

A MACHINE LEARNING APPROACH TO PREDICT FIRST-YEAR STUDENT  
RETENTION RATES AT UNIVERSITY OF NEVADA, LAS VEGAS

by

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# Abstract

First-Year student retention rates refer to the percentage of first-year students who return to the same institution for their sophomore year. The national average in the institutions at the U.S for the year 2016 is at around 77 % which indicates that most of the universities are performing poorly in terms of retaining the first-year students. First-year retention rates act as an important indicator of the student satisfaction as well as the performance of the university. Moreover, universities with low retention rates may face a decline in the admissions of talented students with a notable loss of tuition fees and contributions from alumni. Hence it became important for universities to formulate strategies to identify students at risk and take necessary measures to retain them. Many universities have tried to develop successful intervention programs to help students increase their performance. However, identifying and prioritizing students who need early interventions still remains to be very challenging.

The retention rate at the University of Nevada, Las Vegas (UNLV) is close to 74% which indicate the need for specific intervention programme's to retain the students at risk of dropping out after their first year. In this thesis, we propose the use of predictive modeling methods to identify students who are at risk of dropping out after their first year at an early stage to whom the instructors can offer help. We apply several important classification algorithms from machine learning such as Logistic Regression, Decision trees, and Random forest classifier and evaluate them using metrics useful to the educators at UNLV. We use feature selection methods to identify important variables used in each model to increase the generalization and accuracy of the predictions. We propose to design effective metrics to evaluate the model's performance to help match at-risk students with appropriate supports. The main focus of this research is on students at risk of not being retained at the end of the first year, but it also lays a foundation for future work on other adverse academic outcomes.

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# Chapter 1

## Introduction

The first-year or freshmen retention rate refers to the number of freshmen in a college or university who return for their sophomore year. Many universities are facing huge problems with low or decreasing first-year student retention rates. Low retention rates are a bad indicator of the university's performance and can damage the reputation of the institution in the eyes of students and parents. The reasons behind student dropout after the first year in universities can range from high expectations of the college programs, transition into an interdisciplinary curriculum, economic problems, inability to mix well with other students or struggling due to unfulfilled prerequisite requirements [Lau03]. Many researchers have formulated solutions such as building learning communities, providing additional resources [Tin99], highlighting student participation in campus life and providing academic support [Lau03]. Also, few studies have indicated that the risk of dropping out decreases with an increase in academic performance [AMBS99]. Thus, one way to increase retention is to increase academic success. In recent years, many universities have invested significantly in development and implementation of intervention programs to help at-risk students and support them individually to improve their academic performance.

The success of such intervention programs depends on the university's ability to accurately identify students who need help. In a traditional approach, many universities have used academic performance indicators such as GPA's, absence rates, previous grades, SAT or ACT scores from enrollment data to generate rules that can be used to identify students at risk [BS16]. Although such rule-based systems served as good indicators of identifying at-risk students for some years, they had some downsides such as fewer accuracies, static, expensive to generate and maintain and most importantly they lacked a validation mechanism to verify the predictions. Alternatively, recent research has indicated the potential value of machine learning algorithms such as Logistic

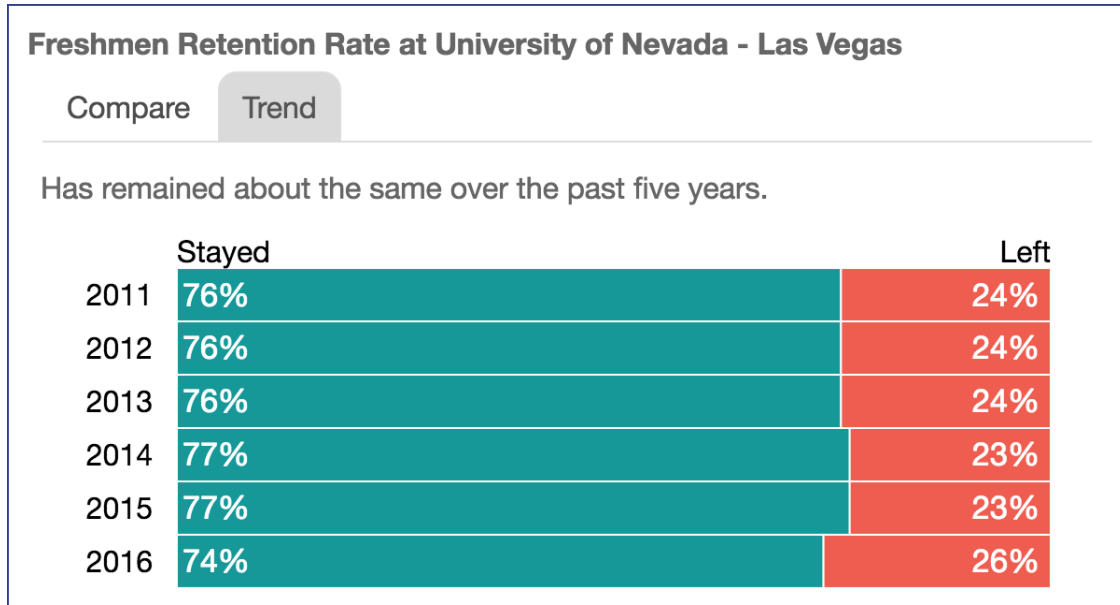


Figure 1.1: Freshmen Retention Rates at UNLV

Regression, Random Forest Classifiers, Decision Trees, Support Vector Machines (SVM) and Neural networks for the problem [Pla13, LAS<sup>+</sup>15, MDDM16]. These algorithms when trained using traditional academic data can identify at-risk students more accurately. The performance of these algorithms can be evaluated using various metrics such as Precision, Recall, and Area Under Curve (AUC) thus giving us a good indicator to validate the results. However, the application of such predictive methods to identify at-risk students is still at its early stages, owing to the implementation complexity and the availability of data. Currently, many universities have defined rules in the collection of data to use for such a research.

Over the recent years, the retention rates at UNLV have displayed a highly varying pattern. It dropped from 77% in 2012 to 74% in 2014 and then increased to 77% in 2015, which later on fell to 74% in 2016 Figure 1.1. Such an unstable pattern of freshmen retention rates has drawn a lot of attention by the educators and administration at UNLV. Hence, a predictive approach to identifying at-risk students and supporting them with additional resources would be quite beneficial to increase the retention rates at UNLV.

## 1.1 Objective

The objective of this thesis is to create predictive models that can be used to identify at-risk students. In this thesis, important machine learning algorithms such as Logistic Regression, Decision

trees, Random Tree Classifiers and SVM's will be trained on real-time student data obtained from UNLV's enrollment census. The trained models will then be used to predict at-risk students from a test dataset which the model has not seen earlier. The models are evaluated and compared using metrics such as precision, recall, and area under the curve to determine which model provides the best results. The results of the analysis such as the evaluation metrics will be converted to risk scores which can be easily understood by the educators and administrators at UNLV. Another contribution of this thesis is to rank students based on risk scores which will be very helpful in an efficient allocation of resources as part of the intervention programs.

## **1.2 Outline**

In Chapter 1, the brief topic of First-Year student retention rates, its importance to universities and the proposed approach to increase the retention rates at UNLV was described.

In Chapter 2, we will discuss the existing research on improving first-year retention rates and the background information required to understand the proposed predictive approach using machine learning. It will also cover the most important and popular algorithms of machine learning.

In Chapter 3, we will describe the methodology adapted for the analysis.

In Chapter 4, we will present the experimental results. The characteristics of datasets used for these methods will also be described.

In Chapter 5, we will summarize the proposed methods and their results along with the possible extension of this thesis.

# Chapter 2

## Background and Preliminaries

### 2.1 Related Work

The prediction of first-year student retention rates and identification of students at risk of not being retained has been a well-researched problem in the area of higher education sector for decades. Early studies involved learning the important factors that lead to student dropout by developing a theoretical model. Tinto is one of the major and earliest researchers in this area. Tinto's student engagement model [Tin99] has served as the basis for a large number of theoretical studies [Bra02]. Similar research was carried out by Ernest Pascarella, Patrick Terenzini, and Alexander Astin, which focused more on the external factors such as the institution's administration and its policies when determining the reasons for student retention [A<sup>+</sup>12]. Tinto in his 2006 study [Tin06] has stated that there has been a huge increase in the number of businesses and organizations to analyze and help institutions with the student retention problem. Later, in the same study, he revealed that there was only little change in the retention rates even with some huge businesses helping the universities. He also described the importance of external factors such as student-faculty relationships, extracurricular program, and orientation programs for first years. Moreover, he incorporated the role of academic factors into his model to make it more suitable to the college structure [Tin06]. Astin in his Input-Environment model [A<sup>+</sup>12], suggests that researchers should consider pre-college factors such as gender, race/ethnicity, family background, high school GPA as important for student retention.

