Predicting Student Performance in a Portuguese Secondary Institution

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Abstract

Qualitative and quantitative factors alike affect student grades. We observed 1,044 students collectively from three terms of math and language arts classes of a Portuguese secondary institution to determine which of these factors is directly influenced by performance. Student grades were tallied over the three terms, from which performance was bisected by the median and binarized into two classes of 0 and 1 (“bad”, “good”, respectively). The dataset was further subjected to an 80:20 train-test split ratio to evaluate the model performance of data outside the training set visa vie implementation of six algorithms. The C5.0 and CART models produced accuracy scores of approximately 63%; whereas logistic regression and random forest models performed approximately 1% lower in terms of accuracy. Implementation of Naïve Bayes classification in conjunction with the neural network model yielded more accurate results of 65% and 69%, respectively. We discuss other metrics like error rate and precision, and note that each model, when cross-validated, has its own limitations that may inhibit or facilitate the prediction of student performance holistically.

Keywords: student performance, machine learning, ensemble methods, data mining

Table of Contents

Predicting Student Performance in a Portuguese Secondary Institution

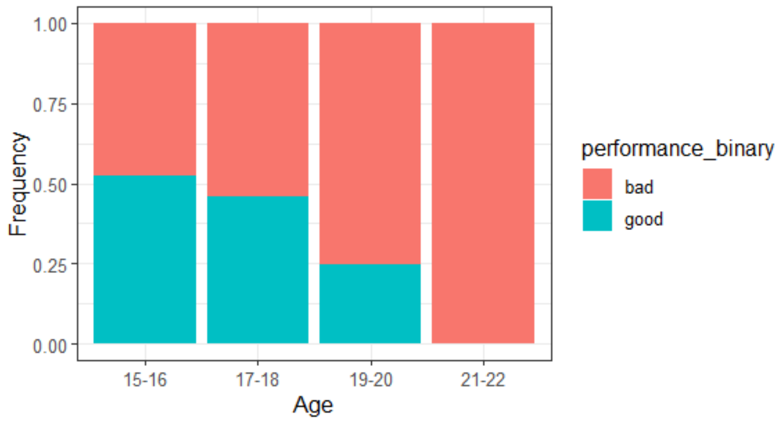
Predicting student performance closes the gap between socio-economic status and other external factors in one secondary educational institution, setting a precedent via proxy model for others to follow suit. The 2018 Program for International Student Assessment (PISA) found that "socio-economic status was a strong predictor of performance in reading, mathematics and science in Portugal. In Portugal, advantaged students outperformed disadvantaged students in reading by 95 score points in PISA 2018" (The Organisation for Economic Co-operation and Development [OECD], 2018). We aim to set a precedent for repeatability, allowing for subsequent iterations of our modeling techniques.

Methodology

Our goal was to measure the impact of socio-economic factors on student performance from which we would select a viable predictive model. We sourced our publicly available dataset from the UCI Machine Learning Repository (Dua, 2019) as two separate .csv files representing Math and Portuguese courses from schools of secondary education. We merged the two groups into one master "student_file.csv" file in R (R Core Team, 2020), ensuring that the dataset had no missing values; this provided us a total of 1,044 rows and 33 columns of observations. Rather than sampling the data, we chose the entire population for our ensuing exploratory data analysis, thereby allowing us to pre-emptively eliminate selection bias. Our preliminary review consisted of evaluating absences from school by age, relying on attendance to provide an initial read on overall student performance. Though we identified 480 outliers in absences, we persisted in building an inclusive model of performance; decidedly, school attendance was not a reliable target for performance. On the other hand, the following descriptive statistics provided important information about the overall distribution. Whereas the minimum student age was 15, the mean, and median were both approximated at 17, suggesting a normally distributed dataset. Performance itself was categorized into “good” if the students’ grades were above the median, and “bad” if they were below. From here, we were able to determine performance by age and gender. Figure 1 shows the normalized age group by performance.

Figure 1

Age Group by Performance: (“Good” or “Bad”) - Normalized



Note. This normalized histogram assuages the comparison of performance across age groups, attributing the highest grades (248 of them) to 15–16-year-olds.

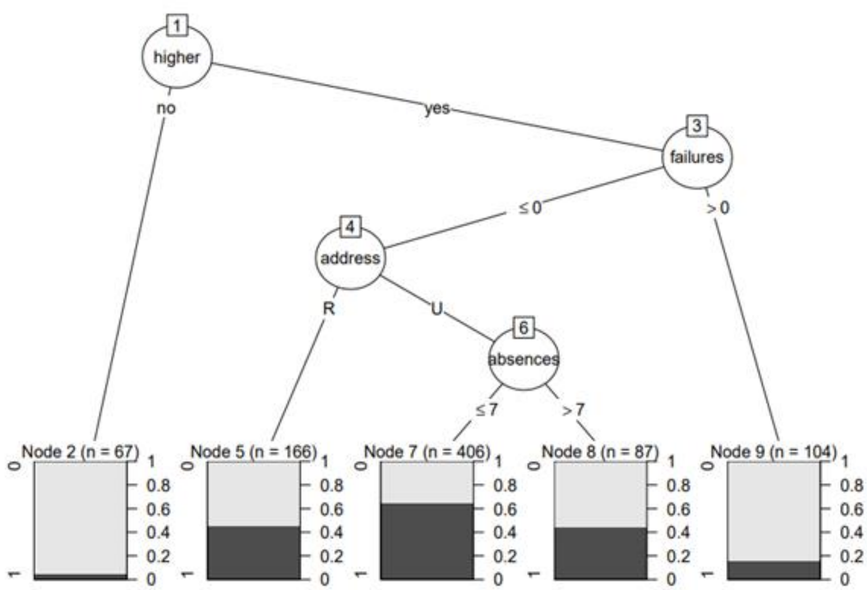
Six of the ensuing models were created with these predictor variables: address, family support, and study time. Nursery school, higher education, failures, and absences were presented as well for a total of seven**.** Logistic regression retained only the predictors of study time and absences.

C5.0

The C5.0 model only utilizes four of the variables for the four decision nodes. Figure 2 illustrates that the root node splits for whether the student is interested in higher education. Students who are not interested in higher education immediately terminate to the leaf node two which contains 67 records and has a low likelihood of performing well. The students interested in higher education branch to the next decision node which splits by students who have failed a class previously and students who have had no previous failures. Students who had at least one previous failure branch to leaf node nine, which represents 104 records with a low chance of performing well. The students who had not failed a class branch to the address decision node. If the student has a rural address, the branch terminates to leaf node five, which is comprised of 166 records and has a moderate likelihood of performing well. Students with urban addresses branch to the final decision node for absences. However, students with more than seven absences terminate at the leaf node (consisting of 87 records) where there is a moderate chance of performing well. Students with seven or less absences terminate at leaf node seven (406 records), the highest likelihood of performing well.

Figure 2

C5.0 Decision Tree Predicting Student Performance



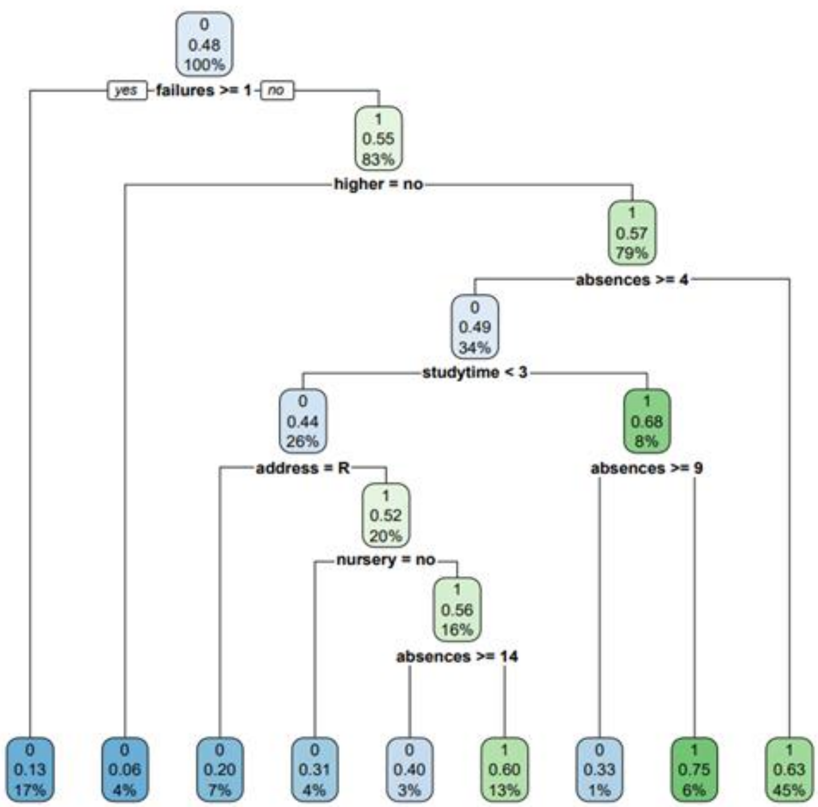
CART

The resulting decision tree (Figure 3) has one root node, seven decision nodes, and nine leaf nodes. The root node begins with the "failures" variable, immediately relegating students with one or more failures to the first leaf node. These students make up 17% of the data set; 13%

have a high-performance value, strongly likening a student's previous class failures to continued poor performance. The next decision node splits based on student interest in higher education, with those not interested in higher education terminating to the second leaf node. They make up 4% of the data set; 6% of these students have a high-performance value, demonstrating that lack of interest in higher education is a strong indicator for likelihood of low performance. Another decision node splits students by address, with rural addresses terminating at the third leaf node. These students make up 7% of the data set and 20% of them have a high performance, making address another strong indicator of student success.

Figure 3

CART Decision Tree Predicting Student Performance



Note. After evaluating this model with the test data set, the accuracy is determined to be 63.55%.

Logistic Regression

Logistic Regression was selected as the regression model of choice for this study due to performance being a binary response. The logistic regression equation takes the parametric form of the logistic regression model:

$$p(y) = \frac{exp\left(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p\right)}{1 + exp\left(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p\right)} + \varepsilon \qquad (1)$$

Study time and absences are used to predict performance using this descriptive form:

$$\hat{p}(performance) = \frac{exp\ (b_0 + b_1(study\ time) + b_2(absences))}{1 + exp\ (b_0 + b_1(study\ time) + b_2(absences))} \qquad (2)$$

Plugging in the coefficients from our training data we have:

$$\hat{p}(performance) = \frac{exp\ (-0.589 + 0.365(study\ time) - 0.052(absences))}{1 + exp\ (-0.589 + 0.365(study\ time) - 0.052(absences))} \qquad (3)$$

The regression coefficient for absences is -0.052. By calculating $e^{-0.052} = .949$, we find that for every additional day of absence, the student’s performance is 5.2% less likely to be improved (Larose, 2019, p. 190). Herein, the *p*-values of study time (0.0000194) and absences (0.000273) were statistically significant at α = 0.05, thereby eliminating the possibility of omitting these variables from this model. When evaluated against the test data set, the accuracy for the logistic regression model was determined to be 62.53%.

Random Forest

The Random Forest ensemble classification method was selected to complement the CART and C5.0 decision trees. Since the data set is relatively small, the random forest contains 100 trees. Once the branching structure of the trees is finalized, the algorithm itself classifies the “records in the original training data set. Every record in the data set is given a classification by every tree. Since these classifications are highly unlikely to be unanimous for all records, each classification is considered a ‘vote’ for that particular target variable value. The value with the largest number of votes is deemed the final classification of the record” (Larose, 2019, p. 91). When evaluated against the test data, accuracy was determined to be 62.62% with a sensitivity of 80.21% and a specificity of 48.31%.

Naïve Bayes

Multiple Naïve Bayes models were created and evaluated utilizing different predictor variables. However, the fourth iteration of the Naïve Bayes classification model contained the strongest accuracy in this study. Our basis for this approach hinges on Bayes Theorem:

$$p(X^*) = \frac{p(Y = y^*)p(Y = y^*)}{p(X^*)} \tag{4}$$

where *x* and *y* are the posterior probabilities (Larose, 2019, pp.113-114). The resulting model showed a higher likelihood of receiving high grades for students with urban addresses, support from family, had attended nursery school, and expressed interest in pursuing higher education. Additionally, fewer absences and fewer previous class failures increases the likelihood of receiving a high grade. The results for study time were uninformative in this model. When evaluating the Naïve Bayes model with the test data set, the accuracy was found to be 64.95% with 90.62% sensitivity and 44.07% specificity.

