Personalized Capstone Project

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Introduction

The main objective is to determine factors/variables that may influence the admission of a student into college within the United States. This analysis will examine seven attributes/variables (Graduate Record Exam Scores (GRE), Grade Point Average (GPA), Rank of University with 1 being very prestigious, socioeconomic status (ranging from 1 to 3 or low to high), gender (female and male were recoded as 0 and 1 respectively) and race (1, 2, 3 indicates that the student identifies as Hispanics, Asian, and African-American respectively). The response or dependent variable in admit, a binary variable where 1 indicates that the student was admitted and 0 not admitted. The dataset was transformed and then baseline prediction was used to first determine the outcome and whether our machine learning algorithm performed better than chance. Additionally, other models were trained and tested to evaluate their accuracy.

Data Wrangling/Transformation

The dataset was transformed, categorical variables (rank, socioeconomic status, gender, race, admit) were changed to factors, and then histogram and boxplots were used to examine distribution of numerical variables (GRE & GPA) and variations in categorical variables (socioeconomic status, gender, race, etc). Both GRE and GPA were observed to have outliers. Excluding outliers, females and males had similar variations in gre scores. However, females had higher GPA scores than males. Variations in GRE score and GPA were observed among different socioeconomic status and race groups. 2.26, 220, and 300 were identified as outliers of GPA and GRE scores and these outliers were removed from dataset. The clean data was then split 80:20 into train and test sets using to caret package.

Data Analysis/Result

0.45 was the mean probability of being admitted into college. The accuracy of the sex-based prediction was 0.5. 0.625 was the accuracy of the socio-economic status on the probability of college admission. The specificity and sensitivity of the sex model is 0.423 & 0.537 while the specificity and sensitivity of the class based model is 0.346 & 0.759. The balance accuracy is approximately 0.5 for both models. However, the F-means score is 0.592 and 0.732 for the sex and class based models respectively. 0.675 was the accuracy of GRE or GPA as a predictor of admission using the QDA method. The accuracy of model using the glm method with GRE scores, GPA, socio-economic status and race as predictors was 0.725. The KNN value with the highest accuracy 0.675 was identified as 51. The accuracy of the decision tree model was observed at 0.675. The most important variables identified by the random forest model were GRE and GPA.

Conclusion

This analysis provided insights on drivers on college admissions examining multiple variables. It was observed that academic performance (GRE scores and GPA) were better predictors of admission than racial and socioeconomic status. To confirm observations, a larger dataset would need to be examined on college admission in the United States.

#Loading packages and librabies

```
if(!require(lubridate))install.packages("lubridate")

## Loading required package: lubridate

##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union

if(!require(readr))install.packages("readr")

## Loading required package: readr

if(!require(ggplot2))install.packages("ggplot2")

## Loading required package: ggplot2

if(!require(tidyverse))install.packages("tidyverse")

## Loading required package: tidyverse

## ── Attaching packages ─────────────────────────────────────── tidyverse
1.3.2 ──
## ✓ tibble  3.1.8      ✓ dplyr   1.0.10
## ✓ tidyr   1.2.1      ✓ stringr 1.4.1
## ✓ purrr   0.3.5      ✓ forcats 0.5.2
## ── Conflicts ──────────────────────────────────────────
tidyverse_conflicts() ──
## ✕ lubridate::as.difftime() masks base::as.difftime()
## ✕ lubridate::date()        masks base::date()
## ✕ dplyr::filter()          masks stats::filter()
## ✕ lubridate::intersect()   masks base::intersect()
## ✕ dplyr::lag()             masks stats::lag()
## ✕ lubridate::setdiff()     masks base::setdiff()
## ✕ lubridate::union()       masks base::union()
```

```
if(!require(caret)) install.packages("caret")

## Loading required package: caret
## Loading required package: lattice
##
## Attaching package: 'caret'
##
## The following object is masked from 'package:purrr':
##
##     lift

if(!require(rpart)) install.packages("rpart")

## Loading required package: rpart

if(!require(dplyr)) install.packages("dplyr")
if(!require(rpart.plot)) installed.packages("rpart.plot")

## Loading required package: rpart.plot

## Warning: package 'rpart.plot' was built under R version 4.2.2

library(rpart.plot)
library(caret)
library(tidyverse)
library(rpart)
library(readr)
library(dplyr)
library(ggplot2)
library(lubridate)
```

#Set working directory

```
getwd()

## [1] "C:/Users/eboley/OneDrive - Partners In Health/Desktop/Data/project"

setwd("C:/Users/eboley/OneDrive - Partners In Health/Desktop/Data/project")
```

#Set Relative folder path

```
College <- read.csv("R/College_admission.csv")
```