In addition to understanding the factors responsible for student dropout, the researchers were interested in identifying students at risk of not being retained in order to intervene and prevent them from dropping out. Early research included usage of statistical and analytical meth-

ods such as logistic regression and discriminant analysis for predicting student retention rates [LAS<sup>+</sup>15, MDDM16, AC17]. The results from these models showed that the learning algorithms were in fact better than many existing rule based models in learning patterns from the existing student data. Educational data mining has emerged into an important field of research in studying student retention, because of its high accuracy and robustness in working with missing data [AH14]. In another study, Jay Bainbridge, James Melitski, Anne Zahradnik, Eitel J. M. Laura, Sandeep Jayaprakash and Josh Baron used fall 2010 undergraduate students data from four different sources and applied classifiers such as logistic regression, support vector machines and c4.5 decision trees for prediction and comparison purposes [BMZ<sup>+</sup>15]. The results showed that logistic regression and SVM trees provided higher classification accuracies compared to the decision trees to predict students at risk.

Serge Herzog a researcher from University of Nevada, Reno (UNR) campus has done some extensive research on student retention and graduate prediction. He used Decision trees and Neural networks to predict student retention of data from UNR [Her06]. Farshid Marbouti, Heidi A. Diefes-Dux, Krishna Madhavan [MDDM16] have compared seven different prediction models for identifying at-risk students using in-semester performance factors (i.e., grades) and based on standards-based grading. Another similar research focused on the problem of imbalanced output class distribution in the field of student retention in which the researchers tested three balancing techniques such as over-sampling, under-sampling and synthetic minority over-sampling (SMOTE) along with machine learning algorithms.

Although predictive analysis using machine learning models have proved to be very effective in identifying at-risk students, they were still not efficient and useful to educators who wanted to develop academic support programs and resources to support the identified students. The primary reason being the lack of understanding of the metrics from the predictive models by the educators. A few researchers analyzed this issue at the high school level and came up with a framework to convert model accuracies to risk scores that could be used by the educators in the efficient allocation of the resources [LAS<sup>+</sup>15]. Though the above-mentioned framework was giving good results, it was restricted to school level data and thus cannot yield accurate results in the university level as both are very different environments with different set of factors. Hence, in this thesis we try to include such an analysis into college level studies of UNLV and compare our results to the existing approaches.

## 2.2 Preliminaries

### 2.2.1 Machine Learning Concepts

Tom Mitchell defined Machine Learning as [Mit97]:

”A computer is said to learn from experience  $E$  with respect to some class of tasks  $T$  and performance measure  $P$ , if its performance at tasks in  $T$ , as measured by  $P$ , improves with experience  $E$ .”

Example: playing chess.

$E$  = the experience of playing many games of chess with different people

$T$  = the task of playing chess.

$P$  = the probability that the program will win the next game.

In general, machine learning tries to learn patterns inherent in the underlying data and remembers it as experience, which it uses for predictions. It was conceptualized from the notion of learning process adopted by a human brain. Just as the human brain gets better at a specific task by repeated learning and previous experiences, a computer will also learn more patterns hidden in the data based on its previous experiences. Additionally the huge processing power of computers enables them to perform such a learning process in identifying patterns from complex data which can be very difficult for a human to understand.

### 2.2.2 Predictive Analytics

Predictive analytics primarily deals with extracting patterns using machine learning models from existing datasets. the extracted patterns are used to predict future events and behaviors in previously unseen data. Predictive analytics is being used in wide range of fields such as education, finance, automobile, and healthcare. The analytics is performed by running different machine learning algorithms on previously collected data. The algorithms try to learn patterns between different properties of the data and preserve the knowledge in model parameters. The resulting model is able to predict the unknown property of a future unseen data.

An illustrative example is shown in Table 2.1 which shows student data captured during admissions at a university. The aim is to predict if the student will be accepted or not by looking at the



Table 2.1: Admissions data at a University

Age	Gender	HSGPA	ACT	Accepted
20	Male	3.89	25.6	1
21	Female	3.20	22.6	1
20	Female	2.50	18.3	0
22	Male	3.10	19.2	0
19	Female	3.60	23.5	1

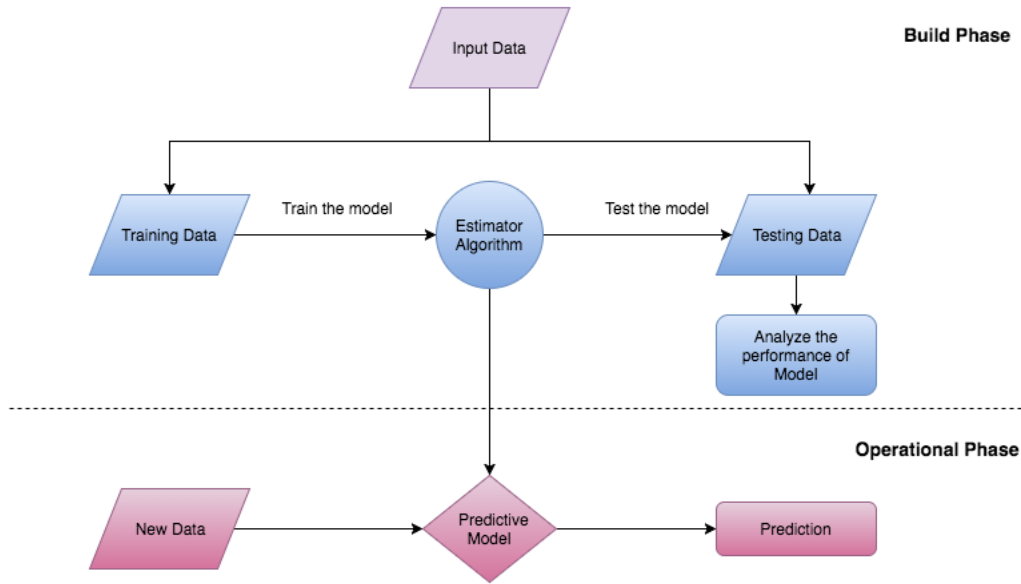


Figure 2.1: Machine Learning Approach

other variables in the data. The column "Accepted" is said to be a dependent variable, and all the other variables are called independent variables. A "1" in the "Accepted" column represents the outcome of the student being accepted into the university and a "0" means he was rejected. To this data we apply a machine learning algorithm, that will learn a prediction model based on the relations between the input independent variables and the output dependent variable. The learned model is then able to predict the output variable by taking other variables as input.

The general approach for applying predictive analysis on a data can be divided into 2 phases as shown in figure 2.1. Build phase deals with the process of creating a prediction model and testing its performance. The process of creating the prediction model is known as training and the data used is known as training data. To test the effectiveness of the created model, it is tested on another set of previously unseen data known as testing data. We use two different data sets to

check the generalization capacity of the model in predicting previously unseen data. If we use all the available data for training, the model may learn too much from the inputs giving rise to the problem of overfitting. Overfitting occurs when a model is performing well on its training data, but not on the other unseen data. A common approach to handle the problem of overfitting is to divide the input data into training and testing sets. The model is then evaluated for performance using test data. The evaluated model is used in the operational phase to perform predictions given a new data. The metrics used to evaluate a model are explained in detail in coming chapters.

### 2.2.3 Selected Models

Based on the way machine learning algorithms "learn" patterns from data, they can be classified into two groups: supervised and unsupervised learning. In supervised learning, we train the machine learning model using data whose possible outcomes are already known whereas, Unsupervised learning is the training of machine learning models using information that is neither classified nor labeled and allowing the algorithm to learn by itself. In our case, since we have data about students along with the labels of the outcome variable, we will do supervised learning. In this section we discuss various models that were used in this thesis to analyze the student data from UNLV. The models selected for comparison were Logistic Regression, Decision Trees, Random Forest, and SVM's.