Neural Network

This linear combination takes the following general form:

$$net_j = \sum_i W_{ij}x_{ij} = W_{0j}x_{0J} + W_{Ij}x_{Ij} + \cdots + W_{Ij}x_{Ij} \tag{5}$$

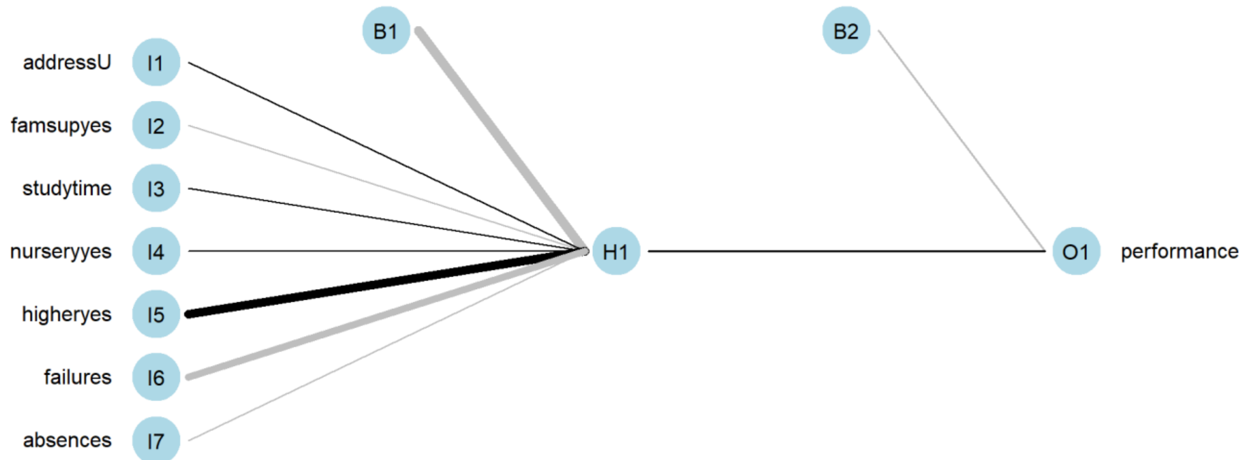
Refining this for our model, we have:

$$net_H = \sum_i W_{iH}x_{iH} = W_{0H}(1) + W_{1H}x_{1H} + W_{2H}x_{2H} + W_{3H}x_{3H} + \cdots + W_{7H}x_{7H} \tag{6}$$

In neural networks represented by Figure 4, we found that family support has the highest weight, thereby having the most influence on student performance in this model.

Figure 4

Neural Network



Note. The higher the family support, the more influence it has on the hidden layer H1, and in turn the performance O1.

Results

To determine which model is the strongest, a full model evaluation was performed on all six models (Table 1). The evaluation measured accuracy, error rate, sensitivity, specificity, precision, and three F measure variations. Neural network has the highest accuracy, 68.80%, and lowest error rate, 31.20%, indicating it had the highest proportion of correct classifications and lowest proportion of incorrect classifications. This model also had the highest precision rate, 63.34%, which signifies the highest proportion of predicted positives to actual positives. Specificity is the proportion of negative records classified negatively, making it sensitive to false positives. The highest specificity, 66.10%, is found in the C5.0 model which shows that it would be a good model if false positives are a priority to avoid. Sensitivity shows the proportion of positive records classified positively and will lower as false negatives increase. Naïve Bayes has the highest sensitivity, 90.63%, making it a strong model if false negatives are more crucial to avoid than false positives. The final evaluation measures conducted for this study were three F scores, which combine precision and specificity weighted into one measure. The neural network model has the highest F_1 , 71.82%, and $F_{0.5}$, 66.48%, while Naïve Bayes has the highest F_2, 81.01%. Since the study does not have disadvantages associated with either false positives or false negatives the neural network model is determined to be the strongest option due to its high accuracy and precision.

Table1

Model Evaluation Table for Student Performance

Evaluation Measure	**C5.0**	**CART**	**Logistic Regression**	**Random Forest**	**Naïve Bayes**	**Neural Network**
Accuracy	0.630841	0.635514	0.625301	0.626168	0.649533	0.687952
Error rate	0.369159	0.364486	0.374699	0.373832	0.350467	0.312048
Sensitivity	0.593750	0.770833	0.605528	0.802083	0.906250	0.829146
Specificity	0.661017	0.525424	0.643519	0.483051	0.440678	0.557870
Precision	0.587629	0.569231	0.610127	0.557971	0.568628	0.633397
F_1	0.590674	0.654867	0.607818	0.658120	0.698795	0.718172
F_2	0.592516	0.719844	0.606442	0.737548	0.810056	0.780880
$F_{0.5}$	0.588843	0.600649	0.609201	0.594136	0.614407	0.664787

Conclusion

We hereby recommend the neural network model for repeated experiments of this magnitude and caliber for its propensity to deliver reliable results based on the metrics presented herein. Selecting different school subjects and tuning the hyperparameters may improve accuracy and precision; notwithstanding, this model has proven useful in identifying outside factors to student performance, allowing schools to more equitably aide student success.

References

Cortez, P., & Silva, A. (2008). *Using data mining to predict secondary school student performance* (pp. 5-12). EUROSIS.

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Larose, C. D., & Larose, D. T. (2019). *Data Science Using Python and R.* Wiley.

R Core Team. (2020). *R*: *A language and environment for statistical computing* (Version 4.0.3) [Computer software]. R Foundation for Statistical Computing. http://www.R-project.org/

The Organisation for Economic Co-operation and Development. (2018). *Program for International Student Assessment (PISA) Results from PISA 2018* [Annual report]. PISA. https://www.oecd.org/pisa/publications/PISA2018_CN_PRT.pdf

Appendix

```r
#read in the students in the math class
student_math <- read.csv("student-mat.csv",sep=";",header=TRUE)
#read in the students in the Portuguese class
student_port <- read.csv("student-por.csv",sep=";",header=TRUE)

#Combine both files into one
student_file <- rbind(student_math, student_port)
dim(student_file)
```

```
## [1] 1044   33
```

```r
#write.csv(student_file, "student_file.csv")
```

```r
#inspect first few rows of merged data file
head(student_file,6)
```

```
##   school sex age address famsize Pstatus Medu Fedu     Mjob     Fjob     reason
## 1     GP   F  18       U     GT3       A    4    4  at_home  teacher     course
## 2     GP   F  17       U     GT3       T    1    1  at_home    other     course
## 3     GP   F  15       U     LE3       T    1    1  at_home    other      other
## 4     GP   F  15       U     GT3       T    4    2   health services       home
## 5     GP   F  16       U     GT3       T    3    3    other    other       home
## 6     GP   M  16       U     LE3       T    4    3 services    other reputation
##   guardian traveltime studytime failures schoolsup famsup paid activities
## 1   mother          2         2        0       yes     no   no         no
## 2   father          1         2        0        no    yes   no         no
## 3   mother          1         2        3       yes     no  yes         no
## 4   mother          1         3        0        no    yes  yes        yes
## 5   father          1         2        0        no    yes  yes         no
## 6   mother          1         2        0        no    yes  yes        yes
##   nursery higher internet romantic famrel freetime goout Dalc Walc health
## 1     yes    yes       no       no      4        3     4    1    1      3
## 2      no    yes      yes       no      5        3     3    1    1      3
## 3     yes    yes      yes       no      4        3     2    2    3      3
## 4     yes    yes      yes      yes      3        2     2    1    1      5
## 5     yes    yes       no       no      4        3     2    1    2      5
## 6     yes    yes      yes       no      5        4     2    1    2      5
##   absences G1 G2 G3
## 1        6  5  6  6
## 2        4  5  5  6
## 3       10  7  8 10
## 4        2 15 14 15
## 5        4  6 10 10
## 6       10 15 15 15
```

```r
sum(is.na(student_file))
```

```
## [1] 0
```

Exploratory Data Analysis (EDA)

```
# sort by age and absence
by_age_absence = student_file[, c("age", "absences")]
head(by_age_absence[order(-by_age_absence$absences),],4)
```

```
##     age absences
## 277  18       75
## 184  17       56
## 75   16       54
## 316  19       40
```

We determine absences by age, since student performance is to some degree based on absenteeism. The highest amount of absences occurs for those at the age of 18 Our end goal is to predict student performance.

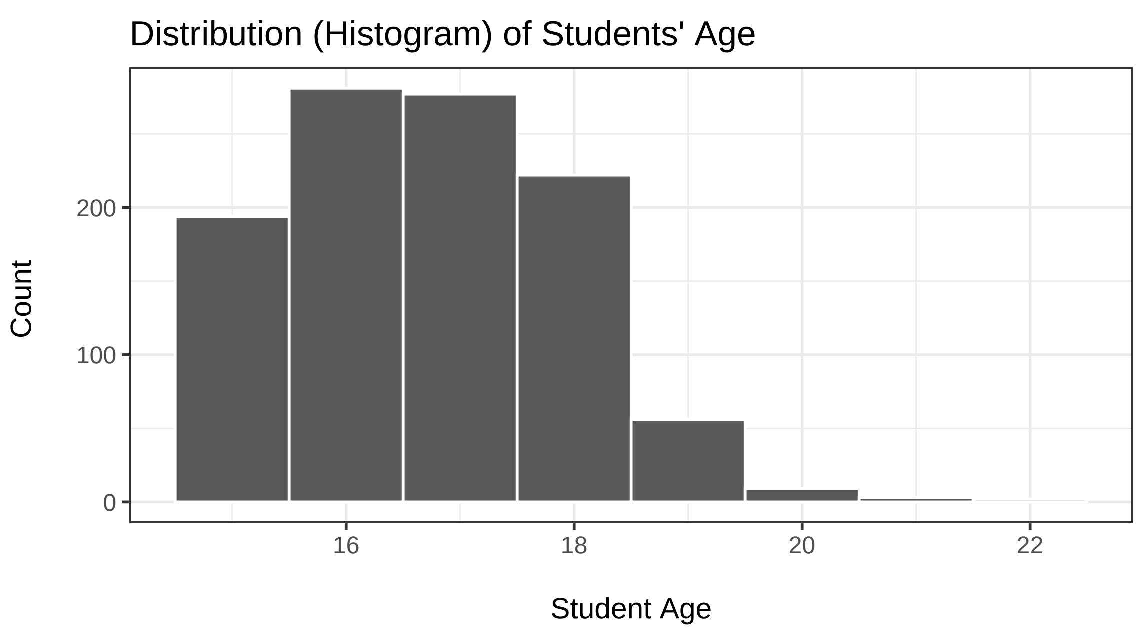
```
absence_outliers <- student_file[which(student_file$absences < -3 |
                                    student_file$absences > 3), ]
dim(absence_outliers)
```

```
## [1] 480  33
```

```
absence_sort <- absence_outliers[order(-absence_outliers$absences), ]
absence_sort_outliers = absence_sort[, c("age", "absences")]
```

We are interested in data that is sensitive to outliers because we want to build an inclusive model with an end goal of predicting the students' performance for the entire population.

