional boosting approaches (Schapire, 1990).
- Data used in this framework does not follow a typical random split into training and testing datasets by aggregating student data over multiple years and randomly partitioning the sample. Instead, data over multiple years are collected for training, using one additional year for testing. This approach is favored as classification models in this problem domain should be trained and tested over full freshmen roster data, reflecting retention (and attrition) for each year.
- Models are trained and tuned using cross-validation. This guarantees that the models' hyperparameters are optimized for the data and task at hand before they are tested on new data.

3 EXPERIMENTAL SETUP

In the experiments we investigated the use of a two-stage early detection framework learnt from data, in the manner described in the previous section, for Spring attrition of Freshman students. The framework is structured as a binary classifier (two classes) where a target value of 1 signals attrition.

The input datasets described below (see section 3.1) were derived from three data sources within the institution: the student information system, enrollment management and student housing.

As the systems were disparate it was necessary to create an ETL process that would produce a cohesive unit of analysis. To facilitate this functionality a combination of relational and object data stores were established with scheduled jobs to create coordinated datasets with appropriately matching elements. It is the case that the data elements within the institution changed over time and it was essential to the process that the year over year data elements were consistent.

3.1 Datasets

In this preliminary study we considered Freshmen data from three academic years (2016, 2017, 2018). We used 2016, 2017 data for training and 2018 data for testing purposes. Freshmen data were extracted, cleaned, transformed and aggregated into a complete dataset (no missing data). Data was imputed using K nearest neighbors (KNN). Each record -the unit of analysis- corresponds to each accepted and registered freshman student in a given semester (Fall and Spring) enriched with school data and demographics using the record format depicted in Table 1. The training (2016+2017) dataset included 2430 records, with 276 attritions distributed in 88 Fall attritions and 188 Spring attritions. The test (2018) dataset included 1303 records, with 150 attritions distributed in 50 Fall attritions and 100 Spring attritions. Each record included the target variables (Attrited_Fall and

Table 1: Features in input data sets.

redictor	Description	Data Type
EARLYACTION	Applied for early action	Binary (1/0)
EARLYDECISION	Applied for early decision	Binary (1/0)
MERITSCHOLAMT	Merit Scholar Amount	Numeric
FINAIDRATING	Financial Aid Rating	Numeric
HSTIER	High School Tier	Numeric
FOREIGN	Foreign Student	Binary (1/0)
FAFSA	Applied for Federal Student Aid	Binary (1/0)
APCOURSES	Took AP courses	Binary (1/0)
MALE	Male	Binary (1/0)
MINORITY	Belongs to a minority group	Binary (1/0)
ATHLETE	Is a student athlete	Binary (1/0)
EARLYDEFERRAL	Applied for early deferral	Binary (1/0)
WAITLISTYN	Was waitlisted	Binary (1/0)
COMMUTE	Is a commuter student	Binary (1/0)
HS_GPA	High School GPA	Numeric
DISTANCE_IN_MILES	Distance from home (in miles)	Numeric
APTITUDE_SCORE	Aptitude Score (SAT/ ACT)	Numeric
FIRSTGENERATION	First Generation College Student	Binary (1/0)
SCHOOL	Joined any of the following Schools: CC (ComSci & Math), CO (Communications & Arts), LA (Liberal Arts), SB (Behavioral Sciences), SI (Science), SM (Management)	Categorical (6 categories), recoded as 6 binary (1/0) vars.
RACE	Race (A, B, H, I, M, N, O, P, W)	Categorical (9 categories), recoded as 9 binary (1/0) vars.
ISPELLRECIPIENT	Is recipient of Pell Grant	Binary (1/0)
ISDEANLIST	Joined Dean's List	Binary (1/0)
ISPROBATION	Is on probation	Binary (1/0)
OCCUPANTS_BLDG	No of occupants in dorm	Numeric
OCCUPANTS_ROOM	No of occupants in dorm's room	Numeric
IS_SINGLE_ROOM	Uses a single room	Binary (1/0)
FS_GPA_NUM	Fall semester GPA, used in Spring predictions	Numeric
ERROR_MEASURE	error measure, used in Spring predictions	Numeric
Target features: Attrited_Spring - Binary (1/0); Attrited_Fall - Binary (1/0)		

Attrited_Spring) which were used alternatively for Fall and Spring predictions.