#### 2.2.3.1 Logistic Regression Model

Logistic Regression is a supervised machine learning classification algorithm that is used to predict the probability of a categorical dependent variable. In logistic regression, the dependent variable is a binary variable that contains data coded as 1 (yes, success, etc.) or 0 (no, failure, etc.). It is a variation of linear regression, where a model is constructed in supervision of the available data to calculate the unknown outcome variable. In linear regression input values (x) are combined linearly using weights or coefficient values to predict an output value (y), whereas logistic regression calculates the probability of getting the outcome dependent variable (y). The general equation for this learning approach with one independent variable and a dependent output variable 'y' is as shown in the Equation2.1

$$P(y = 1) = g(\beta_0 + \beta_1 * x) \quad (2.1)$$

where the coefficient ' $\beta_0$ ' is the bias and ' $\beta_1$ ' is the coefficient for the single input value (x) which are learned from the available input data during training and 'g' is a mathematical function known

as Sigmoid function, that maps the linear combination of inputs into the range of  $[0,1]$ , thus giving us probabilities and is defined as shown in the Equation 2.2. For the case of multiple independent input variables, the input values ( $x$ ) are represented as a vector  $X$  along with equal number of coefficients to be learned.

$$g(z) = \frac{1}{1 + e^{-z}} \quad (2.2)$$

As an illustrative example, consider the problem of identifying if a student will pass an exam based on the number of hours he studies before the exam. In this case, we can define the input independent variable as the `number_of_hours_studied` which takes a numerical value and the output variable as `Student_Passed` which takes values 0 or 1. Hence our logistic regression problem then represents the probability of the student passing an exam given the number of hours he studied before the exam. A rule of thumb in logistic regression is if the probability is  $> 0.5$  then the decision is true. Hence you end up with a model that finds the probability of a student passing the exam as shown in Equation 2.3

$$P(y = 1) = P(\text{Student\_Passed} = \text{True}) = 0.82 * (\text{number\_of\_hours\_studied}) - 0.32. \quad (2.3)$$

### 2.2.3.2 Decision Trees

A decision tree is a supervised machine learning algorithm which is mostly useful for classification problems and works for both continuous and categorical input and output variables. In simple terms, a decision tree uses the tree representation to solve the problem, in which each branch represents a choice between a number of alternatives of an attribute in the internal nodes leading to a final decision in the leaf node. Decision trees where the output variable is categorical are known as Classification trees.

The general approach of constructing a decision tree from the training data involves splitting the entire data at the root node into a subset based on a requirement (generally, a decision on an attribute). The process of splitting based on decisions of different internal node attributes continues until a subset at a node has all the same value of the target variable, or when splitting no longer adds value to the predictions. The main goal of decision trees is to find the best split of each node of the tree. But measuring the "goodness" of a given split is a subjective question so, in practice, different metrics are used for evaluating splits. Two main metrics used to evaluate the splits are :

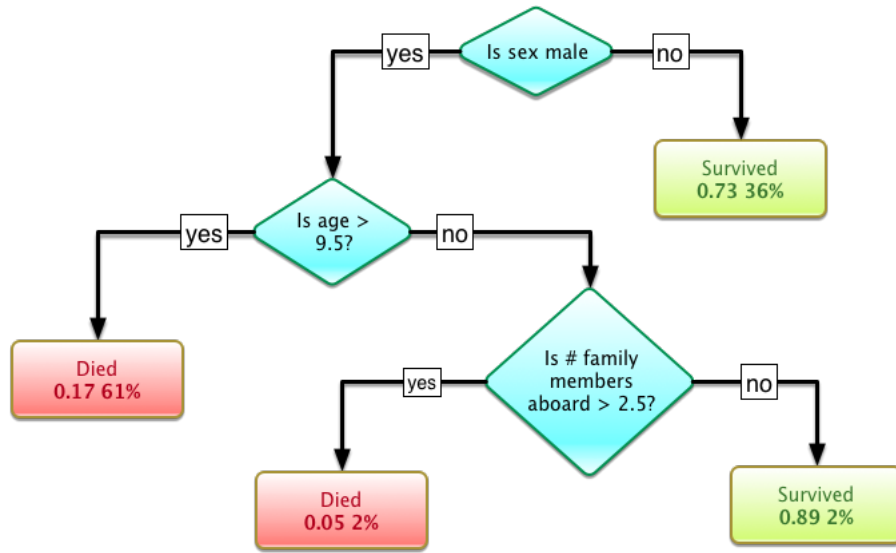


Figure 2.2: Classification tree of passenger survival in Titanic

**Gini impurity** : It is a measure of how often a randomly chosen element from the set would be incorrectly labeled if it was randomly labeled according to the distribution of labels in the subset. It reaches its minimum (zero) when all cases in the node fall into a single target category.

**Information gain** : For each node of the tree, the information gain value represents the expected amount of information that would be needed to specify whether a new instance should be classified yes or no, given that the example reached that node. The node with highest information gain value yields the best split.

For illustration purpose, consider the classification tree showing survival of passengers on the Titanic ship when it sank in Figure 2.2. The figures under the leaf nodes show the probability of survival and the percentage of observations in the leaf. The tree was constructed using gini impurity as the goodness evaluation metric. From the tree we can make the following inferences:

1. If the passenger is a male and has an age greater than 9.5 then he did not survive the titanic sink.
2. All the female passengers had a survival probability of 0.73.
3. If the passenger was male, had an age less than 9.5 and had lesser than 2.5 family members aboard survived the sink with a probability of 0.89.

### 2.2.3.3 Random Forest Classifiers

Random forest classifier is another supervised machine learning algorithm that can be used for both classification and regression problems. It is generally classified into a special type of machine learning method known as an Ensemble method in which a combination of weak classifiers is used to form a strong classifier which can be used to perform better predictive analysis. In case of the random forests, decision trees are the weak learners. Although decision trees perform really well on some datasets, they are generally called weak learners as they tend to have high variance when they are trained on different subsections of the same data. Here, variance refers to the spread of the predictions and occurs when a model is sensitive to small changes in the training data which is the case of overfitting. This happens due to the greedy approach employed by decision tree algorithm along with information gain or gini index metrics, to learn rules from the training data.

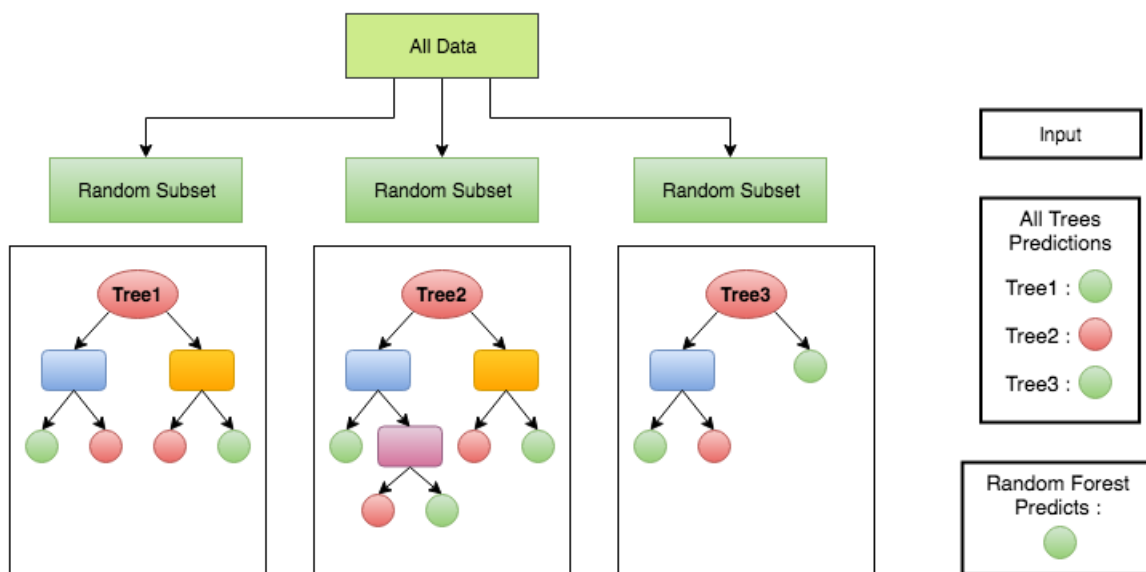


Figure 2.3: Random forest trees

Random forests on the other hand create a number of decision trees during training by using different subsections of the training data. Moreover the process of finding the root node and splitting the feature nodes occurs randomly in random forests. Once we have a forest of trees, decisions from different trees are combined to make a final decision regarding the data. This way the random forests will generalize the predictions better as the combination of decisions will not be sensitive to the trained data. The more the number of trees in the random forest the better

generalized are the predictions.