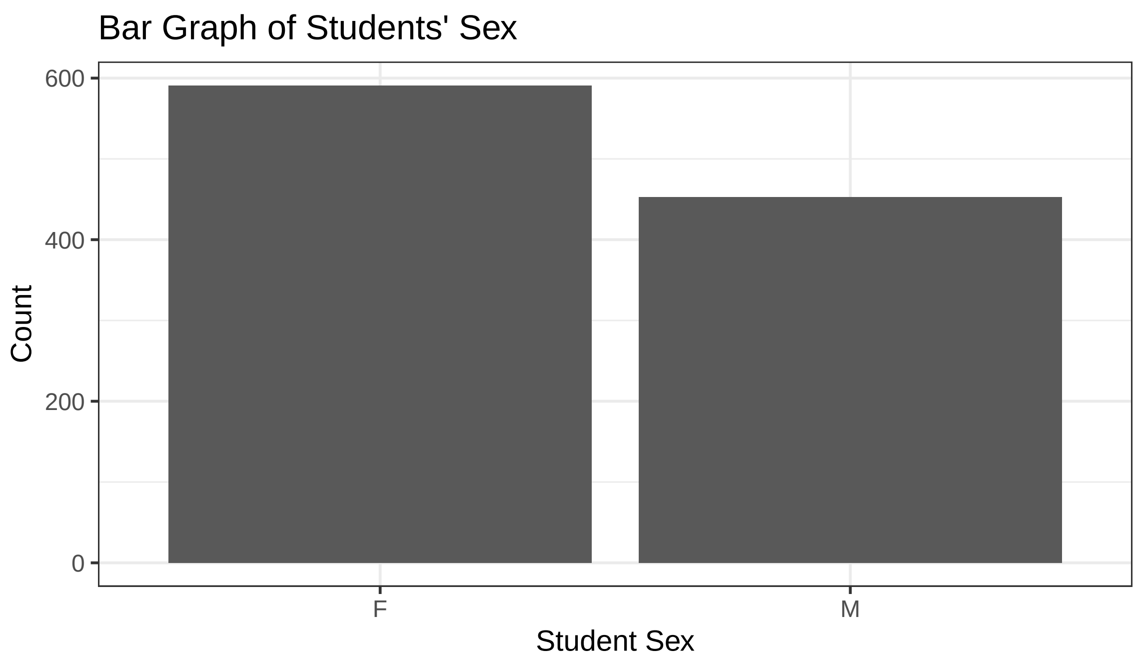
```
library(ggplot2); library(tidyverse)
ggplot(student_file, aes(age) ) + geom_histogram(binwidth = 1, color="white") +
  labs(x = "\nStudent Age", y = "Count \n") +
  ggtitle("Distribution (Histogram) of Students' Age") + theme_bw()
```



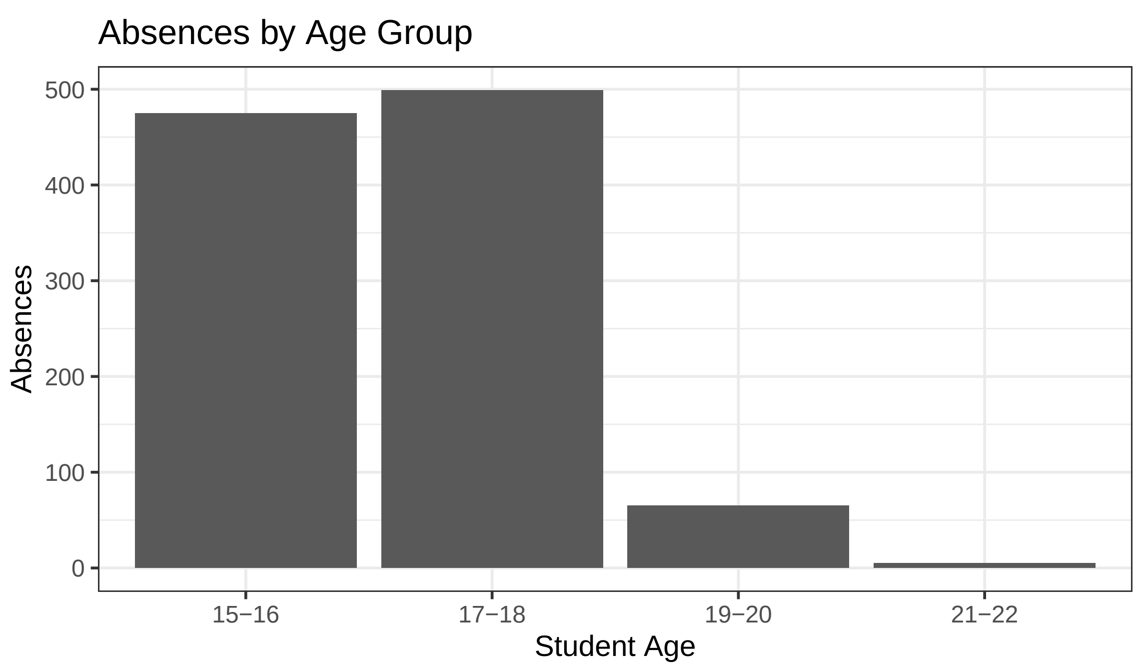

```
summary(student_file$age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   15.00   16.00   17.00   16.73   18.00   22.00
```

```
student_file %>% count(sex) %>% ggplot(aes(x = reorder(sex, -n), y = n)) +
  geom_bar(stat = 'identity') + labs(x = "Student Sex", y = "Count") +
  ggtitle("Bar Graph of Students' Sex") + theme_bw()
```



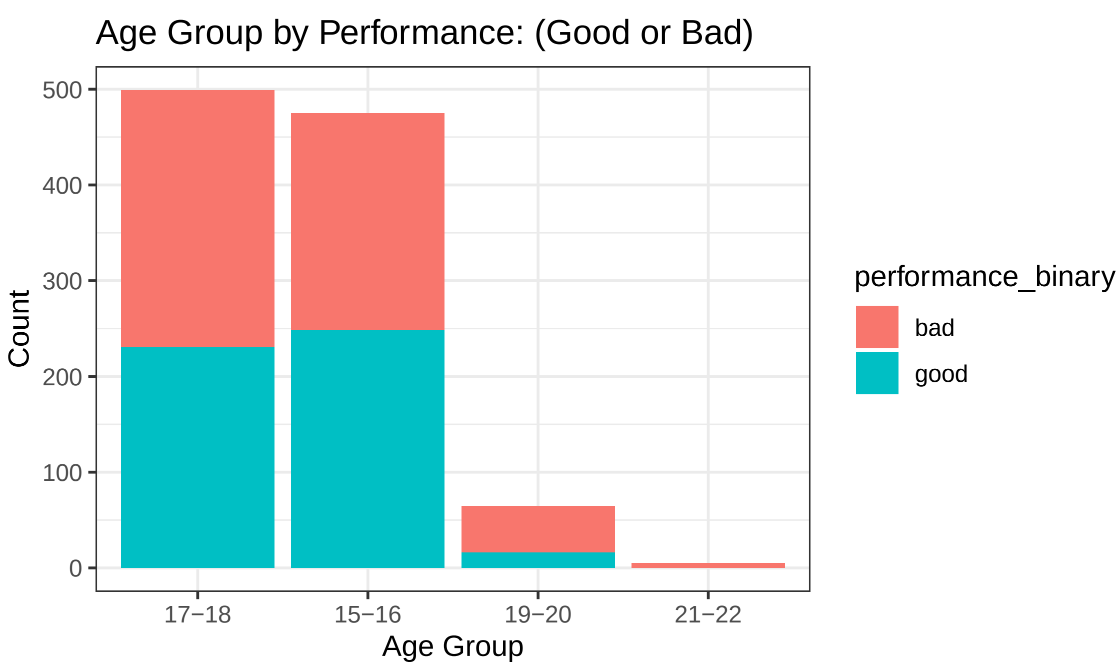

```
student_file[student_file$age >= 15 & student_file$age <= 16, "age_group"] <- "15-16"
student_file[student_file$age >= 17 & student_file$age <= 18, "age_group"] <- "17-18"
student_file[student_file$age >= 19 & student_file$age <= 20, "age_group"] <- "19-20"
student_file[student_file$age >= 21 & student_file$age <= 22, "age_group"] <- "21-22"
ggplot(student_file) + geom_bar( aes(age_group))+ labs(x = "Student Age",
y = "Absences") + ggtitle("Absences by Age Group") + theme_bw()
```



```r
#Sum grades (G1, G2, and G3) into new column "Grades"
student_file$Grades <- rowSums(student_file[c("G1", "G2", "G3")])
#Binarize Grades into new variable called "performance"
student_file <- student_file %>% mutate(performance =
                                        ifelse(Grades > median(Grades), 1, 0))
student_file <- student_file %>% mutate(performance_binary =
                                        ifelse(Grades > median(Grades), "good", "bad"))
```

```r
#convert address into new column of binarized dummy variable
student_file$address_type <- ifelse(student_file$address=="U", 1, 0)
#convert family support into new column of binarized dummy variable
student_file$famsup_binary <- ifelse(student_file$famsup=="yes", 1, 0)
```

```r
#Bar Graph of Age with overlay of Higher Education response (higher = yes, no)

ggplot(student_file, aes(fct_infreq(age_group))) +
  geom_bar(stat="count", aes(fill=performance_binary)) +
  labs(x = "Age Group", y = "Count") +
  ggtitle("Age Group by Performance: (Good or Bad)") +
  theme_bw()
```



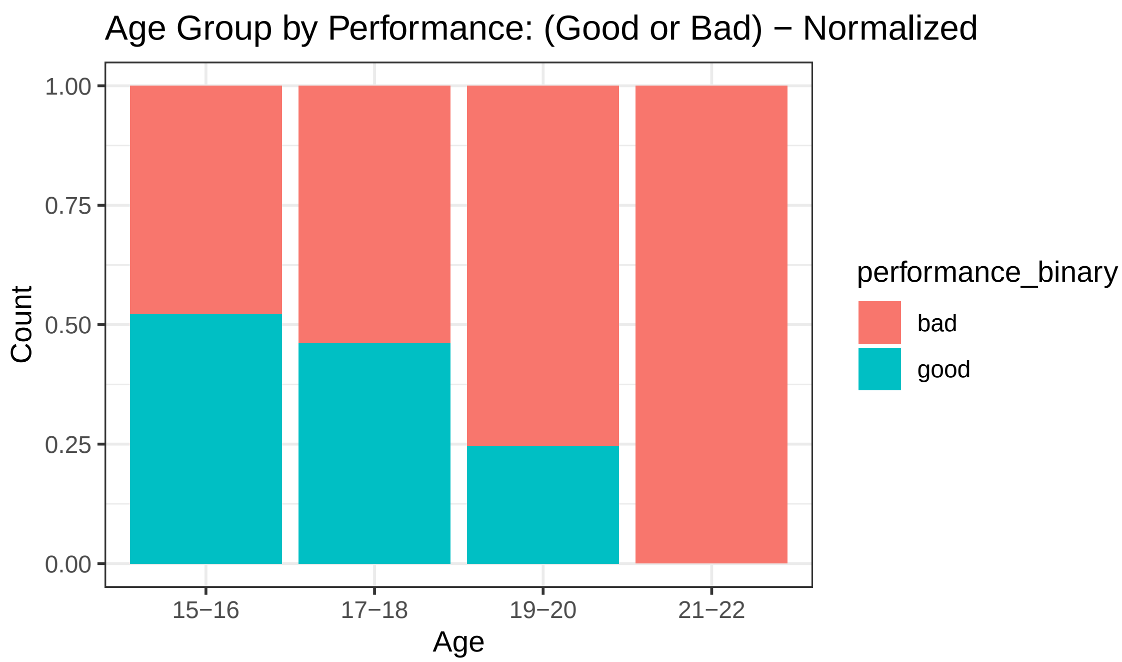
Preliminary Findings Between Age, Sex, and Performance

From the age group bar graph overlayed with "good" and "bad" performance (grades), it is evident that the age group of 17-18 has a slightly greater frequency of bad performance (260) than good (230). Ages 15-16 appear to have the best student performance among all groups.

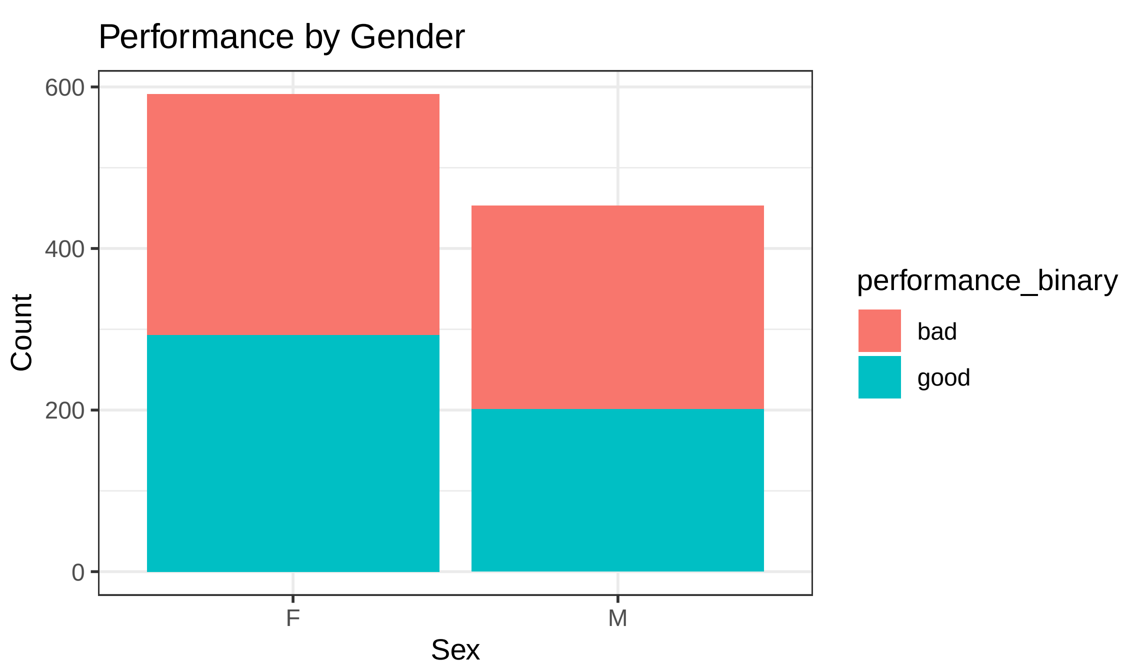
While the strength of this graph is in its depiction of the overall distribution (providing us with amounts of "good" and "bad" grades in each respective age category), it does little to provide a comparison of the number of "good" and "bad" grades by the age groups themselves.