3.2 Methods

We performed sixteen experiments, using two different classification algorithms for the first-stage (Fall) models; four different classification algorithms for the Spring models, and two sets of predictors to train the Spring models: one including both Fall semester GPA and the error measure, and the other keeping Fall semester GPA, but excluding the error measure. The purpose of this was to be able to compare the actual impact in predictive performance introduced by the inclusion of the error measure.

The first-stage (Fall) classifiers were trained with two different algorithms:

- XGB: XGBtree, an improvement on gradient boosting trees introduced by Chen and Guestrin (2016), widely regarded as the machine learning algorithm of choice for many winning teams of machine learning competitions when dealing with structured data, without resorting to stack ensembles.
- LOG: Logistic Regression, the workhorse of binary and multinomial classification in statistical modelling.

For the second-stage (Spring) classifiers we chose four different algorithms:

- XGB: XGBtree, (Chen and Guestrin, 2016)
- RF: The Random Forests algorithm (Breiman, 2001), a variation of bagging applied to decision trees.

- LOG: logistic regression
- LDA: Linear discriminant Analysis, a traditional classification method that finds a linear combination of features to separate two or more classes. LDA requires continuous predictors that are normally distributed, but in practice this restriction can be relaxed.

The chosen classifiers are either state-of-the-art (e.g. XGB and RF) or well-proven classification algorithms. They are also substantially different in their theoretical underpinnings and should therefore yield non-identical prediction errors.

3.3 Computational Details

Enrollment management data was stored in a MongoDb database as it tended to be the most variant. Extraction scripts were used to generate flat structures for export to the final data stores. This was combined with the flattened structures from the student information system which uses Oracle database, and the housing information which is stored in MS-SQL Server. Ultimately the extracted data was stored in a MariaDb, where SQL scripts comprised the final steps in the ETL to generate the final units of analysis exports.

The two-stage boosted framework was coded using a combination of Python 3.6 using the scikit-learn and pandas libraries, and SPSS Modeler 18.2, for rapid prototyping, given the number of experiments conducted in this preliminary exploration. We used the Bayesian optimization library scikit-optimize (skopt) for hyperparameter tuning in the first stage, and the rfbopt library (https://rbfopt.readthedocs.io) for hyperparameter optimization of XGBtree and Random Forests in SPSS Modeler for the second stage.

The experiments were run on an Intel Xeon server, 2.90GHz, 8 processors, 64GB RAM. Parallel processing was coded into the system to make use of all n cores during training and tuning.

4 RESULTS AND DISCUSSION

Table 2 displays the assessment of predictive performance of the two-stage classification framework for the sixteen experiments described in section 3.2.

Accuracy and ROC AUC are reported, although the prevalent predictive performance metric is ROC AUC in this case, given the unbalanced nature of the datasets. Predictive performance is slightly higher in the first stage when using logistic regression vs XGBtree, but both values (0.66 and 0.64) are rather low, which confirms the challenges faced by researchers when trying to make predictions of Fall semester freshmen attrition.

When analysing the results on Spring predictions we can verify that the inclusion of the error measure in the list of Spring predictors enhances the predictive performance of the classification models. Predictive performance improvement was moderate but consistent. For error measures derived with a first stage (Fall) using logistic regression, three out of four classifiers had better predictive performance when the error measure is included as a predictor. The AUC value for XGBtree is 0.78, greater than the AUC value when the error measure is excluded (0.759). Similarly, the AUC value for Random Forests is 0.802, greater than 0.796. In the case of LDA, the different in AUC is much more substantial: 0.817 vs 0.639. For logistic regression, instead, the results are reversed: the AUC when excluding the error measure is higher (0.808 vs. 0.816). When using XGBtree in the first stage we have similar results: the AUC values are either higher when including the error measure, or at least remain the same. The AUC value for XGBtree is 0.782, greater than the AUC value when the error measure is excluded (0.766). For Random Forests and Logistic Regression, the inclusion of the error measure does not change the AUC value (0.792 and 0.816 respectively). For LDA, we see a considerable drop in predictive performance, but still, the inclusion of the error measure improves the AUC value (0.684 vs. 0.639).