The figure 2.3 explains the construction of random forests from the available input data. The initial training data is split into random subsets using which individual decision trees are constructed.

#### **2.2.3.4 Support Vector Machines**

#### **2.2.4 Evaluation Methods**

# Chapter 3

## Methodology

### 3.1 Data Collection

The Operations Support and Reporting Office at UNLV is responsible for extracting information regarding student enrollment and performance from the UNLV Data Warehouse and reporting the census to Integrated Postsecondary Education Data System (IPEDS). The data used in this thesis were obtained from the census data submitted to IPEDS every year. The following subsections will describe more information about the data.

### 3.2 Data Preparation

#### 3.2.1 Data Description

The census data from the Operations Support and Reporting Office was exported into a csv file to be used by the analysis. The raw data consisted of a total of 17,708 freshmen student records captured cohort-wise from the academic year 2012 to 2016. The data consisted of a variety of information about each student, such as pre-college academics, standardized test scores, the social and economic status of the student, freshmen year academics and finally if the student was retained in the sophomore year. On the whole, a total of 41 attributes were captured for each student. Table 3.1 describes the variables and their types. The following subsections describe in detail about the dataset.

Table 3.1: Description of data fields for first-year student data

No.	Feature	Type	Description
1	Cohort_Year	Multi Nominal	First Fall Academic year of the student
2	SummerAdmit	Binary Nominal	If Student was admitted in prior summer
3	AltAdmit	Binary Nominal	If Student was Transferred or admitted differently
4	F1_EnrollCredits	Numerical	Count of semester credits enrolled for admit term
5	F1_MidtermGPA	Numerical	F1 mid-term GPA
6	F1_GPA	Numerical	Term GPA for first fall term (admit term)
7	F1_Math_Type	Multi Nominal	Type of Math Course Taken in F1 term
8	F1_MathGradePass	Binary Nominal	F1 Math Grade Passed or Failed
9	F1_GPA_units	Numerical	Units completed in first fall (for GPA)
10	F1_Complete	Binary Nominal	Completed first fall term (final census)
11	S1_Retain	Binary Nominal	Enrolled in 1st spring (S1) - yes or no
12	S1_EnrollCredits	Numerical	Count of semester credits enrolled for S1 term
13	S1_GPA_units	Numerical	Units completed in S1 (for GPA)
14	S1_MathTaken	Binary Nominal	If Math taken in S1 term
15	S1_GPA	Numerical	Term GPA for S1 term
16	S1_Complete	Binary Nominal	If student completed S1 term
17	Yr1_MathTakenOverall	Multi Nominal	Type of Math taken in First year
18	Mom_Edu_Level	Multi Nominal	Highest education level of Mother
19	Dad_Edu_Level	Multi Nominal	Highest education level of Father
20	First_Gen	Binary Nominal	If the kid is the first to attend college
21	Gender	Binary Nominal	Student Gender
22	Housing	Multi Nominal	on or off-campus housing
23	IPEDS_Race	Multi Nominal	IPEDS race/ethnicity data
24	Marital_Status	Multi Nominal	Marital status of the student in admit term
25	CoreHSGPA	Multi Nominal	Core high school GPA of the student
26	UnwHSGPA	Multi Nominal	Unweighted high school GPA of the student
27	SAT_ACT_Score	Numerical	ACT scores scaled to SAT scores
28	ACT_SAT	Binary Nominal	If the student has taken ACT or SAT

*Continued on next page*



Table 3.1 – *Continued from previous page*

No.	Feature	Type	Description
29	F1_Residency	Binary Nominal	In state or Out of State in F1 term
30	F1_TuitionRes	Multi Nominal	Tuition status of the student in F1 term
31	F1_MillScholar	Binary Nominal	1st fall Millennium Scholarship recipient
32	WUE	Binary Nominal	Western Undergrad Exchange student
33	Age_Admit_Pcensus	Numerical	Age at time of preliminary census of first fall term
34	College1	Multi Nominal	First fall college
35	FA_INFO_REC'D	Binary Nominal	FAFSA info recorded
36	PELL_Eligibility	Binary Nominal	If student is eligible for PELL grant
37	PELL_DISB_AMT	Numerical	PELL Grant Disbursed amount
38	MILL_DISB_AMT	Numerical	Millennium Scholarship disbursed amount
39	Other_SCHOL_AMT	Numerical	Other Scholarships disbursed amount
40	LOAN_DISB_AMT	Numerical	Student Loan disbursed amount
41	F2_Retained	Binary Nominal	If the student was retained in Fall 2 term( F2)

### 3.2.2 Feature Extraction

Feature extraction involves creating important useful features from the available raw data. Based on the problem statement and the data collection techniques at UNLV. The raw data was used to generate the following important features.

#### 3.2.2.1 Computation of SAT\_ACT\_Score Variable

The admissions office at UNLV requires the students to report scores of standardized exams such as ACT and SAT during their admission process. From the raw dataset, we noticed that the ACT and SAT scores were missing for many students. Especially 56% of students did not have ACT scores while only 28% did not have SAT scores. Hence to capture the importance of the standardized scores into our analysis, we converted the available ACT composite scores to equivalent SAT composite scores based on the conversion table from [Hal]. The term SAT\_ACT\_Score was used to refer to this converted scores variable.

### **3.2.2.2 Computation of F2\_Not\_Retained Variable**

The main focus of this thesis is to identify the students who are at the risk of not being retained after their freshmen year. In the raw dataset the flag F2\_Retain captures the aspect of student being retained and hence can serve as the outcome variable. We then compute the complement of this flag to obtain the feature F2\_Not\_Retained which takes 0 if the student was retained and 1 if the student was not retained. The problem of identifying students who are at the risk of not being retained after first year is then a binary classification task with F2\_Not\_Retained as the outcome variable.

## **3.3 Data Preprocessing**

Data Preprocessing is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis. Therefore, certain steps are executed to convert the data into a tiny clean dataset. This technique is performed before the execution of any predictive Analysis.

### **3.3.1 Handling Outliers in Data**

Generally the process of collecting data from different sources can introduce outliers into the dataset. This may be due to a faulty data extraction program or a human error. In predictive data analysis outliers can have significant effect on the predictive power of the models as they can introduce huge bias into the model. Hence it is almost always essential to check for outliers in the dataset before performing any analysis. Outliers were identified in our dataset. Data plots with index on x-axis and values on y-axis was used to demonstrate the presence of outlier in a feature.

#### **3.3.1.1 UnwHSGPA scores**

There were a few outliers identified for variable UnwHSGPA, as shown in figure 3.1a. The outliers of the UnwHSGPA were replaced by mean value of the said dataset excluding all the outliers. Data plot of the variable UnwHSGPA after removing outliers is shown in figure 3.1b

### **3.3.2 Handling Missing Values**

In this subsection, we will discuss how we handled missing values in the dataset. The table 3.2 shows variables along with the count of missing values. Machine learning deals with the usage of

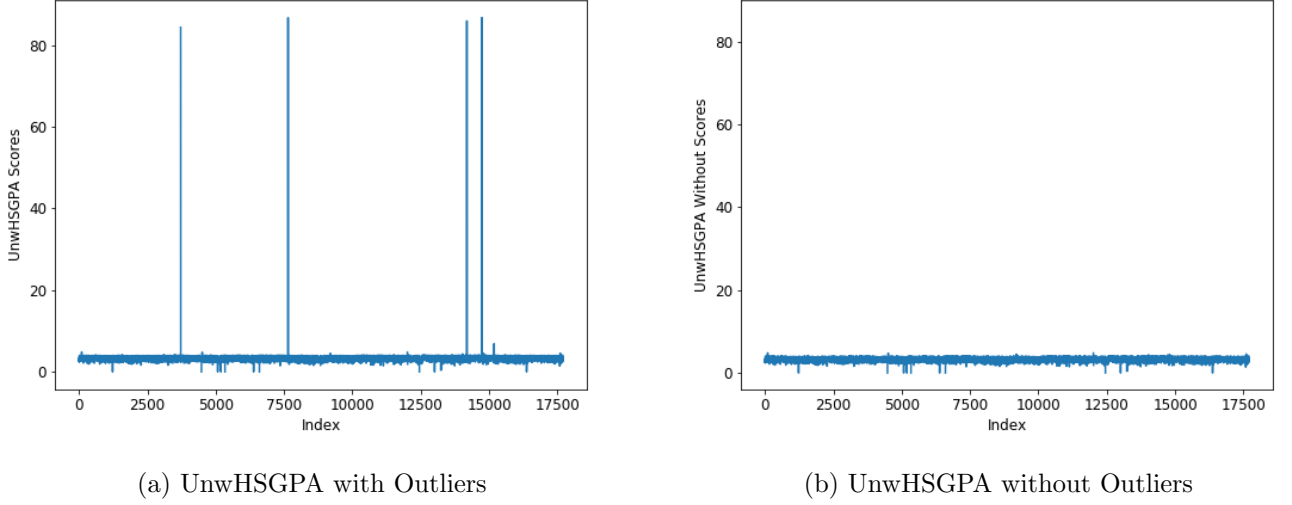


Figure 3.1: Removing Outliers from UnwHSGPA

Table 3.2: Variables with missing values and their count

Variable	Number of missing values
SAT_ACT_Score	830
UnwHSGPA	1933
CoreHSGPA	3463
F1_MidtermGPA	286
F1_MathGradePass	4989