Normalizing Age group by our target (performance) assuages this analysis in such capacity. From here, we can conclude from our preliminary findings that the younger the student, the better the overall grade (greater than the median), with the highest amount (248) and frequency of good grades for the 15-16 year age group.

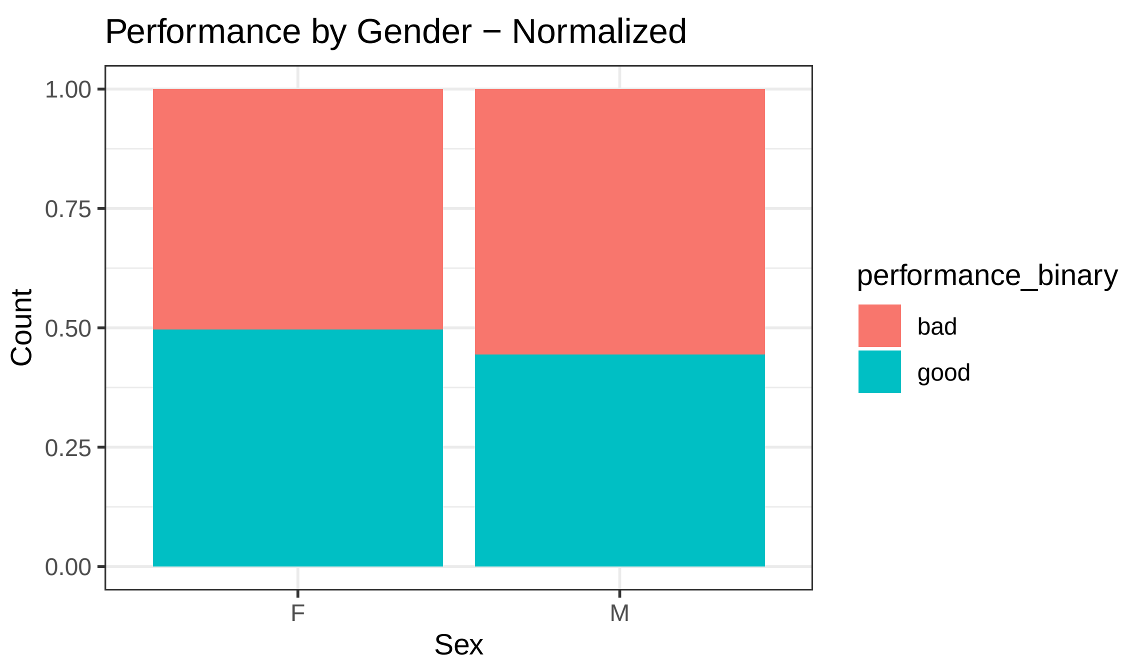
```r
#Normalized Bar Graph of Age Groups with overlay of response
ggplot(student_file, aes(age_group)) + geom_bar(aes(fill = performance_binary),
  position = "fill") + labs(x = "Age", y = "Count")+
  ggtitle("Age Group by Performance: (Good or Bad) - Normalized") + theme_bw()
```




```r
#Bar Graph of Sex with overlay of Performance (good, bad)
ggplot(student_file, aes(fct_infreq(sex))) + geom_bar(stat="count", aes(fill=performance_binary)) +
  labs(x = "Sex", y = "Count")+
  ggtitle("Performance by Gender") + theme_bw()
```



```r
#Normalized Bar Graph of Sex with overlay of Higher Education response
ggplot(student_file, aes(sex)) +
  geom_bar(aes(fill = performance_binary),
position = "fill")+ labs(x = "Sex", y = "Count")+
ggtitle("Performance by Gender - Normalized") + theme_bw()
```



Moreover, it is important to note, that not only are there are more females than males in the dataset, females also have a higher amount (293) and frequency of good grades (performance) than their male counterparts (201).

```r
#Contingency Table - Response Type by Sex: by Columns
contingency_table <- table(student_file$performance_binary, student_file$sex)
contingency_table_col <- addmargins(A = contingency_table, FUN = list(total = sum),
                                    quiet = TRUE)
contingency_table_col
```

```
##
##           F    M total
##   bad   298  252   550
##   good  293  201   494
##   total 591  453  1044
```

```r
#Contingency Table - Age by Response Type: by Columns
contingency_table <- table(student_file$performance_binary, student_file$age_group)
contingency_table_col <- addmargins(A = contingency_table, FUN = list(total = sum),
                                    quiet = TRUE)
contingency_table_col
```

```
##
##         15-16 17-18 19-20 21-22 total
##   bad     227   269    49     5   550
##   good    248   230    16     0   494
##   total   475   499    65     5  1044
```

Train_Test Split of the Data ("student_file.csv")

```
#Train_Test Split data into 80/20

set.seed(7)
n <- dim(student_file)[1]; cat('\n Student File Dataset:', n)
```

```
##
##  Student File Dataset: 1044
```

```
train_ind <- runif(n) < 0.80
student_train <- student_file[ train_ind, ]
student_test <- student_file[ !train_ind, ]

#check size dimensions of respective partions
n_train <- dim(student_train)[1]
cat('\n Student Train Dataset:', n_train)
```

```
##
##  Student Train Dataset: 830
```

```
n_test <- dim(student_test)[1]
cat('\n Student Test Dataset:', n_test)
```

```
##
##  Student Test Dataset: 214
```

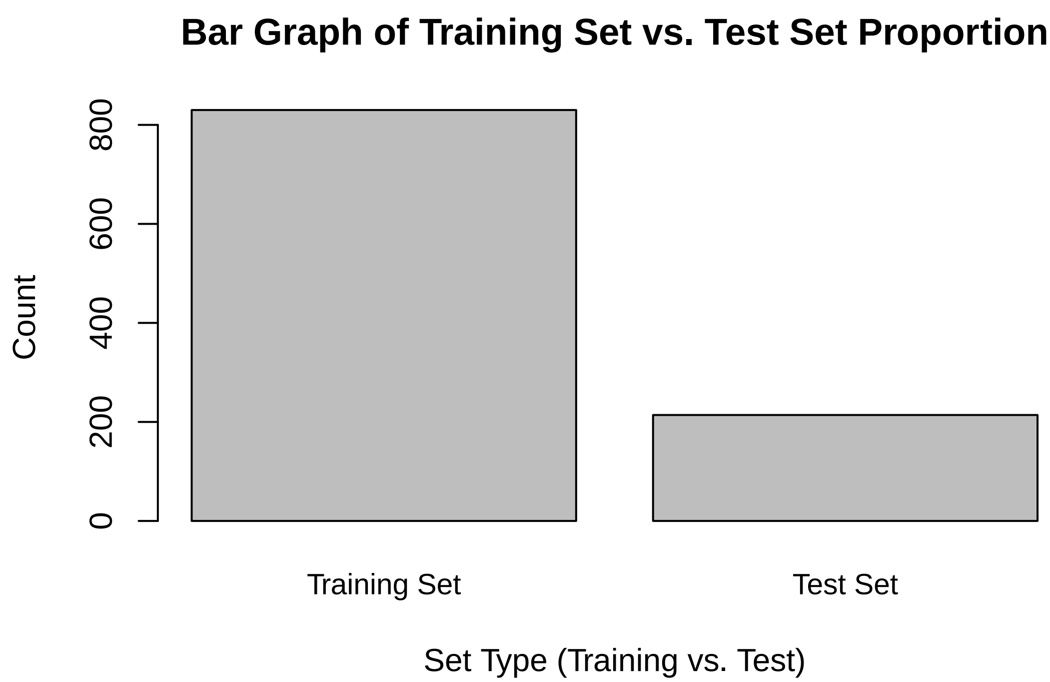
```
table(student_train$performance_binary)
```

```
##
##  bad good
##  432  398
```

```
to.resample <- which(student_train$performance_binary == "good")

#figure out percentage of true values

percent_true = table(student_train$performance_binary)["good"]/
  dim(student_train)[1]*100
cat("\n", percent_true,"percent of the students have good performance.")
```

```
##
##  47.95181 percent of the students have good performance.
```

```
#Bar Graph confirming Proportions

mydata <- c(n_train, n_test)

barplot(mydata, main="Bar Graph of Training Set vs. Test Set Proportion",
        xlab="Set Type (Training vs. Test)", ylab = "Count",
        names.arg=c("Training Set", "Test Set"), cex.names=0.9)
```




```
# Validate the partition by testing for the difference in mean age
# for the training set versus the test set
mean_train = mean(student_train$age)
mean_test = mean(student_test$age)
difference_mean = mean_train - mean_test
cat("\n The difference between the mean of the test set vs. the train set is",
    difference_mean)
```

```
##
##  The difference between the mean of the test set vs. the train set is -0.1035919
```

```
# Validate the partition by testing for the difference in proportion of good
# performance for the training set versus the test set.
prop_train_good = table(student_train$performance_binary)["good"] /
  dim(student_train)[1]
prop_test_good = table(student_test$performance_binary)["good"] /
  dim(student_test)[1]
difference_proportion = prop_train_good - prop_test_good
cat("\n The difference between the proportions of the test set vs. the train set is",
    difference_proportion)
```

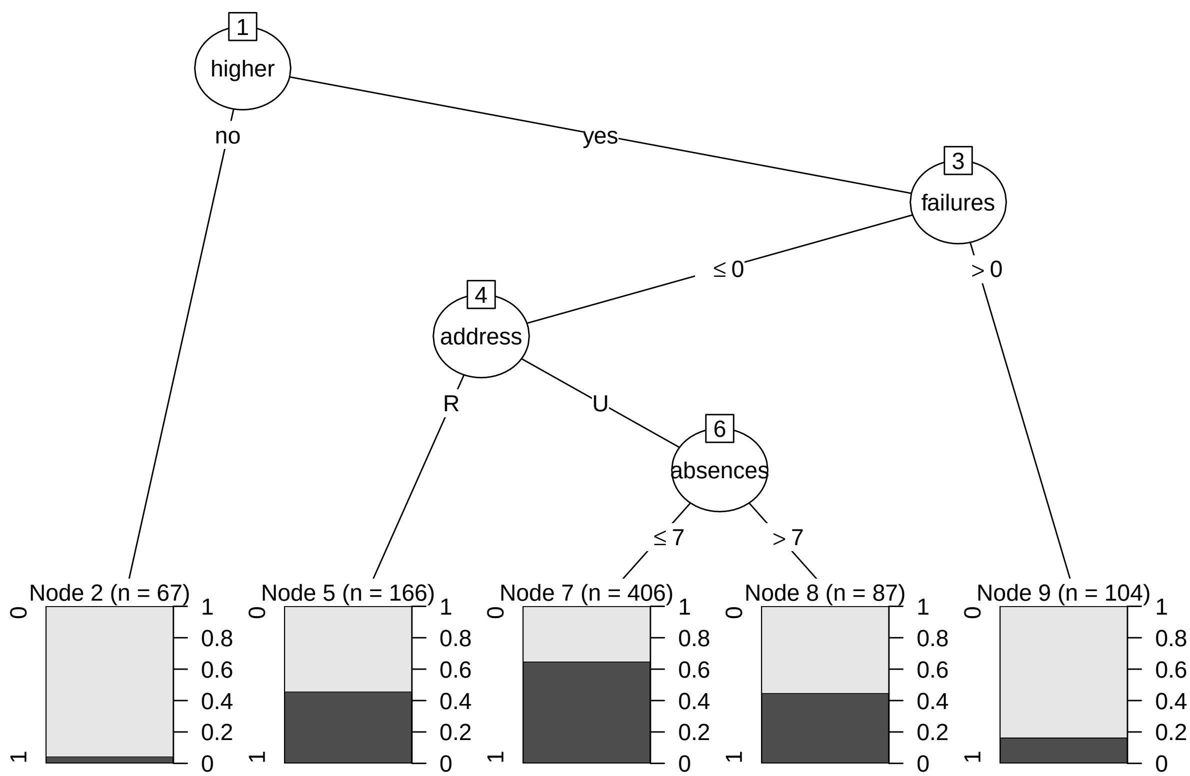
```
##
##  The difference between the proportions of the test set vs. the train set is 0.03091994
```

```
# Preparing (converting) variables to factor and numeric as necessary

#Training Data
student_train$higher <- as.factor(student_train$higher)
student_train$address <- as.factor(student_train$address)
student_train$famsup <- as.factor(student_train$famsup)
student_train$performance <- as.factor(student_train$performance)
```

```r
student_train$studytime <- as.numeric(student_train$studytime)
student_train$nursery <- as.factor(student_train$nursery)
student_train$failures <- as.numeric(student_train$failures)
student_train$absences <- as.numeric(student_train$absences)

#Test Data
student_test$higher <- as.factor(student_test$higher)
student_test$address <- as.factor(student_test$address)
student_test$famsup <- as.factor(student_test$famsup)
student_test$performance <- as.factor(student_test$performance)
student_test$studytime <- as.numeric(student_test$studytime)
student_test$nursery <- as.factor(student_test$nursery)
student_test$absences <- as.numeric(student_test$absences)
student_test$failures <- as.numeric(student_test$failures)
```