3 significant digits

```
options(digits = 3)
```

#Recoding categorical & numerical variables

```
College_clean <- College %>%
  mutate(GreLevels=ifelse(gre<440,"Low",ifelse(gre<580,"Medium","High"))) %>%
  mutate(Gender=ifelse(Gender_Male == 0, "female","male")) %>%
  mutate(Demo = recode(Race,
```

```
                        "1" = "Hispanics",
                        "2" = "Asian",
                        "3" = "African-American"))%>%
  mutate(Socioeco = recode(ses,
                            "1" = "Low",
                            "2" = "Medium",
                            "3" = "High"))
```

#Summary of data

```
summary(College_clean)

##      admit             gre             gpa              ses         Gender_Male
##  Min.   :0.000   Min.   :220   Min.   :2.26   Min.   :1.00   Min.   :0.000
##  1st Qu.:0.000   1st Qu.:520   1st Qu.:3.13   1st Qu.:1.00   1st Qu.:0.000
##  Median :0.000   Median :580   Median :3.40   Median :2.00   Median :0.000
##  Mean   :0.318   Mean   :588   Mean   :3.39   Mean   :1.99   Mean   :0.475
##  3rd Qu.:1.000   3rd Qu.:660   3rd Qu.:3.67   3rd Qu.:3.00   3rd Qu.:1.000
##  Max.   :1.000   Max.   :800   Max.   :4.00   Max.   :3.00   Max.   :1.000
##       Race            rank        GreLevels             Gender
##  Min.   :1.00   Min.   :1.00   Length:400         Length:400
##  1st Qu.:1.00   1st Qu.:2.00   Class :character   Class :character
##  Median :2.00   Median :2.00   Mode  :character   Mode  :character
##  Mean   :1.96   Mean   :2.48
##  3rd Qu.:3.00   3rd Qu.:3.00
##  Max.   :3.00   Max.   :4.00
##      Demo             Socioeco
##  Length:400         Length:400
##  Class :character   Class :character
##  Mode  :character   Mode  :character
##
##
##

str(College_clean)

## 'data.frame':    400 obs. of  11 variables:
##  $ admit      : int  0 1 1 1 0 1 1 0 1 0 ...
##  $ gre        : int  380 660 800 640 520 760 560 400 540 700 ...
##  $ gpa        : num  3.61 3.67 4 3.19 2.93 3 2.98 3.08 3.39 3.92 ...
##  $ ses        : int  1 2 2 1 3 2 2 2 1 1 ...
##  $ Gender_Male: int  0 0 0 1 1 1 1 0 1 0 ...
##  $ Race       : int  3 2 2 2 2 1 2 2 1 2 ...
##  $ rank       : int  3 3 1 4 4 2 1 2 3 2 ...
##  $ GreLevels  : chr  "Low" "High" "High" "High" ...
##  $ Gender     : chr  "female" "female" "female" "male" ...
##  $ Demo       : chr  "African-American" "Asian" "Asian" "Asian" ...
##  $ Socioeco   : chr  "Low" "Medium" "Medium" "Low" ...

#Data type as numeric (admit, ses, race, gender, and rank), GreLevels as
character variable
```

#Transforming categorical variables (admit, ses, gender, rank)

```
College_clean$admit <- as.factor(College_clean$admit)
College_clean$ses <- as.factor(College_clean$ses)
College_clean$Race <- as.factor(College_clean$Race)
College_clean$Gender_Male <- as.factor(College_clean$Gender_Male)
College_clean$rank <- as.factor(College_clean$rank)
College_clean$GreLevels <- as.factor(College_clean$GreLevels)
College_clean$Gender <- as.factor(College_clean$Gender)
College_clean$Demo <- as.factor(College_clean$Demo)
College_clean$Socioeco <- as.factor(College_clean$Socioeco)
```