mathematical models on the data and hence it cannot be applied to datasets that have missing values. The general approach is to fill the missing value with a suitable value. The process of filling missing values in the data is known as Imputation. Researchers frequently use the mean, mode or median of the observed given values to substitute in the missing field.

### 3.3.2.1 Imputing SAT\_ACT\_Score

The SAT\_ACT\_Score variable had 830 missing values. By looking at the table, it can be inferred that presence of missing values in SAT\_ACT\_Score variable had very little impact on the percentage of students not being retained. A total of 24.1% students were not retained when a value was present in the variable and 25.6% were not retained when the variable had a missing value.

Moreover, the boxplot of the SAT\_ACT\_Score vs F2\_NotRetained (Figure 3.2) also shows that SAT\_ACT\_Score has very low impact on the student dropout. Based on the above facts, the missing

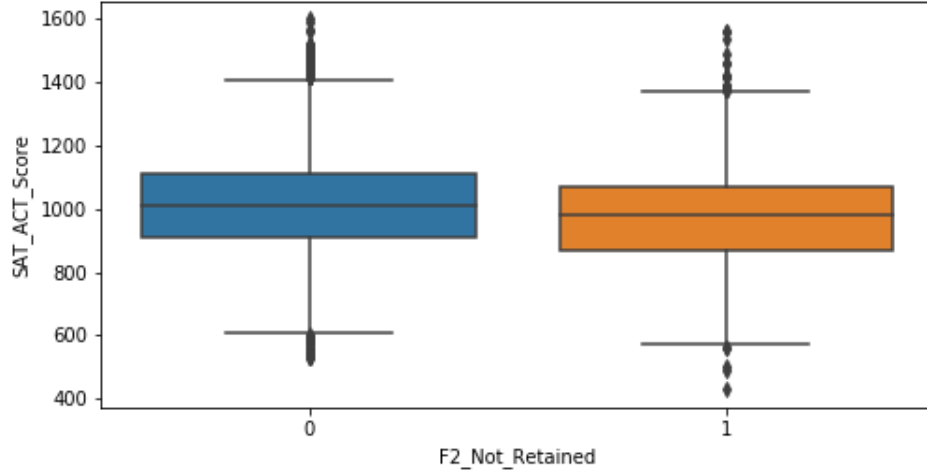


Figure 3.2: Boxplot of the SAT\_ACT\_Score vs F2\_NotRetained

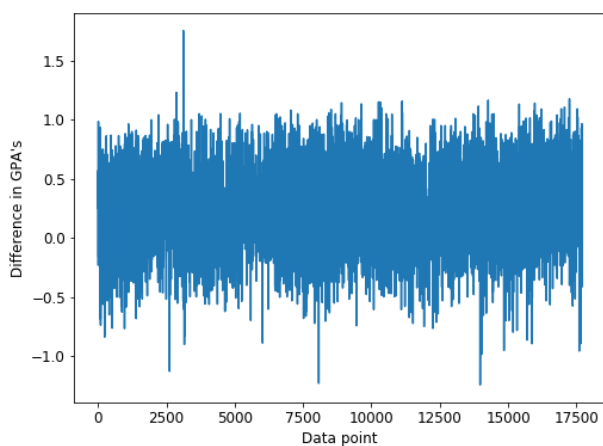
values in this variable were replaced by the mean value.

### 3.3.2.2 Imputing CoreHSGPA and UnwHSGPA

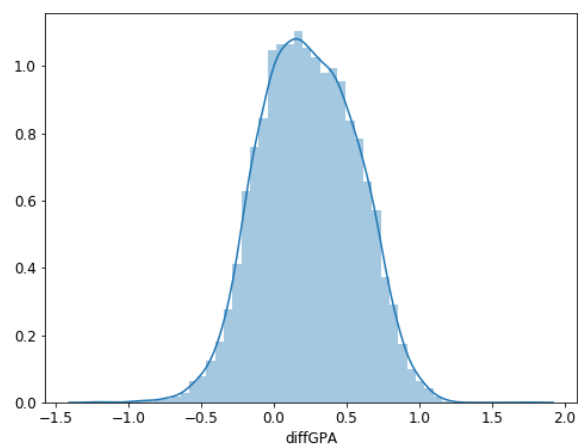
The CoreHSGPA variable had 3463 missing values, whereas the UnwHSGPA had 1943 missing values. Before imputing, we tried to analyze the relation between both the variables (Figure 3.3). For this we calculated the difference between CoreHSGPA and UnwHSGPA of available records and plotted them as shown in figure 3.3a. We can clearly observe that majority of the differences were lying in the range of  $[-1,1]$ , which indicates that the two variables had very close relation. Similar pattern was revealed from the distribution plot of the variable differences as shown in figure( 3.3b), which revealed that the differences followed a gaussian distribution with a mean of 0.23. Based on the above facts, we replaced the missing values with the available variable scores. The remaining missing values were replaced by the mean value of the respective variable.

### 3.3.2.3 Imputing F1\_MidtermGPA

The F1\_MidtermGPA variable had 286 missing values which adds up to a very small percentage in the overall data. We analyzed the distribution plot of F1\_MidtermGPA (figure 3.4) and noticed that it also follows a gaussian distribution with mean value of 2.5272 and a standard deviation of 0.851. Considering the above information we imputed the missing value of the variable with its mean as it would not shift the centrality of the variable.



(a) Difference between CoreHSGPA and UnwHSGPA



(b) Distribution

Figure 3.3: Analyzing difference between CoreHSGPA and UnwHSGPA

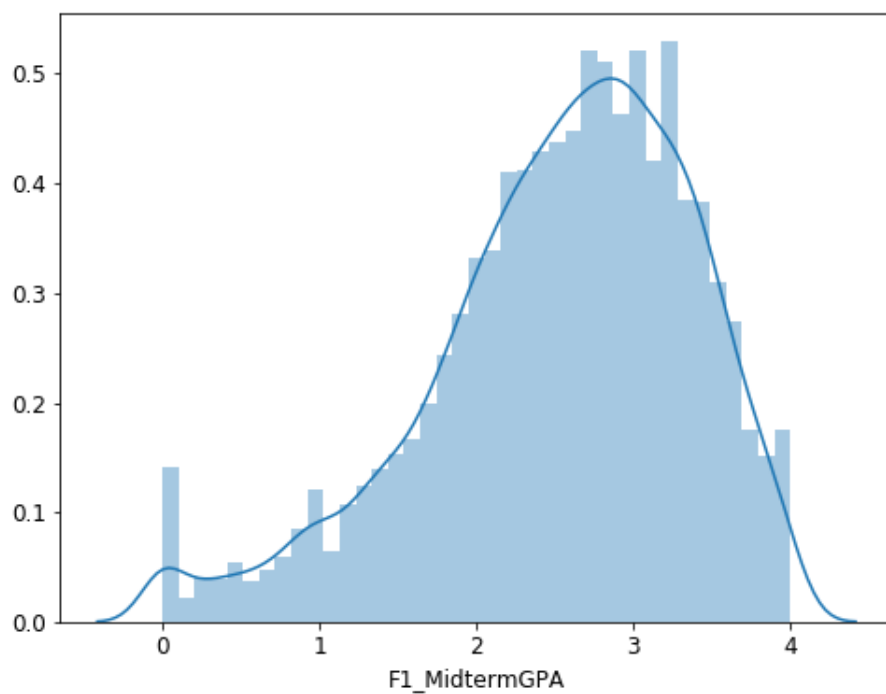


Figure 3.4: Distribution plot of the F1\_MidtermGPA

#### **3.3.2.4 Imputing F1\_MathGradePass**

F1\_MathGradePass is a categorical variable with values 'Y' or 'N', where a 'Y' represents if a student got a passing grade in math taken during his first fall term and 'N' if he got a failing grade. It had a total of 4989 missing values in the variable. Such a large number of missing values for this variable is attributed to the fact that a student who did not take any math course will not have a value in this variable. Hence the missing value was replaced with a 'N'.