C5.0 Model

```r
library(C50); library(caret)
#Run training set through C5.0 to obtain Model 1, and assign to C5
C5 <- C5.0(formula <- performance ~ address + famsup + studytime + nursery +
           higher + failures + absences, data = student_train, control =
           C5.0Control(minCases=50))
plot(C5, label="performance")
```



```
X = data.frame(performance = student_train$performance,
                    address = student_train$address,
                    famsup = student_train$famsup,
                    studytime = student_train$studytime,
                    nursery = student_train$nursery,
                    higher = student_train$higher,
                    failures = student_train$failures,
                    absences = student_train$absences)

#Subset predictor variables from test data set into new df
test.X = data.frame(performance = student_test$performance,
                    address = student_test$address,
                    famsup = student_test$famsup,
                    studytime = student_test$studytime,
                    nursery = student_test$nursery,
                    higher = student_test$higher,
                    failures = student_test$failures,
                    absences = student_test$absences)

#run test data through training data model
student_test$pred_c5 <- predict(object = C5, newdata = test.X)
```

C5.0 Model Evaluation

```
t1_c5 <- table(student_test$performance, student_test$pred_c5)
t1_c5 <- addmargins(A = t1_c5, FUN = list(Total = sum), quiet =
TRUE); t1_c5
```

```
##
##            0   1 Total
##   0       78  40   118
##   1       39  57    96
##   Total 117  97   214
```

```
student_test[c('performance', 'pred_c5')] <- lapply(student_test[
  c('performance', 'pred_c5')], as.factor)
confusionMatrix(student_test$pred_c5, student_test$performance, positive='1')
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 78 39
##          1 40 57
##
##                Accuracy : 0.6308
##                  95% CI : (0.5624, 0.6956)
##     No Information Rate : 0.5514
##     P-Value [Acc > NIR] : 0.01126
##
##                   Kappa : 0.2545
##
##  Mcnemar's Test P-Value : 1.00000
```

```
##
##             Sensitivity : 0.5938
##             Specificity : 0.6610
##          Pos Pred Value : 0.5876
##          Neg Pred Value : 0.6667
##              Prevalence : 0.4486
##          Detection Rate : 0.2664
##    Detection Prevalence : 0.4533
##       Balanced Accuracy : 0.6274
##
##        'Positive' Class : 1
##
```

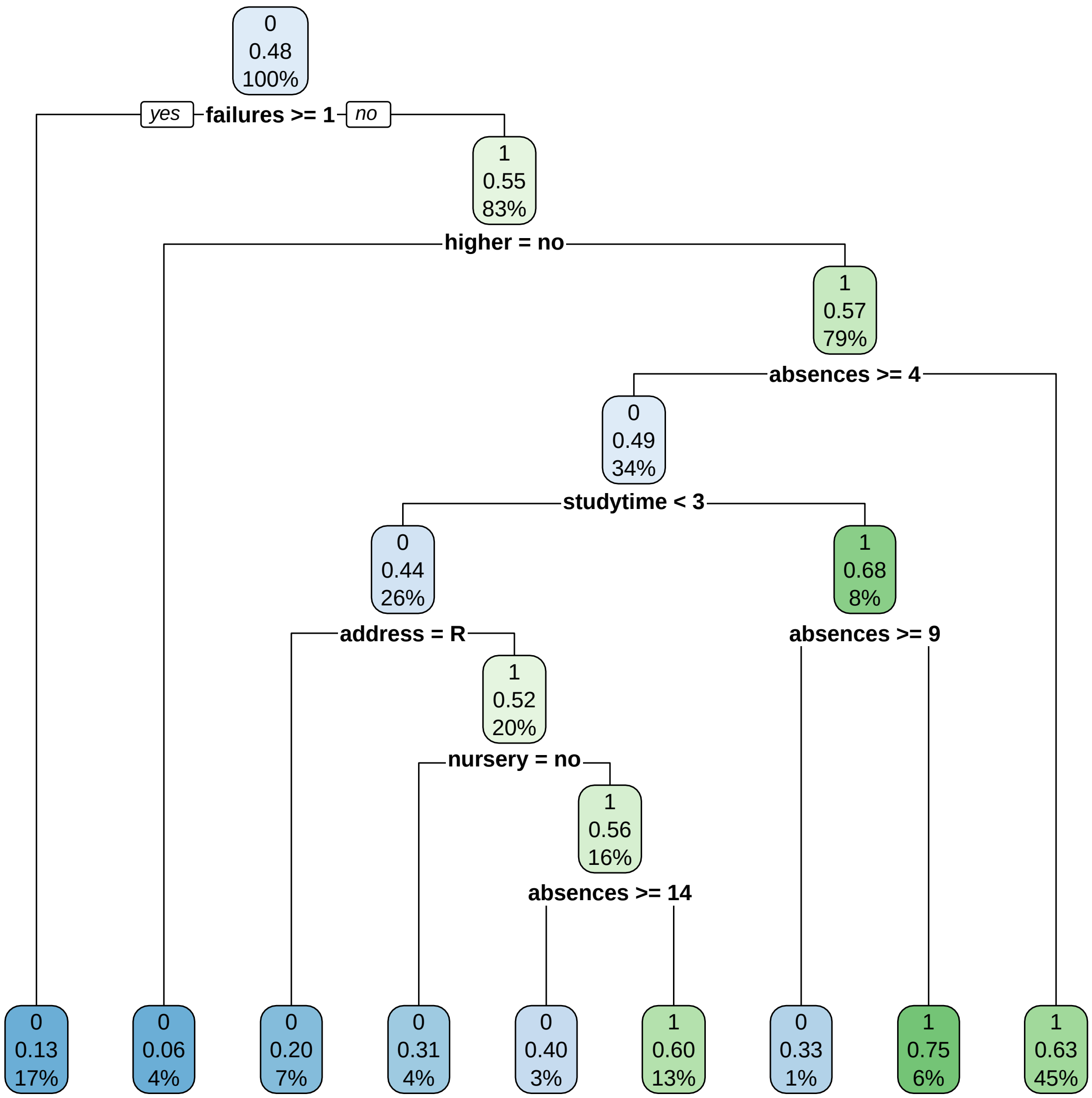
```
accuracy_c5 = (t1_c5[1,1]+t1_c5[2,2])/t1_c5[3,3]
error_rate_c5 = (1-accuracy_c5)
sensitivity_c5 = t1_c5[2,2]/ t1_c5[2,3]
specificity_c5 = t1_c5[1,1]/t1_c5[1,3]
precision_c5 = t1_c5[2,2]/t1_c5[3,2]
F_1_c5 = 2*(precision_c5*sensitivity_c5)/(precision_c5+sensitivity_c5)
F_2_c5 = 5*(precision_c5*sensitivity_c5)/((4*precision_c5)+sensitivity_c5)
F_0.5_c5 = 1.25*(precision_c5*sensitivity_c5)/((0.25*precision_c5)+sensitivity_c5)


cat("\n Accuracy:",accuracy_c5, "\n Error Rate:",error_rate_c5,
    "\n Sensitivity:",sensitivity_c5,
"\n Specificity:",specificity_c5, "\n Precision:",precision_c5, "\n F1:",F_1_c5,
"\n F2:",F_2_c5,
"\n F0.5:",F_0.5_c5)
```

```
##
##  Accuracy: 0.6308411
##  Error Rate: 0.3691589
##  Sensitivity: 0.59375
##  Specificity: 0.6610169
##  Precision: 0.5876289
##  F1: 0.5906736
##  F2: 0.5925156
##  F0.5: 0.588843
```

CART Model

```
library(rpart); library(rpart.plot)
cart_train <- rpart(formula = performance ~ address + famsup +
                    studytime + nursery + higher + failures + absences,
                    data = student_train, method = "class")

X_CART = data.frame(performance = student_test$performance,
                    address = student_test$address,
                    famsup = student_test$famsup,
                    studytime = student_test$studytime,
                    nursery = student_test$nursery,
                    higher = student_test$higher,
                    failures = student_test$failures,
                    absences = student_test$absences)
```

```r
rpart.plot(cart_train)
```




```r
library(caret)
student_test$predCART <- predict(object = cart_train, newdata = X_CART,
                                 type = "class")
head(student_test$predCART)
```

```
## [1] 1 1 0 1 1 1
## Levels: 0 1
```

```r
table_CART <- table(student_test$performance, student_test$predCART)
table_CART <- addmargins(A=table_CART, FUN=list(Total=sum), quiet = TRUE);
table_CART
```

```
##
##           0   1 Total
##   0      62  56   118
##   1      22  74    96
##   Total  84 130   214
```

```
student_test[c('performance', 'predCART')] <-
  lapply(student_test[c('performance', 'predCART')], as.factor)
confusionMatrix(student_test$predCART, student_test$performance, positive='1')
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 62 22
##          1 56 74
##
##                Accuracy : 0.6355
##                  95% CI : (0.5672, 0.7)
##     No Information Rate : 0.5514
##     P-Value [Acc > NIR] : 0.0077294
##
##                   Kappa : 0.2868
##
##  Mcnemar's Test P-Value : 0.0001866
##
##             Sensitivity : 0.7708
##             Specificity : 0.5254
##          Pos Pred Value : 0.5692
##          Neg Pred Value : 0.7381
##              Prevalence : 0.4486
##          Detection Rate : 0.3458
##    Detection Prevalence : 0.6075
##       Balanced Accuracy : 0.6481
##
##        'Positive' Class : 1
##
```

```
accuracy_CART = (table_CART[1,1]+table_CART[2,2])/table_CART[3,3]
error_rate_CART = (1-accuracy_CART)
sensitivity_CART = table_CART[2,2]/ table_CART[2,3]
specificity_CART = table_CART[1,1]/table_CART[1,3]
precision_CART = table_CART[2,2]/table_CART[3,2]
F_1_CART = 2*(precision_CART*sensitivity_CART)/(precision_CART+sensitivity_CART)
F_2_CART = 5*(precision_CART*sensitivity_CART)/((4*precision_CART)+
                                                  sensitivity_CART)
F_0.5_CART = 1.25*(precision_CART*sensitivity_CART)/((0.25*precision_CART)+
                                                       sensitivity_CART)

cat("\n Accuracy:",accuracy_CART, "\n Error Rate:",error_rate_CART,
    "\n Sensitivity:",sensitivity_CART,
"\n Specificity:",specificity_CART, "\n Precision:",precision_CART, "\n F1:",
F_1_CART,
"\n F2:",F_2_CART,
"\n F0.5:",F_0.5_CART)
```

```
##
##  Accuracy: 0.635514
##  Error Rate: 0.364486
##  Sensitivity: 0.7708333
##  Specificity: 0.5254237
##  Precision: 0.5692308
##  F1: 0.6548673
##  F2: 0.7198444
##  F0.5: 0.6006494
```

Logistic Regression

```r
logreg <- glm(formula = performance  ~ studytime + absences,
                data = student_train,
                family = binomial)
options(scipen = 999)
summary(logreg)
```

```
##
## Call:
## glm(formula = performance ~ studytime + absences, family = binomial,
##     data = student_train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5625  -1.0839  -0.8063   1.1400   1.9740
##
## Coefficients:
##             Estimate Std. Error z value  Pr(>|z|)
## (Intercept) -0.58902    0.19508  -3.019  0.002533 **
## studytime    0.36505    0.08545   4.272 0.0000194 ***
## absences    -0.05236    0.01439  -3.639  0.000273 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1149.2  on 829  degrees of freedom
## Residual deviance: 1111.6  on 827  degrees of freedom
## AIC: 1117.6
##
## Number of Fisher Scoring iterations: 4
```