#Finding missing data

```
is.na(College_clean)

##        admit   gre   gpa   ses Gender_Male  Race  rank GreLevels Gender
Demo
##   [1,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##   [2,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##   [3,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##   [4,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##   [5,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##   [6,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##   [7,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##   [8,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##   [9,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##  [10,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##  [11,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##  [12,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##  [13,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##  [14,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##  [15,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [16,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [17,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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FALSE
##  [18,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [19,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [20,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
FALSE
##  [21,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [22,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [23,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [25,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [26,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [27,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [28,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [29,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [30,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [31,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [38,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [39,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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##  [41,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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## [239,] FALSE FALSE FALSE FALSE       FALSE FALSE FALSE     FALSE  FALSE
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```
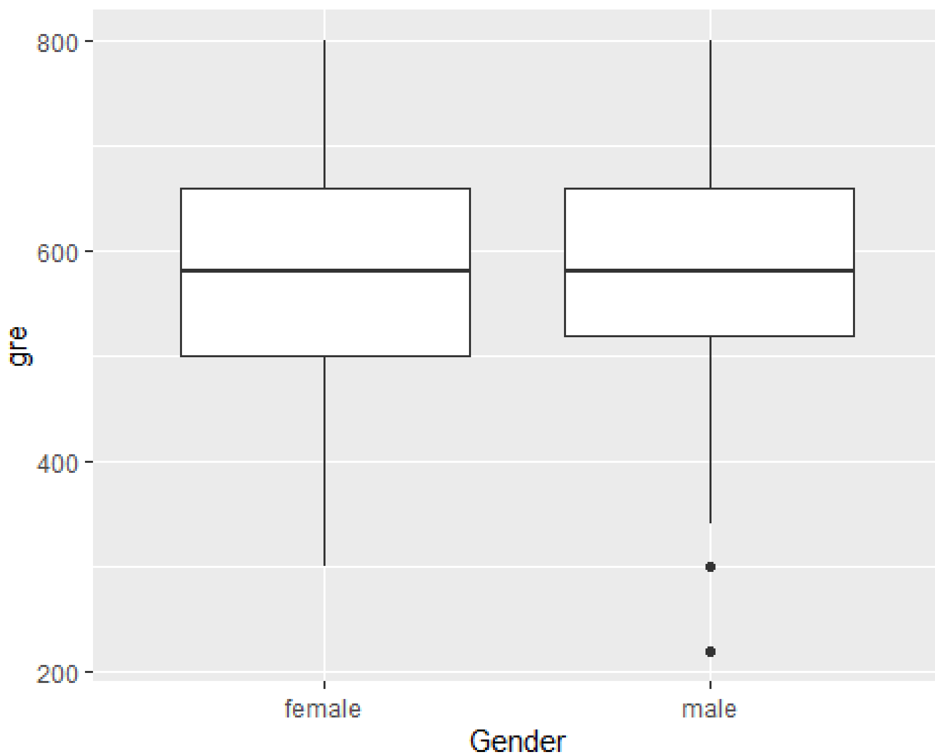

```
sum(is.na(College_clean))
```

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

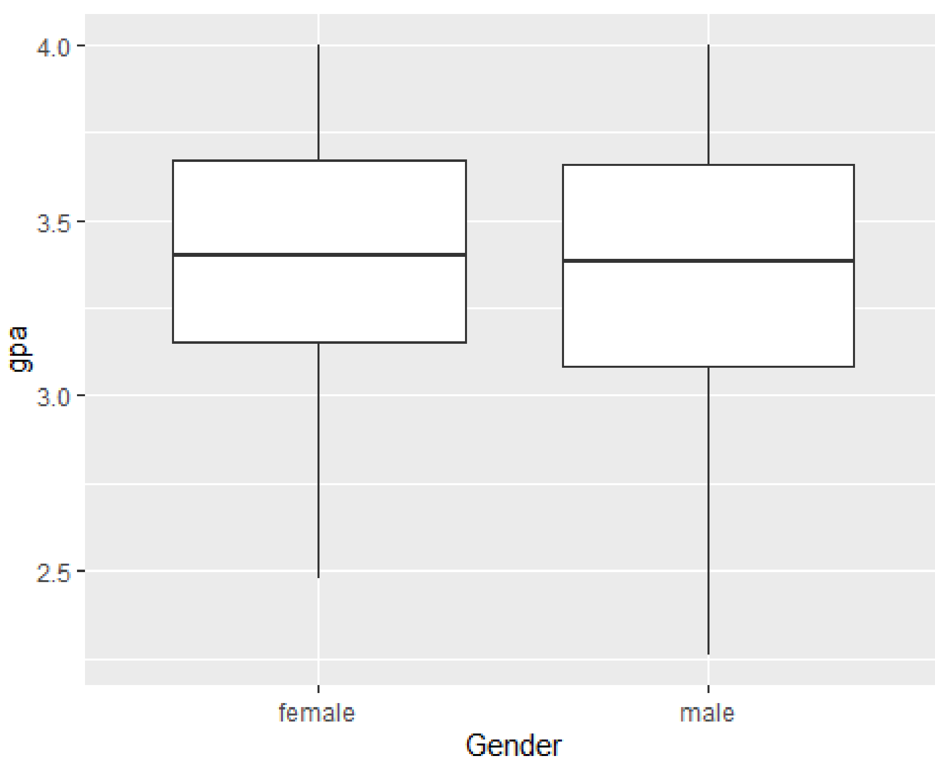
```
#there is no missing values in dataset
```

#Distribution of gre & gpa scores among gender