Figure 4 depicts the feature importance charts for each of the sixteen experiments. The error measure plays a prominent role as a predictor in all but one scenario, ranking among the five most relevant predictors (the only exception is the case in which XGBTree is used for Fall prediction, and logistic regression for Spring prediction).

These results suggest that the inclusion of the error measure can be beneficial and will tend to increase predictive performance. It could certainly be meaningful to consider its inclusion when implementing an ensemble of classifiers: some classifiers could be trained with inclusion of the error measure, and others without it, and then allow the ensemble, either through voting or through stacking, to produce the final prediction. For details of this approach check (Lauría et al., 2018).

A surprising outcome is the fact that logistic regression outperformed both XGBtree and Random Forests, two state of the art classifiers. This may be due to limited hyperparameter optimization.

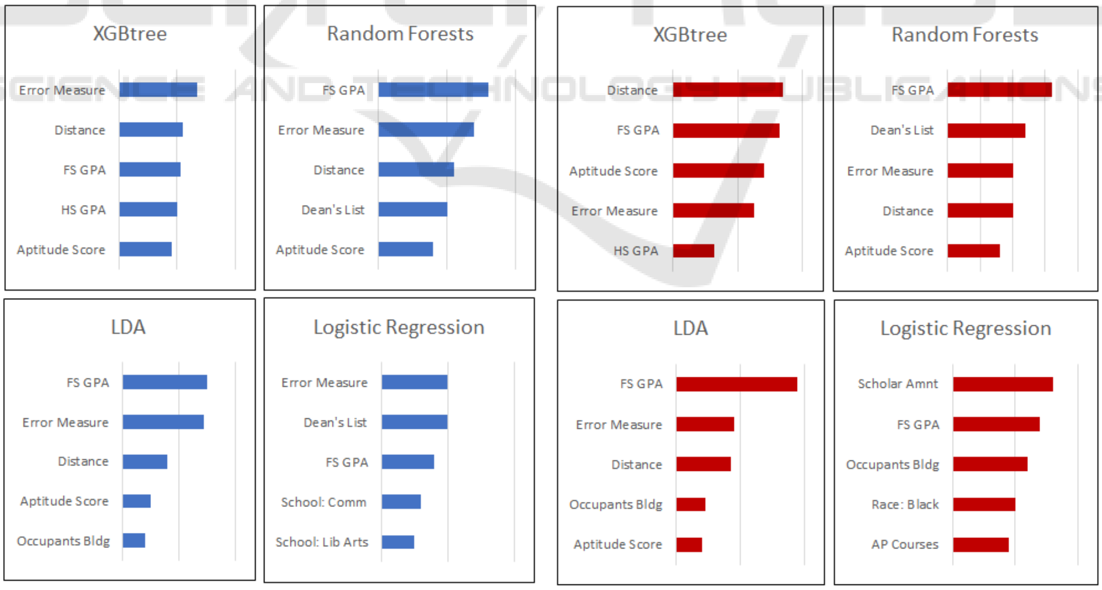
Table 2: Stack Predictive Performance Results.

First Stage: Fall		Second Stage: Spring				
Classifier	LOG	**Include error measure**	**XGB**	**RF**	**LDA**	**LOG**
ROC AUC	0.66	▪ **Accuracy**	91.54%	93.06%	81.17%	92.42%
		▪ **ROC AUC**	0.78	0.802	0.817	0.808
		Exclude error measure	**XGB**	**RF**	**LDA**	**LOG**
		▪ **Accuracy**	91.54%	93.22%	70.31%	92.18%
		▪ **ROC AUC**	0.759	0.796	0.639	0.816

(a) Using Logistic Regression for Fall prediction

First Stage: Fall		Second Stage: Spring				
Classifier	XGB	**Include error measure**	**XGB**	**RF**	**LDA**	**LOG**
ROC AUC	0.64	▪ **Accuracy**	91.54%	93.30%	73.42%	92.34%
		▪ **ROC AUC**	0.782	0.792	0.684	0.816
		Exclude error measure	**XGB**	**RF**	**LDA**	**LOG**
		▪ **Accuracy**	91.94%	93.22%	70.31%	92.18%
		▪ **ROC AUC**	0.766	0.792	0.639	0.816

(b) Using XGBtree for Fall prediction



(a) Using Logistic Regression for Fall prediction. (b) Using XGBtree for Fall prediction.