None of the variables should be removed from the model because there exists statistical significance with the $p-$values associated with each of the predictors.

$$\hat{p}(y) = \frac{\exp(b_0 + b_1x_1 + b_2x_2 + \cdots + b_px_p)}{1 + \exp(b_0 + b_1x_1 + b_2x_2 + \cdots + b_px_p)}$$

$$\hat{p}(performance) = \frac{\exp(b_0 + b_1(study\ time) + b_2(absences))}{1 + \exp(b_0 + b_1(study\ time) + b_2(absences))}$$

Validating the model using the test dataset, we have the following:

```r
logreg_test <- glm(formula = performance ~ studytime + absences, data = student_test,
                   family = binomial)
options(scipen = 999)
summary(logreg_test)
```

```
##
## Call:
## glm(formula = performance ~ studytime + absences, family = binomial,
##     data = student_test)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.4589  -1.1062  -0.8896   1.2200   1.6604
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.95272    0.39953  -2.385   0.0171 *
## studytime    0.45467    0.18446   2.465   0.0137 *
## absences    -0.02810    0.02207  -1.273   0.2029
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 294.4  on 213  degrees of freedom
## Residual deviance: 286.2  on 211  degrees of freedom
## AIC: 292.2
##
## Number of Fisher Scoring iterations: 4
```

To obtain the predicted values of the response variable (higher) for each record, we have the following:

```r
#set.seed(7)
student_train$pred_probab <- predict(object = logreg, newdata = student_train,
                                     type='response')
head(student_train$pred_probab)
```

```
## [1] 0.4829183 0.4055252 0.5990260 0.4829183 0.4055252 0.5352102
```

```r
student_train$predict <- (student_train$pred_probab > 0.5)*1
head(student_train$predict)
```

```
## [1] 0 0 1 0 0 1
```

```r
library(caret)
table_logreg <- table(student_train$performance, student_train$predict)
table_logreg <- addmargins(A=table_logreg, FUN=list(Total=sum), quiet = TRUE);
table_logreg
```

```
##
##           0   1 Total
##   0     278 154   432
##   1     157 241   398
##   Total 435 395   830
```

```r
student_train[c('performance', 'predict')] <- lapply(
  student_train[c('performance', 'predict')], as.factor)
```

```r
confusionMatrix(student_train$predict, student_train$performance, positive='1')
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 278 157
##          1 154 241
##
##                Accuracy : 0.6253
##                  95% CI : (0.5914, 0.6583)
##     No Information Rate : 0.5205
##     P-Value [Acc > NIR] : 0.0000000007302
##
##                   Kappa : 0.2491
##
##  Mcnemar's Test P-Value : 0.9097
##
##             Sensitivity : 0.6055
##             Specificity : 0.6435
##          Pos Pred Value : 0.6101
##          Neg Pred Value : 0.6391
##              Prevalence : 0.4795
##          Detection Rate : 0.2904
##    Detection Prevalence : 0.4759
##       Balanced Accuracy : 0.6245
##
##        'Positive' Class : 1
##
```

```r
accuracy_logreg = (table_logreg[1,1]+table_logreg[2,2])/table_logreg[3,3]
error_rate_logreg = (1-accuracy_logreg)
sensitivity_logreg = table_logreg[2,2]/ table_logreg[2,3]
specificity_logreg = table_logreg[1,1]/table_logreg[1,3]
precision_logreg = table_logreg[2,2]/table_logreg[3,2]
F_1_logreg = 2*(precision_logreg*sensitivity_logreg)/(precision_logreg
                                                      +sensitivity_logreg)
F_2_logreg = 5*(precision_logreg*sensitivity_logreg)/((4*precision_logreg)+
                                                  sensitivity_logreg)
F_0.5_logreg = 1.25*(precision_logreg*sensitivity_logreg)/
  ((0.25*precision_logreg)+sensitivity_logreg)

cat("\n Accuracy:",accuracy_logreg, "\n Error Rate:",error_rate_logreg,
    "\n Sensitivity:",sensitivity_logreg,
"\n Specificity:",specificity_logreg, "\n Precision:",precision_logreg,"\n F1:",
F_1_logreg,
"\n F2:",F_2_logreg,
"\n F0.5:",F_0.5_logreg)
```

```
##
##  Accuracy: 0.6253012
##  Error Rate: 0.3746988
##  Sensitivity: 0.6055276
##  Specificity: 0.6435185
```

```
##  Precision: 0.6101266
##  F1: 0.6078184
##  F2: 0.6064419
##  F0.5: 0.6092012
```

Random Forest

```r
library(randomForest)

rf <- randomForest(formula = performance ~ address + famsup + studytime +
                     nursery + higher + failures + absences,
                     data = student_train, ntree=100, type = "classification")
#head(rf$predicted)

student_test$nursery = as.factor(student_test$nursery)

X_RF = data.frame(performance = student_test$performance,
                    address = student_test$address,
                    famsup = student_test$famsup,
                    studytime = student_test$studytime,
                    nursery = student_test$nursery,
                    higher = student_test$higher,
                    failures = student_test$failures,
                    absences = student_test$absences)

student_test$predRF <- predict(object = rf, newdata = X_RF)
table_RF <- table(student_test$performance, student_test$predRF)
table_RF <- addmargins(A=table_RF, FUN=list(Total=sum), quiet = TRUE); table_RF
```

```
##
##           0   1 Total
##   0      57  61   118
##   1      19  77    96
##   Total  76 138   214
```

```r
student_test[c('performance', 'predRF')] <- lapply(student_test[c('performance',
                                                   'predRF')], as.factor)
confusionMatrix(student_test$predRF, student_test$performance, positive='1')
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 57 19
##          1 61 77
##
##                Accuracy : 0.6262
##                  95% CI : (0.5576, 0.6912)
##     No Information Rate : 0.5514
##     P-Value [Acc > NIR] : 0.0161
##
##                   Kappa : 0.274
##
##  Mcnemar's Test P-Value : 0.000004563
```

```
##
##             Sensitivity : 0.8021
##             Specificity : 0.4831
##          Pos Pred Value : 0.5580
##          Neg Pred Value : 0.7500
##              Prevalence : 0.4486
##          Detection Rate : 0.3598
##    Detection Prevalence : 0.6449
##       Balanced Accuracy : 0.6426
##
##        'Positive' Class : 1
##
```

```
accuracy_RF = (table_RF[1,1]+table_RF[2,2])/table_RF[3,3]
error_rate_RF = (1-accuracy_RF)
sensitivity_RF = table_RF[2,2]/ table_RF[2,3]
specificity_RF = table_RF[1,1]/table_RF[1,3]
precision_RF = table_RF[2,2]/table_RF[3,2]
F_1_RF = 2*(precision_RF*sensitivity_RF)/(precision_RF+sensitivity_RF)
F_2_RF = 5*(precision_RF*sensitivity_RF)/((4*precision_RF)+sensitivity_RF)
F_0.5_RF = 1.25*(precision_RF*sensitivity_RF)/((0.25*precision_RF)+
                 sensitivity_RF)

cat("\n Accuracy:",accuracy_RF, "\n Error Rate:",error_rate_RF,
    "\n Sensitivity:",sensitivity_RF,
"\n Specificity:",specificity_RF, "\n Precision:",precision_RF, "\n F1:",F_1_RF,
"\n F2:",F_2_RF,
"\n F0.5:",F_0.5_RF)
```

```
##
##  Accuracy: 0.6261682
##  Error Rate: 0.3738318
##  Sensitivity: 0.8020833
##  Specificity: 0.4830508
##  Precision: 0.557971
##  F1: 0.6581197
##  F2: 0.7375479
##  F0.5: 0.5941358
```

Naive Bayes

Naive Bayes predicted performance based on address and higher:

```
library(e1071)
nb01<- naiveBayes(formula = performance ~ address + higher, data=student_train)
nb01
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
```

```
##         0         1
## 0.5204819 0.4795181
##
## Conditional probabilities:
##    address
## Y           R         U
##   0 0.3356481 0.6643519
##   1 0.2035176 0.7964824
##
##    higher
## Y            no         yes
##   0 0.148148148 0.851851852
##   1 0.007537688 0.992462312
```

The predictions for this formula when evaluated with the test data set:

```
#Naive Bayes Model #1
student_test$nb01predict<- predict(object=nb01, newdata= student_test)
nb01.t <- table(student_test$performance, student_test$nb01predict)
rownames(nb01.t)<- c("Actual:0","Actual:1")
colnames(nb01.t)<- c("Predicted:0", "Predicted:1")
nb01.t <- addmargins(A=nb01.t, FUN=list(Total=sum), quiet=TRUE); nb01.t
```

```
##
##           Predicted:0 Predicted:1 Total
##   Actual:0          45          73   118
##   Actual:1          24          72    96
##   Total             69         145   214
```

```
student_test[c('performance', 'nb01predict')] <- lapply(
  student_test[c('performance', 'nb01predict')], as.factor)
confusionMatrix(student_test$nb01predict, student_test$performance,positive='1')
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 45 24
##          1 73 72
##
##                Accuracy : 0.5467
##                  95% CI : (0.4774, 0.6147)
##     No Information Rate : 0.5514
##     P-Value [Acc > NIR] : 0.5825
##
##                   Kappa : 0.1254
##
##  Mcnemar's Test P-Value : 0.000001095
##
##             Sensitivity : 0.7500
##             Specificity : 0.3814
##          Pos Pred Value : 0.4966
##          Neg Pred Value : 0.6522
##              Prevalence : 0.4486
##          Detection Rate : 0.3364
##    Detection Prevalence : 0.6776
```

```
##       Balanced Accuracy : 0.5657
##
##        'Positive' Class : 1
##
```

```
accuracy_nb01 = (nb01.t[1,1]+nb01.t[2,2])/nb01.t[3,3]
error_rate_nb01 = (1-accuracy_nb01)
sensitivity_nb01 = nb01.t[2,2]/ nb01.t[2,3]
specificity_nb01 = nb01.t[1,1]/nb01.t[1,3]
precision_nb01 = nb01.t[2,2]/nb01.t[3,2]
F_1_nb01 = 2*(precision_nb01*sensitivity_nb01)/(precision_nb01+sensitivity_nb01)
F_2_nb01 = 5*(precision_nb01*sensitivity_nb01)/((4*precision_nb01)+
                                                  sensitivity_nb01)
F_0.5_nb01 = 1.25*(precision_nb01*sensitivity_nb01)/((0.25*precision_nb01)+
                                                       sensitivity_nb01)


cat("\n Accuracy:",accuracy_nb01, "\n Error Rate:",error_rate_nb01,
    "\n Sensitivity:",sensitivity_nb01,
"\n Specificity:",specificity_nb01, "\n Precision:",precision_nb01, "\n F1:",
F_1_nb01,
"\n F2:",F_2_nb01,
"\n F0.5:",F_0.5_nb01)
```

```
##
##  Accuracy: 0.546729
##  Error Rate: 0.453271
##  Sensitivity: 0.75
##  Specificity: 0.3813559
##  Precision: 0.4965517
##  F1: 0.5975104
##  F2: 0.6805293
##  F0.5: 0.5325444
```

Naive Bayes predicted performance based on famsup and nursery:

```
#Naive Bayes Model #2
nb02<- naiveBayes( formula = performance ~ famsup + nursery, data=student_train)
nb02
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##         0         1
## 0.5204819 0.4795181
##
## Conditional probabilities:
##    famsup
## Y          no       yes
##   0 0.4027778 0.5972222
##   1 0.3844221 0.6155779
```

```
##
##    nursery
## Y          no       yes
##   0 0.2268519 0.7731481
##   1 0.1683417 0.8316583
```