#### **3.3.3 Data Transformations**

Now that we have a cleaned dataset, we need to apply transformations on the data before they can be inputted to a machine learning algorithm. This step is essential as our dataset has a lot of categorical variables which need to be converted to numerical values before we perform any further analysis.

The general approach is to encode the categories with numerical values. One-hot encoding is a popular encoding technique used in machine learning in which a categorical variable is converted into a binary vector, where each possible value of the categorical variable is assigned to a dummy variable with a default value of '0' and the dummy variable which was the value of the categorical variable will have the value '1'. In simple terms, applying one-hot encoding to a categorical variable results in an one-hot vector, where only one element is non-zero, or hot. There were a total of 23 categorical variables in our raw dataset which were one-hot encoded to yield a total of 85 variables. We noticed that applying transformations on our raw data resulted in a huge increase in the number of variables available for analysis. Having more number of variables can result in poor performance of the model, as there might be some variables that are redundant and irrelevant to our prediction problem. To handle such scenarios, feature selection is useful as it automates the process of selecting features that are important to the prediction model. The next subsection describes in detail about the feature selection process used in this thesis.

#### **3.3.4 Feature Selection**

Feature selection is the process of identifying and selecting features from our raw data that contribute most to the prediction of our output variable. Feature selection methods are useful to identify and remove unneeded, irrelevant and redundant attributes from data that do not contribute to the accuracy of a predictive model. There are various feature selection methods available

Table 3.3: Tests based on type of input and output variables

		Response Type	
		Quantitative	Categorical
Feature type	Quantitative	Correlation	Chi-Square Test
	Categorical	ANOVA	Chi-Square Test

in machine learning that can be applied to the available dataset. One key factor to consider before using a particular method is to have an idea of the models you are going to use on your data.

One of the feature selection approaches deals with the idea of identifying the relationship of features with the output variable to decide their importances. To find such relationships, we need to identify the data type of features and the output variable. The table 3.3 shows the types of tests used based on input feature types and output response types. The tests are as follows:

**Correlation** : In general, we use the Pearson correlation coefficient to measure the strength of a linear association between two numerical variables. The higher the magnitude of the correlation coefficient, the greater is the variables influence on predicting output variable.

**ANOVA** : ANOVA refers to "Analysis of Variance" which is a collection of statistical models and their associated procedures (such as "variation" among and between groups) used to analyze the differences among group means.

**Chi-Square** : A chi-square test, also written as  $\chi^2$  test is used to determine whether there is a significant difference between the expected frequencies and the observed frequencies in one or more categories.

In our dataset, the response variable is a categorical with categories {'Y', 'N'} and input features are both categorical and quantitative. Hence an appropriate choice of test to find relationships between the input features and output response is to use the Chi-square test. In machine learning the process of using such statistical tests on the dataset is known as Univariate selection. Hence univariate selection using Chi-Square test was applied on the transformed dataset to yield 51 important features as opposed to the 85 features obtained after data transformation.

### 3.4 Exploratory Data Analysis

Exploratory data analysis (EDA) is an approach employed to analyze data sets and summarize their main characteristics, often with visual methods, without making any assumptions about its contents. It is an important step to take before diving into statistical modeling or predictive analysis

because it provides the important information and context needed to develop an appropriate model for the problem. In this section we try to uncover some important patterns inherent in our data with appropriate plots.

### 3.4.1 Academic year Vs F2\_Not\_Retained

As a first step, the proportion of students retained and not retained in an academic year was plotted in the figure 3.5, to understand the distribution of students dropping out at the end of each year. Each cohort includes data about students who were in their F1 semester in that specific year. From the plot, we can infer that the number of students who drop out after their first-year varies very slightly for each year. More importantly, we see a pattern of increasing student dropout proportion rates as opposed to an expected decrease due to efforts made by educators to improve student retention over the years.

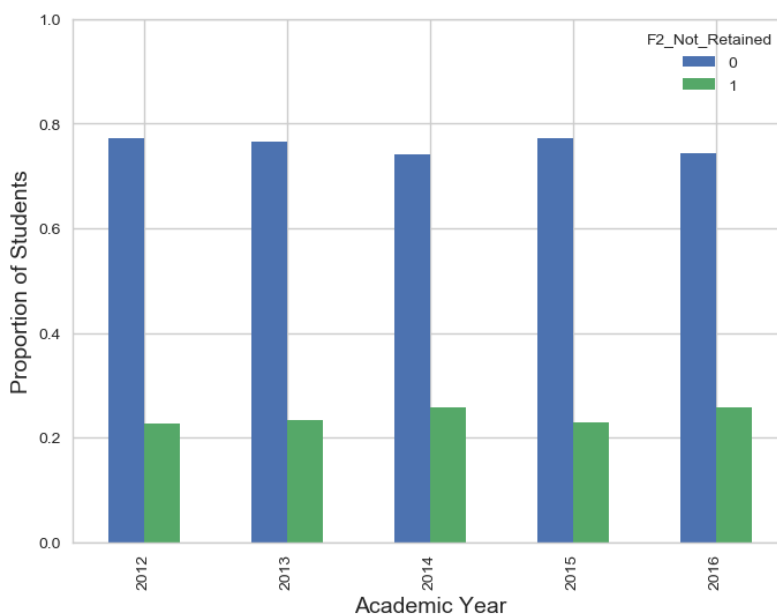


Figure 3.5: Academic Year vs F2\_NotRetained

### 3.4.2 IPEDS Race Vs F2\_Not\_Retained

In this section, we tried to analyze the patterns observed by different categories of the IPEDS Race with respect to student retention. For this, we first plotted the different IPEDS Race categories on x-axis and the count of students belonging to that particular race on y-axis as shown in figure 3.6. We observed that the student population of different races was very different at UNLV with higher



populations belonging to Asian, Hispanic and White races.