Figure 4: Feature Importance of Second Stage (Spring) classifiers.

Random forests and especially XGBtree have a very large number of hyperparameters, which require large number of runs to attain optimal hyperparameter configurations. In future work we may need to reconsider the strategy used for tuning the models. Also, the drop in LDA's predictive performance deserves further analysis: the LDA algorithm exhibits different behaviour when the error measure is derived from logistic regression and XGBtree in the Fall prediction.

5 SUMMARY AND CONCLUDING COMMENTS

The current research has several limitations. First, the study imposed a limited group of classification algorithms. Although the experiments included state of the art algorithms, such as XGBTree, a broader, less discretionary analysis is probably necessary. The purpose of the study at this preliminary stage is not to identify an optimal architecture but rather to empirically test the validity and effectiveness of the proposed framework. Second, the error measure included as a predictor in the Spring model is limited to the use of false positives from the Fall semester. Students who attrite in the Fall but were not predicted to attrite -false negatives-, are excluded from the Spring predictions as they are no longer part of the dataset (they have left the College); the Spring model therefore does not learn from Fall's Type II errors. This is a design consideration: we use weaker predictions of the Fall semester to enhance Spring predictions over the remaining students.

The impetus of this research stems from the need of to develop better methods for prediction of (freshmen) student attrition. Hopefully this paper will provide the motivation for other researchers and practitioners to work on new and better predictive models of student retention.

REFERENCES

Bean, J. P., 1982. Conceptual models of student attrition: How theory can help the institutional researcher. New Dir. Institutional Res. 1982, 17–33. https://doi.org/10.1002/ir.37019823604

Breiman, L., 2001. Random Forests. Mach Learn 45, 5–32.

Cabrera, A. F., Nora, A., Castaneda, M. B., 1993. College Persistence: Structural Equations Modeling Test of an Integrated Model of Student Retention. J. High. Educ. 64, 123–139. https://doi.org/10.2307/2960026

Chen, T., Guestrin, C., 2016. XGBoost: A Scalable Tree Boosting System. CoRR abs/1603.02754.

DeBerard, M. S., Spielmans, G. I., Julka, D. L., 2004. Predictors of academic achievement and retention among college freshmen: A longitudinal study. Coll. Stud. J. 38, 66–80.

Delen, D., 2010. A comparative analysis of machine learning techniques for student retention management. Decis. Support Syst. 49, 498–506. https://doi.org/10.1016/j.dss.2010.06.003

Delen, D., Topuz, K., Eryarsoy, E., 2020. Development of a Bayesian Belief Network-based DSS for predicting and understanding freshmen student attrition. Featur. Clust. Bus. Anal. Defin. Field Identifying Res. Agenda 281, 575–587. https://doi.org/10.1016/j.ejor.2019.03.037

Herzog, S., 2005. Measuring Determinants of Student Return VS. Dropout/Stopout VS. Transfer: A First-to-Second Year Analysis of New Freshmen. Res. High. Educ. 46, 883–928. https://doi.org/10.1007/s11162-005-6933-7

Lauría, E. J. M., Presutti, E., Kapogiannis, M., Kamath, A., 2018. Stacking Classifiers for Early Detection of Students at Risk, in: Proceedings of the 10th International Conference on Computer Supported Education - Volume 2: CSEDU,. SciTePress, pp. 390–397.

Ram, S., Wang, Y., Currim, F., Currim, S., 2015. Using big data for predicting freshmen retention, in: 2015 International Conference on Information Systems: Exploring the Information Frontier, ICIS 2015. Association for Information Systems.

Schapire, R.E., 1990. The Strength of Weak Learnability. Mach Learn 5, 197–227. https://doi.org/10.1023/A:1022648800760

Seidel, E., Kutieleh, S., 2017. Using predictive analytics to target and improve first year student attrition. Aust. J. Educ. 61, 000494411771231. https://doi.org/10.1177/0004944117712310

Tinto, V., 1975. Dropout from Higher Education: A Theoretical Synthesis of Recent Research. Rev. Educ. Res. 45, 89–125.