The predictions for this formula when evaluated with the test data set:

```
student_test$nb02predict<- predict(object=nb02, newdata= student_test)
nb02.t <- table(student_test$performance,student_test$nb02predict)
rownames(nb02.t)<- c("Actual:0","Actual:1")
colnames(nb02.t)<- c("Predicted:0", "Predicted:1")
nb02.t <- addmargins(A=nb02.t, FUN=list(Total=sum), quiet=TRUE); nb02.t
```

```
##
##             Predicted:0 Predicted:1 Total
##   Actual:0           55          63   118
##   Actual:1           49          47    96
##   Total             104         110   214
```

```
student_test[c('performance', 'nb02predict')] <- lapply(
  student_test[c('performance', 'nb02predict')], as.factor)
confusionMatrix(student_test$nb02predict, student_test$performance,positive='1')
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 55 49
##          1 63 47
##
##                Accuracy : 0.4766
##                  95% CI : (0.4081, 0.5458)
##     No Information Rate : 0.5514
##     P-Value [Acc > NIR] : 0.9881
##
##                   Kappa : -0.0437
##
##  Mcnemar's Test P-Value : 0.2193
##
##             Sensitivity : 0.4896
##             Specificity : 0.4661
##          Pos Pred Value : 0.4273
##          Neg Pred Value : 0.5288
##              Prevalence : 0.4486
##          Detection Rate : 0.2196
##    Detection Prevalence : 0.5140
##       Balanced Accuracy : 0.4778
##
##        'Positive' Class : 1
##
```

```
accuracy_nb02 = (nb02.t[1,1]+nb02.t[2,2])/nb02.t[3,3]
error_rate_nb02 = (1-accuracy_nb02)
sensitivity_nb02 = nb02.t[2,2]/ nb02.t[2,3]
specificity_nb02 = nb02.t[1,1]/nb02.t[1,3]
```

```r
precision_nb02 = nb02.t[2,2]/nb02.t[3,2]
F_1_nb02 = 2*(precision_nb02*sensitivity_nb02)/(precision_nb02+sensitivity_nb02)
F_2_nb02 = 5*(precision_nb02*sensitivity_nb02)/((4*precision_nb02)+
                                                  sensitivity_nb02)
F_0.5_nb02 = 1.25*(precision_nb02*sensitivity_nb02)/((0.25*precision_nb02)+
                                                       sensitivity_nb02)

cat("\n Accuracy:",accuracy_nb02, "\n Error Rate:",error_rate_nb02,
    "\n Sensitivity:",sensitivity_nb02,
"\n Specificity:",specificity_nb02, "\n Precision:",precision_nb02, "\n F1:",
F_1_nb02,
"\n F2:",F_2_nb02,
"\n F0.5:",F_0.5_nb02)
```

```
##
##  Accuracy: 0.4766355
##  Error Rate: 0.5233645
##  Sensitivity: 0.4895833
##  Specificity: 0.4661017
##  Precision: 0.4272727
##  F1: 0.4563107
##  F2: 0.4757085
##  F0.5: 0.4384328
```

```r
#Naive Bayes Model #3
nb03<- naiveBayes(formula = performance ~ address + famsup, data=student_train)
nb03
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##         0         1
## 0.5204819 0.4795181
##
## Conditional probabilities:
##    address
## Y           R         U
##   0 0.3356481 0.6643519
##   1 0.2035176 0.7964824
##
##    famsup
## Y          no       yes
##   0 0.4027778 0.5972222
##   1 0.3844221 0.6155779
```

```r
student_test$nb03predict<- predict(object=nb03, newdata= student_test)
nb03.t <- table(student_test$performance, student_test$nb03predict)
rownames(nb03.t)<- c("Actual:0","Actual:1")
colnames(nb03.t)<- c("Predicted:0", "Predicted:1")
nb03.t <- addmargins(A=nb03.t, FUN=list(Total=sum), quiet=TRUE)
```

```r
student_test[c('performance', 'nb03predict')] <- lapply(
  student_test[c('performance', 'nb03predict')], as.factor)
confusionMatrix(student_test$nb03predict, student_test$performance,positive='1')
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 36 23
##          1 82 73
##
##                Accuracy : 0.5093
##                  95% CI : (0.4403, 0.5781)
##     No Information Rate : 0.5514
##     P-Value [Acc > NIR] : 0.904
##
##                   Kappa : 0.062
##
##  Mcnemar's Test P-Value : 0.00000001512
##
##             Sensitivity : 0.7604
##             Specificity : 0.3051
##          Pos Pred Value : 0.4710
##          Neg Pred Value : 0.6102
##              Prevalence : 0.4486
##          Detection Rate : 0.3411
##    Detection Prevalence : 0.7243
##       Balanced Accuracy : 0.5328
##
##        'Positive' Class : 1
##
```

```r
accuracy_nb03 = (nb03.t[1,1]+nb03.t[2,2])/nb03.t[3,3]
error_rate_nb03 = (1-accuracy_nb03)
sensitivity_nb03 = nb03.t[2,2]/ nb03.t[2,3]
specificity_nb03 = nb03.t[1,1]/nb03.t[1,3]
precision_nb03 = nb03.t[2,2]/nb03.t[3,2]
F_1_nb03 = 2*(precision_nb03*sensitivity_nb03)/(precision_nb03+sensitivity_nb03)
F_2_nb03 = 5*(precision_nb03*sensitivity_nb03)/((4*precision_nb03)+
                                                  sensitivity_nb03)
F_0.5_nb03 = 1.25*(precision_nb03*sensitivity_nb03)/((0.25*precision_nb03)+
                                                       sensitivity_nb03)


cat("\n Accuracy:",accuracy_nb03, "\n Error Rate:",error_rate_nb03,
    "\n Sensitivity:",sensitivity_nb03,
"\n Specificity:",specificity_nb03, "\n Precision:",precision_nb03, "\n F1:",
F_1_nb03,
"\n F2:",F_2_nb03,
"\n F0.5:",F_0.5_nb03)
```

```
##
##  Accuracy: 0.5093458
##  Error Rate: 0.4906542
```

```
##  Sensitivity: 0.7604167
##  Specificity: 0.3050847
##  Precision: 0.4709677
##  F1: 0.5816733
##  F2: 0.67718
##  F0.5: 0.5097765
```

```
#Naive Bayes Model #4
nb04<- naiveBayes(formula = performance ~ address + famsup + studytime +
                    nursery + higher + failures + absences, data=student_train)
nb04
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##         0         1
## 0.5204819 0.4795181
##
## Conditional probabilities:
##    address
## Y           R         U
##   0 0.3356481 0.6643519
##   1 0.2035176 0.7964824
##
##    famsup
## Y          no       yes
##   0 0.4027778 0.5972222
##   1 0.3844221 0.6155779
##
##    studytime
## Y       [,1]      [,2]
##   0 1.847222 0.8286022
##   1 2.123116 0.8472319
##
##    nursery
## Y          no       yes
##   0 0.2268519 0.7731481
##   1 0.1683417 0.8316583
##
##    higher
## Y            no         yes
##   0 0.148148148 0.851851852
##   1 0.007537688 0.992462312
##
##    failures
## Y         [,1]      [,2]
##   0 0.43981481 0.8208919
##   1 0.05025126 0.2406696
##
##    absences
```

```
## Y        [,1]     [,2]
##   0 5.111111 6.920273
##   1 3.396985 4.688610
```

```
student_test$nb04predict<- predict(object=nb04, newdata= student_test)
nb04.t <- table(student_test$performance, student_test$nb04predict)
rownames(nb04.t)<- c("Actual:0","Actual:1")
colnames(nb04.t)<- c("Predicted:0", "Predicted:1")
nb04.t <- addmargins(A=nb04.t, FUN=list(Total=sum), quiet=TRUE)

student_test[c('performance', 'nb04predict')] <- lapply(
  student_test[c('performance', 'nb04predict')], as.factor)
confusionMatrix(student_test$nb04predict, student_test$performance,positive='1')
```

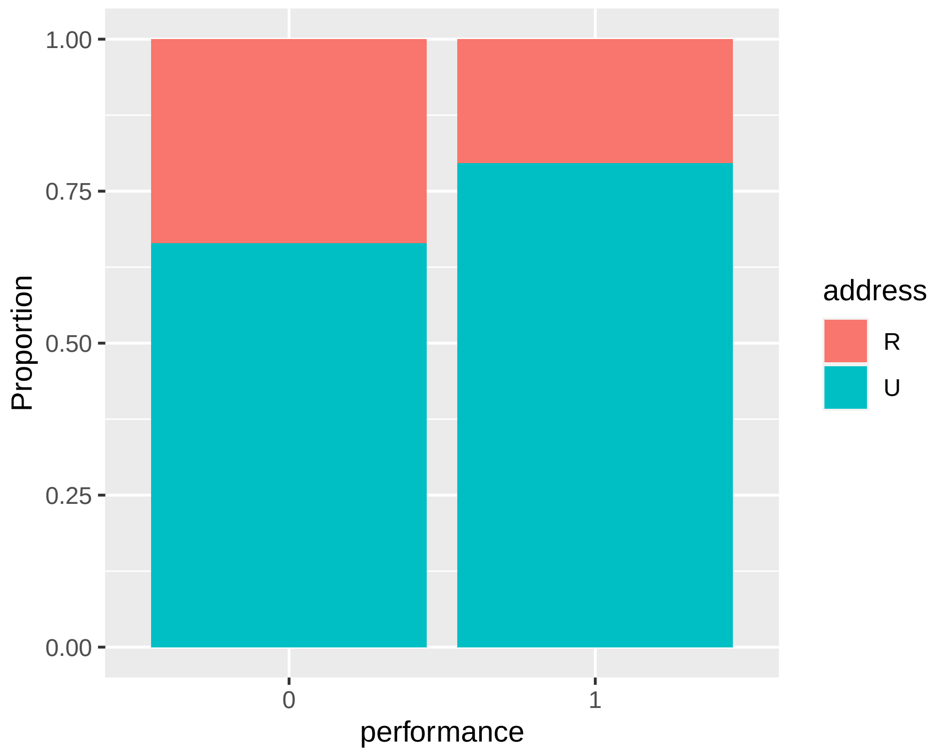
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 52  9
##          1 66 87
##
##                Accuracy : 0.6495
##                  95% CI : (0.5815, 0.7133)
##     No Information Rate : 0.5514
##     P-Value [Acc > NIR] : 0.002239
##
##                   Kappa : 0.3287
##
##  Mcnemar's Test P-Value : 0.0000000001004
##
##             Sensitivity : 0.9062
##             Specificity : 0.4407
##          Pos Pred Value : 0.5686
##          Neg Pred Value : 0.8525
##              Prevalence : 0.4486
##          Detection Rate : 0.4065
##    Detection Prevalence : 0.7150
##       Balanced Accuracy : 0.6735
##
##        'Positive' Class : 1
##
```

```
accuracy_nb04 = (nb04.t[1,1]+nb04.t[2,2])/nb04.t[3,3]
error_rate_nb04 = (1-accuracy_nb04)
sensitivity_nb04 = nb04.t[2,2]/ nb04.t[2,3]
specificity_nb04 = nb04.t[1,1]/nb04.t[1,3]
precision_nb04 = nb04.t[2,2]/nb04.t[3,2]
F_1_nb04 = 2*(precision_nb04*sensitivity_nb04)/(precision_nb04+sensitivity_nb04)
F_2_nb04 = 5*(precision_nb04*sensitivity_nb04)/((4*precision_nb04)+
                                                  sensitivity_nb04)
F_0.5_nb04 = 1.25*(precision_nb04*sensitivity_nb04)/((0.25*precision_nb04)+
                                                       sensitivity_nb04)

cat("\n Accuracy:",accuracy_nb04, "\n Error Rate:",error_rate_nb04,
    "\n Sensitivity:",sensitivity_nb04,
```

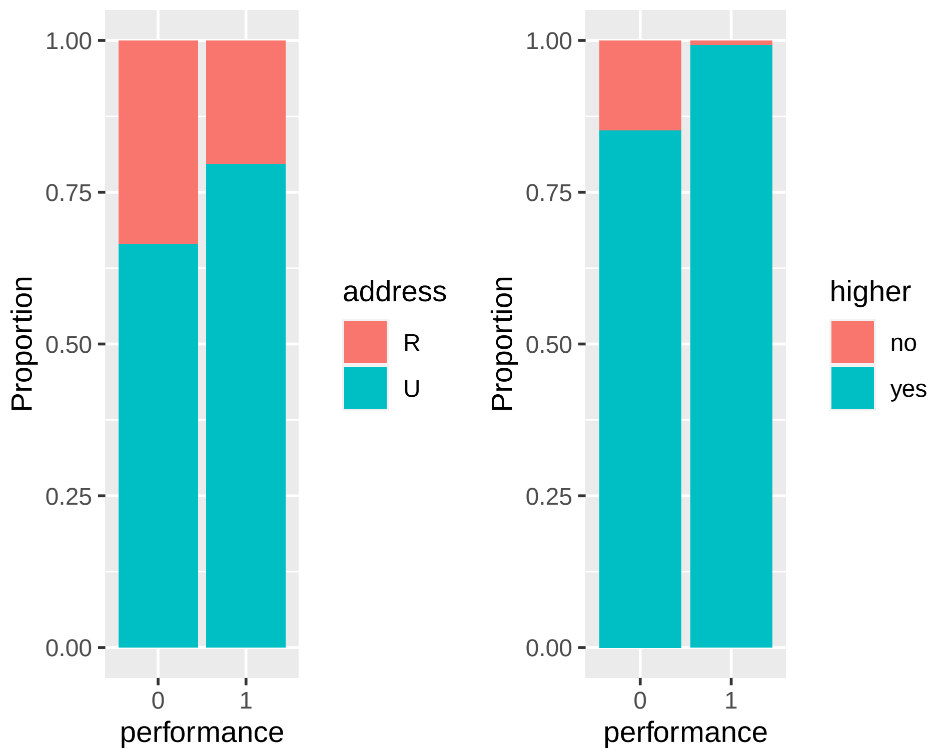
```
"\n Specificity:",specificity_nb04, "\n Precision:",precision_nb04, "\n F1:",
F_1_nb04,
"\n F2:",F_2_nb04,
"\n F0.5:",F_0.5_nb04)
```