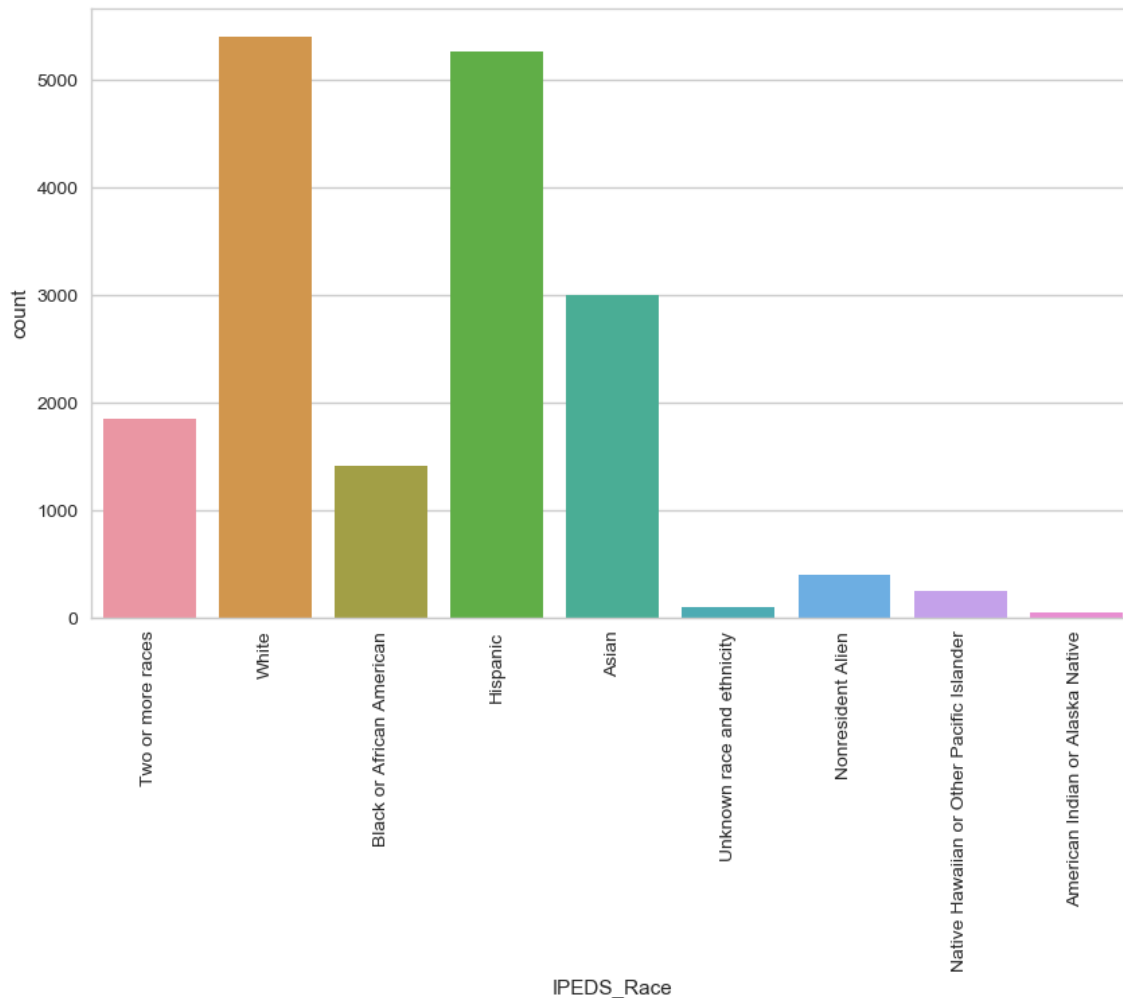


Figure 3.6: IPEDS Race vs F2\_NotRetained

Although fig 3.6 gives us a good idea about the type of students at UNLV, it is not sufficient to help us understand the retention patterns among the different categories. For this, we calculated the retention rates of each race category and tabulated them in table 3.4. Considering the student distributions in each race category and their retention rates from table, we conclude that the Asian race category had the highest student retention followed by Hispanic and White categories. On the whole we observe that the student's race is useful in predicting if he/she will be retained after the first year.

Table 3.4: Retention Rates of each IPEDS Race Category

IPEDS Race	F2_Retained	F2_Not_Retained
Asian	85.75%	14.25%
American Indian or Alaska Native	53.48%	46.51%
Black or African American	66.83%	33.17%
Hispanic	74.34%	25.66%
Native Hawaiian or Other Pacific Islander	68.65%	31.35%
Nonresident Alien	86.14%	13.86%
Two or more races	74.23%	25.76%
Unknown race and ethnicity	75.26 %	24.74%
White	74.38%	25.61%

### 3.4.3 Mom\_Education\_Level Vs F2\_Not\_Retained

In this section, we tried to analyze the patterns observed by different categories of the Mom's Education Level with respect to student retention. For this, we plotted the different categories of Mom\_Education\_Level variable on x-axis and the count of students whose Mom's education level belonged to that category on y-axis as shown in figure 3.7. We observed that the level of Mom's education of students at UNLV was highly distributed. It especially gives us the information that most of the student's Mom's had a minimum education of High School or more. However this does not explain much about the effect of Mom's education level on student's retention.

To get a better understanding of the effect of Mom's Education on students retention, we calculated the retention rates of students from each category of the variable and tabulated them in table 3.5. Considering the student distributions in each category and the retention rates of the variable from table, we notice many expected patterns such as more students were retained if their Mom had an Education level higher than bachelor's. But strangely we also noticed that the retention rate of students with their Mom's education level as Less than HS Graduate was also good at UNLV. This gives us a hint of the variability of patterns inherent in the students data from UNLV.

### 3.4.4 Dad\_Education\_Level Vs F2\_Not\_Retained

In this section, we tried to analyze the patterns observed by different categories of the Dad's Education Level with respect to student retention. For this, we plotted the different categories of

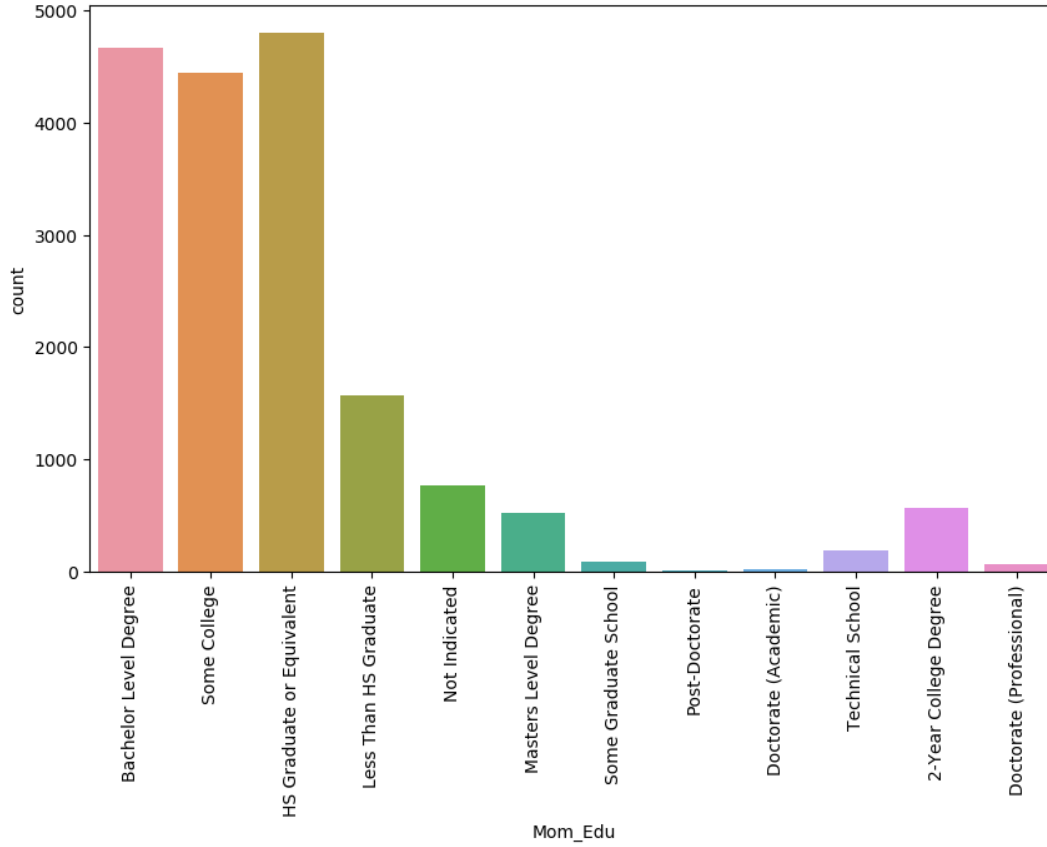


Figure 3.7: Count plot of Mom's Education Level

Table 3.5: Retention Rates w.r.t Mom's Education Level's

Mom's Education Level	F2_Retained	F2_Not_Retained
Post-Doctorate	100.00%	00.00%
Doctorate (Professional)	84.37%	15.62%
Doctorate (Academic)	77.78%	22.22%
Masters Level Degree	76.14%	23.86%
Bachelor Level Degree	78.76%	21.24%
Some College	74.76%	25.24%
Some Graduate School	78.82%	21.17%
2-Year College Degree	74.82%	25.18%
HS Graduate or Equivalent	74.20%	25.79%
Less Than HS Graduate	74.52%	25.47%
Technical School	69.64%	30.36%
Not Indicated	77.46%	22.53%

Dad\_Education\_Level variable on x-axis and the count of students belonging to that category on y-axis as shown in figure 3.8. We observed that the level of Dad's education of students at UNLV was highly distributed. It especially gives us the information that most of the student's Dad's had a minimum education of High School or more.