```
##
##  Accuracy: 0.6495327
##  Error Rate: 0.3504673
##  Sensitivity: 0.90625
##  Specificity: 0.440678
##  Precision: 0.5686275
##  F1: 0.6987952
##  F2: 0.8100559
##  F0.5: 0.6144068
```

```
ggplot(student_train, aes(performance)) +
  geom_bar(aes(fill=address),position="fill")+ylab("Proportion")
```




```
library(ggplot2);library(gridExtra)
plotadd<- ggplot(student_train, aes(performance))+
  geom_bar(aes(fill=address),position="fill")+ylab("Proportion")
plothigh<- ggplot(student_train, aes(performance))+
  geom_bar(aes(fill=higher),position="fill")+ylab("Proportion")
grid.arrange(plotadd, plothigh,nrow=1)
```



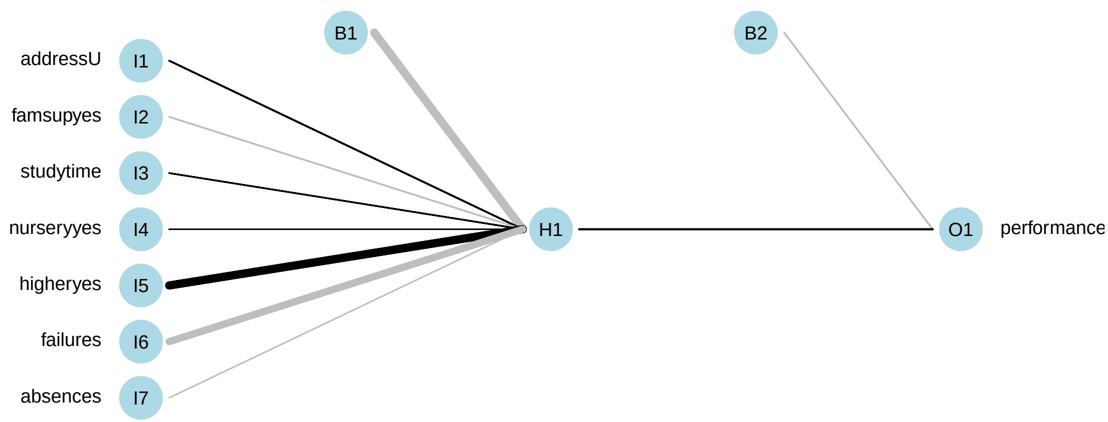
Neural Network

```
library(nnet)
library(NeuralNetTools)
neunet <- nnet(performance ~ address + famsup + studytime +
               nursery + higher + failures + absences,
               data = student_train, size = 1)
```

```
## # weights:  10
## initial  value 589.192090
## iter  10 value 521.825217
## iter  20 value 495.452662
## iter  30 value 494.027863
## iter  40 value 489.580412
## iter  50 value 489.431383
## final  value 489.431321
## converged
```

```
X_train <- subset(x=student_train, select =c("address", "famsup",
                                             "studytime", "nursery", "higher",
                                             "failures", "absences"))
student_train$pred_nnet <- predict(object = neunet, newdata =  X_train)

#head(student_train$pred_nnet)

student_train$predict_nnet <- (student_train$pred_nnet > 0.5)*1
#head(student_train$predict_nnet)
```

```r
plotnet(neunet)
```




```r
neunet$wts
```

```
##  [1] -19.4691154   1.4401849  -0.8018977   0.9469798   0.8391144  18.4772478
##  [7] -15.6204436  -0.1163643  -2.0201118   2.9029234
```

```r
library(caret)
student_test$address <- as.factor(student_test$address)
student_test$famsup <- as.factor(student_test$famsup)
student_test$higher <- as.factor(student_test$higher)
student_test$freetime <- as.factor(student_test$freetime)
student_test$age <- as.numeric(student_test$age)

student_test$age.mm <- (student_test$age - min(student_test$age)) /
(max(student_test$age) - min(student_test$age))

X_test <- subset(x=student_test, select =c("address", "famsup",
                                             "studytime", "nursery", "higher",
                                             "failures", "absences"))

table_nnet <- table(student_train$performance, student_train$predict_nnet)
table_nnet <- addmargins(A=table_nnet, FUN=list(Total=sum), quiet = TRUE);
table_nnet
```

```
##
##           0   1 Total
##   0     241 191   432
##   1      68 330   398
##   Total 309 521   830
```

```r
student_train[c('performance', 'predict_nnet')] <- lapply(
  student_train[c('performance', 'predict_nnet')], as.factor)
confusionMatrix(student_train$predict_nnet, student_train$performance,
                positive='1')
```

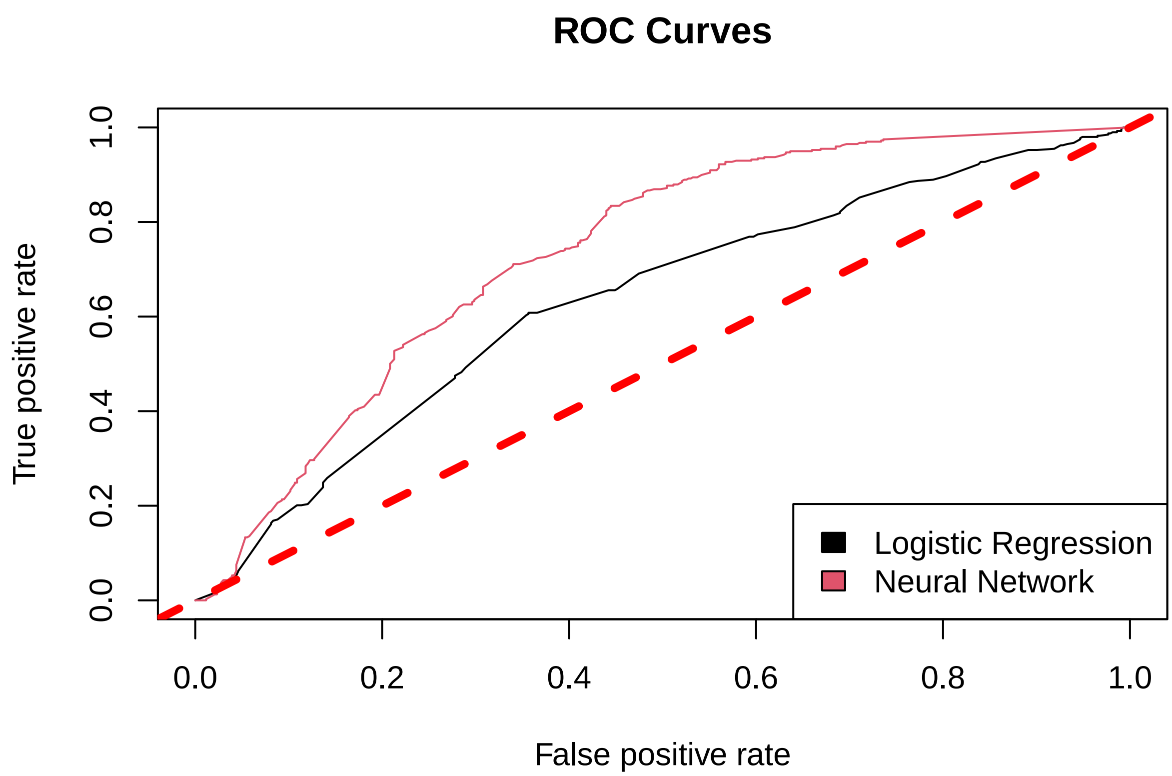
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 241  68
##          1 191 330
##
##                Accuracy : 0.688
##                  95% CI : (0.6552, 0.7194)
##     No Information Rate : 0.5205
##     P-Value [Acc > NIR] : < 0.00000000000000022
##
##                   Kappa : 0.3824
##
##  Mcnemar's Test P-Value : 0.00000000000003437
##
##             Sensitivity : 0.8291
##             Specificity : 0.5579
##          Pos Pred Value : 0.6334
##          Neg Pred Value : 0.7799
##              Prevalence : 0.4795
##          Detection Rate : 0.3976
##    Detection Prevalence : 0.6277
##       Balanced Accuracy : 0.6935
##
##        'Positive' Class : 1
##
```

```r
accuracy_nnet = (table_nnet[1,1]+table_nnet[2,2])/table_nnet[3,3]
error_rate_nnet = (1-accuracy_nnet)
sensitivity_nnet = table_nnet[2,2]/ table_nnet[2,3]
specificity_nnet = table_nnet[1,1]/table_nnet[1,3]
precision_nnet = table_nnet[2,2]/table_nnet[3,2]
F_1_nnet = 2*(precision_nnet*sensitivity_nnet)/(precision_nnet+sensitivity_nnet)
F_2_nnet = 5*(precision_nnet*sensitivity_nnet)/((4*precision_nnet)+
                                                  sensitivity_nnet)
F_0.5_nnet = 1.25*(precision_nnet*sensitivity_nnet)/((0.25*precision_nnet)+
                                                       sensitivity_nnet)

cat("\n Accuracy:",accuracy_nnet, "\n Error Rate:",error_rate_nnet,
    "\n Sensitivity:",sensitivity_nnet,
"\n Specificity:",specificity_nnet, "\n Precision:",precision_nnet, "\n F1:",
F_1_nnet,
"\n F2:",F_2_nnet,
"\n F0.5:",F_0.5_nnet)
```

```
##
##  Accuracy: 0.6879518
##  Error Rate: 0.3120482
```

```
##   Sensitivity: 0.8291457
##   Specificity: 0.5578704
##   Precision: 0.6333973
##   F1: 0.7181719
##   F2: 0.7808803
##   F0.5: 0.6647865
```

```r
library(ROCR)

# List of predictions
preds_list <- list(student_train$pred_probab,
                   student_train$pred_nnet)

# List of actual values (same for all)
m <- length(preds_list)
actuals_list <- rep(list(student_train$performance), m)

# Plot the ROC curves
pred <- prediction(preds_list, actuals_list)
rocs <- performance(pred, "tpr", "fpr")
plot(rocs, col = as.list(1:m), main = "ROC Curves")
abline(0, 1, col='red', lty=2, lwd=4)
legend(x = "bottomright",
       legend = c("Logistic Regression", "Neural Network"),
       fill = 1:m)
```



Model Evaluation Formulas:

Evaluation Measure	**Formula**
Accuracy	$\frac{TN+TP}{GT}$
Error rate	$1 - Accuracy$
Sensitivity	$\frac{TP}{TAP}$
Specificity	$\frac{TN}{TAN}$
Precision	$\frac{TP}{TPP}$
F_1	$2 \cdot \frac{precision \cdot recall}{precision+recall}$
F_2	$5 \cdot \frac{precision \cdot recall}{(4 \cdot precision)+recall}$
$F_{0.5}$	$1.25 \cdot \frac{precision \cdot recall}{(0.25 \cdot precision)+recall}$

Model Evaluation Table:

Evaluation Measure	**C5.0**	**CART**	**Logistic Regression**	**Random Forest**	**Naive Bayes**	**Neural Network**
Accuracy	0.6308411	0.635514	0.6253012	0.6261682	0.6495327	0.6879518
Error rate	0.3691589	0.364486	0.3746988	0.3738318	0.3504673	0.3120482
Sensitivity	0.59375	0.7708333	0.6055276	0.8020833	0.90625	0.8291457
Specificity	0.6610169	0.5254237	0.6435185	0.4830508	0.440678	0.5578704
Precision	0.5876289	0.5692308	0.6101266	0.557971	0.5686275	0.6333973
F_1	0.5906736	0.6548673	0.6078184	0.6581197	0.6987952	0.7181719
F_2	0.5925156	0.7198444	0.6064419	0.7375479	0.8100559	0.7808803
$F_{0.5}$	0.588843	0.6006494	0.6092012	0.5941358	0.6144068	0.6647865