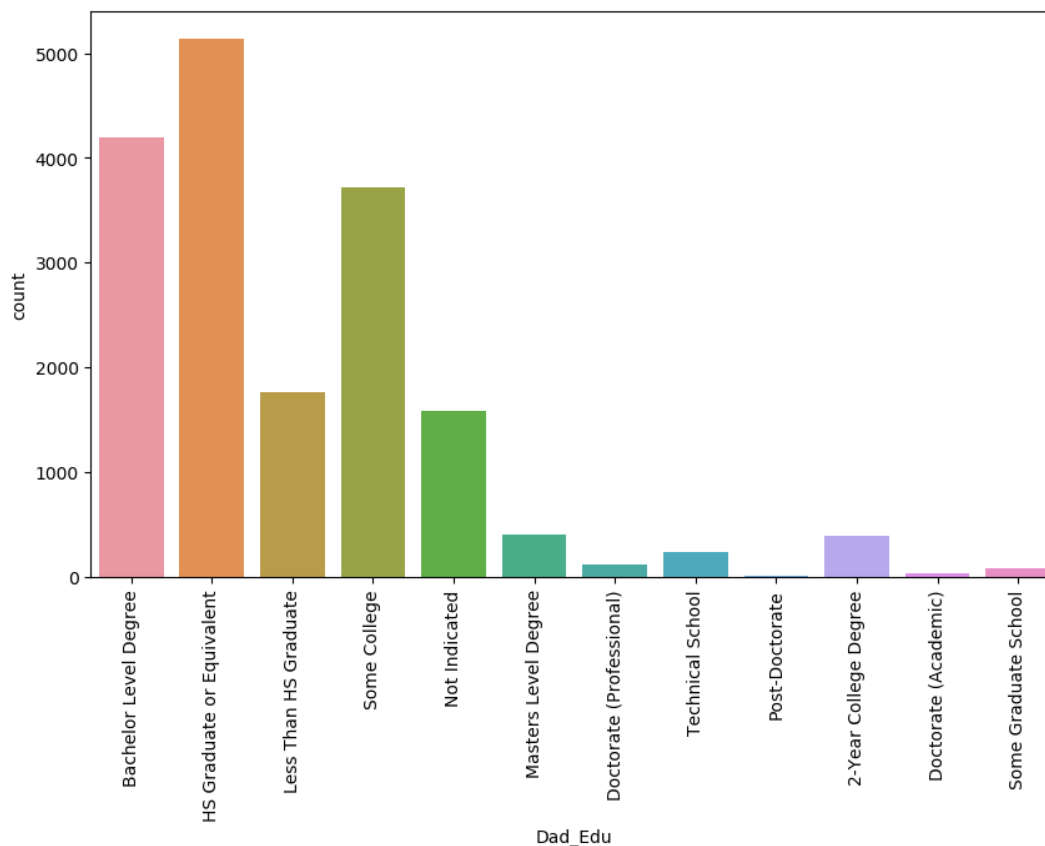


Figure 3.8: Count plot of Dad's Education Level

To get a better understanding of the effect of Dad's Education on students retention, we calculated the retention rates of students from each category of the variable and tabulated them in table 3.6. Considering the student distributions in each category and the retention rates of the variable from table, we notice many expected patterns such as more students were retained if their Dad had an Education level higher than bachelors'. But strangely we also noticed that the retention rate of students with their Dad's education level as Less than HS Graduate was also good at UNLV. This gives us a hint of the variability of patterns inherent in the students data from UNLV.

Table 3.6: Retention Rates w.r.t. Dad's Education Level's

<b>Dad's Education Level</b>	<b>F2_Retained</b>	<b>F2_Not_Retained</b>
Post-Doctorate	86.66%	13.34%
Doctorate (Professional)	77.86%	22.14%
Doctorate (Academic)	86.84%	13.16%
Masters Level Degree	75.80%	24.20%
Bachelor Level Degree	80.34%	19.66%
Some College	76.30%	23.70%
Some Graduate School	76.62%	23.38%
2-Year College Degree	81.15%	19.75%
HS Graduate or Equivalent	73.36%	26.64%
Less Than HS Graduate	73.86%	26.14%
Technical School	69.50%	30.50%
Not Indicated	71.78%	28.22%

### 3.4.5 College1 Vs F2\_Not\_Retained

In this section, we tried to analyze the patterns observed by different categories of the student's college in his F1 term with respect to student retention. For this, we plotted the different categories of College1 variable on x-axis and the count of students belonging to that category on y-axis as shown in figure 3.9. We observed that the count of students belonging to a college was quite distributed with more students from College of Sciences followed by Lee Business school.

To get a better understanding of the effect of student's college on retention, we calculated the retention rates of students from each college and tabulated them in table 3.7. Considering the student distributions in each college and the retention rates of the variable from table, we notice patterns such as more students were retained in College of Sciences and College of Engineering which had higher student counts. Eventhough other colleges had lesser student populations, their student retention rates were similar and around an average of 75% . This gives us a hint of the variability of patterns inherent in the students data from UNLV.

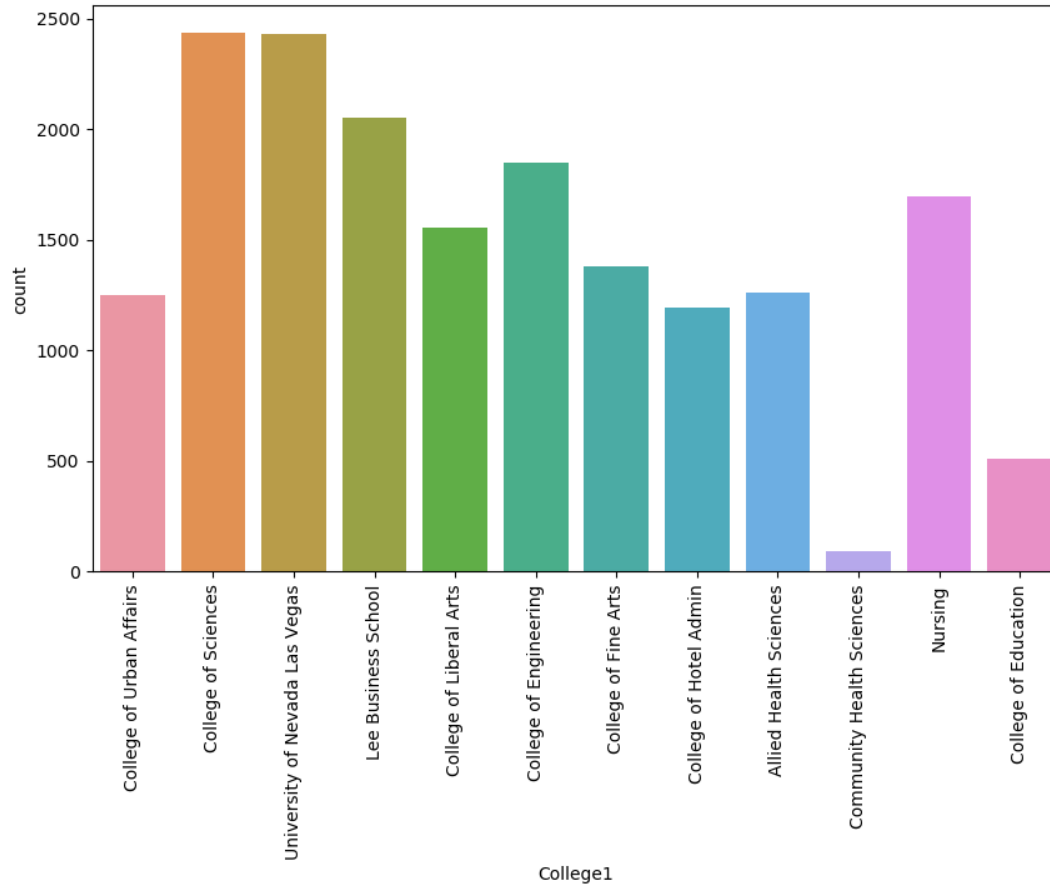


Figure 3.9: Count plot of College1 variable

Table 3.7: Retention Rates w.r.t. student's College

College1	F2_Retained	F2_Not_Retained
College of Hotel Admin	80.98%	19.02%
College of Sciences	78.62%	21.38%
College of Engineering	77.63%	23.37%
College of Education	77.73%	23.27%
College of Fine Arts	76.61%	23.39%
College of Liberal Arts	76.06%	23.94%
Lee Business School	75.31%	24.69%
Nursing	75.14%	24.86%
Allied Health Sciences	73.53%	26.57%
University of Nevada Las Vegas	73.07%	26.93%
College of Urban Affairs	70.97%	29.03%
Community Health Sciences	64.51%	35.59%

## Chapter 4

# Experimental Results

### 4.1 Analysis of Predictive Models

#### 4.1.1 Evaluation using Traditional Metrics

## Chapter 5

## Conclusion



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# Curriculum Vitae

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