```
College_clean %>%
  ggplot(aes(Gender,gre))+
  geom_boxplot()
```

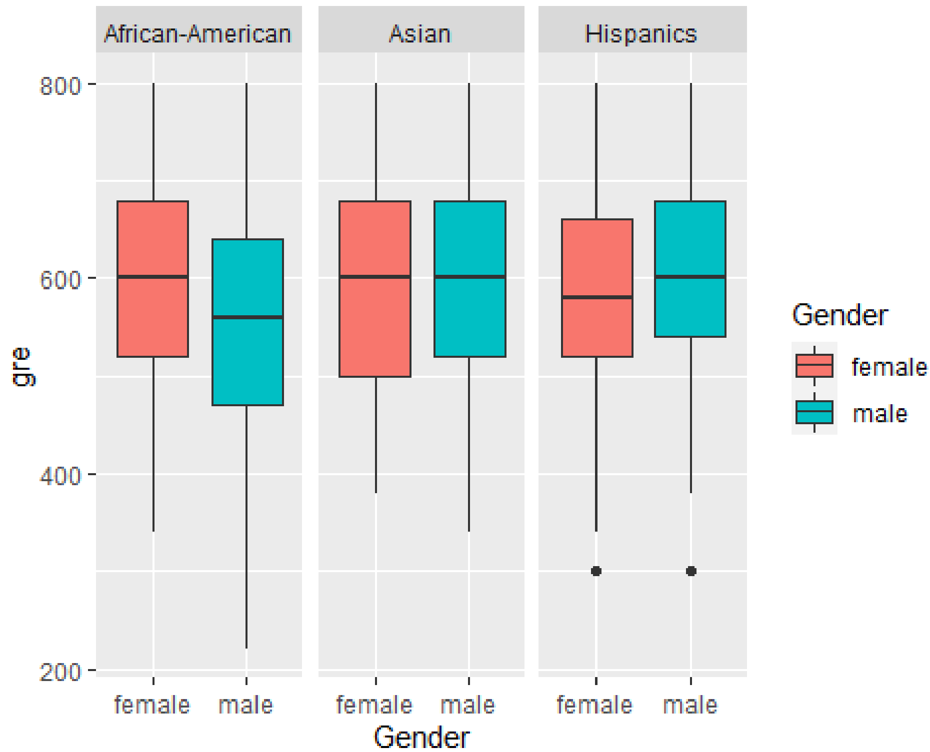



```
College_clean %>%
  ggplot(aes(Gender,gpa))+
  geom_boxplot()
```

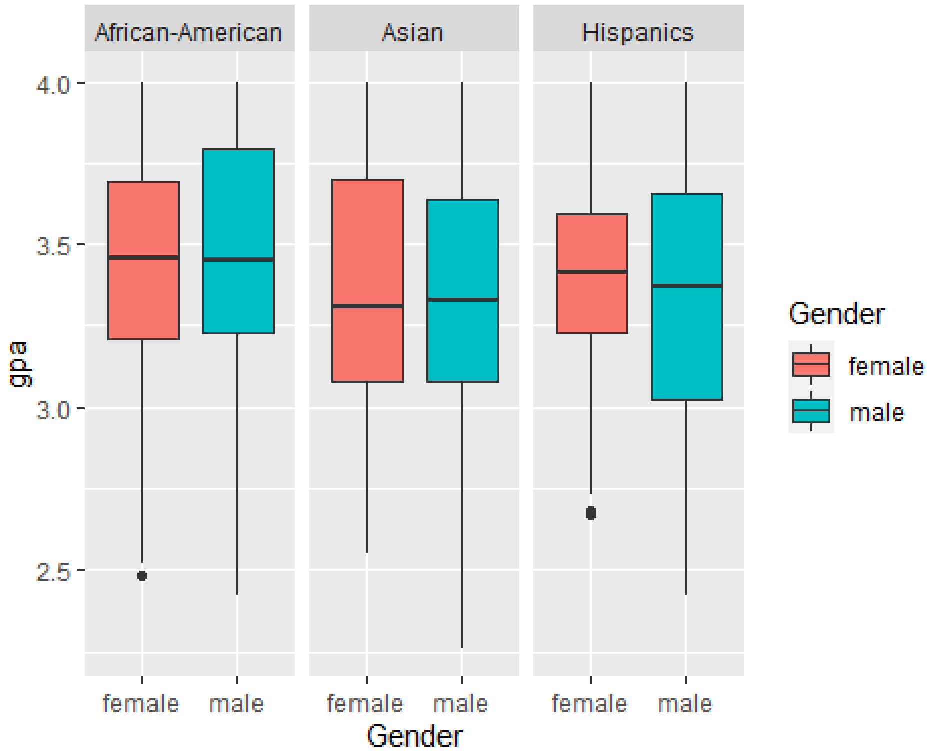


#Variation in gre & gpa by gender, race and socioenomic status

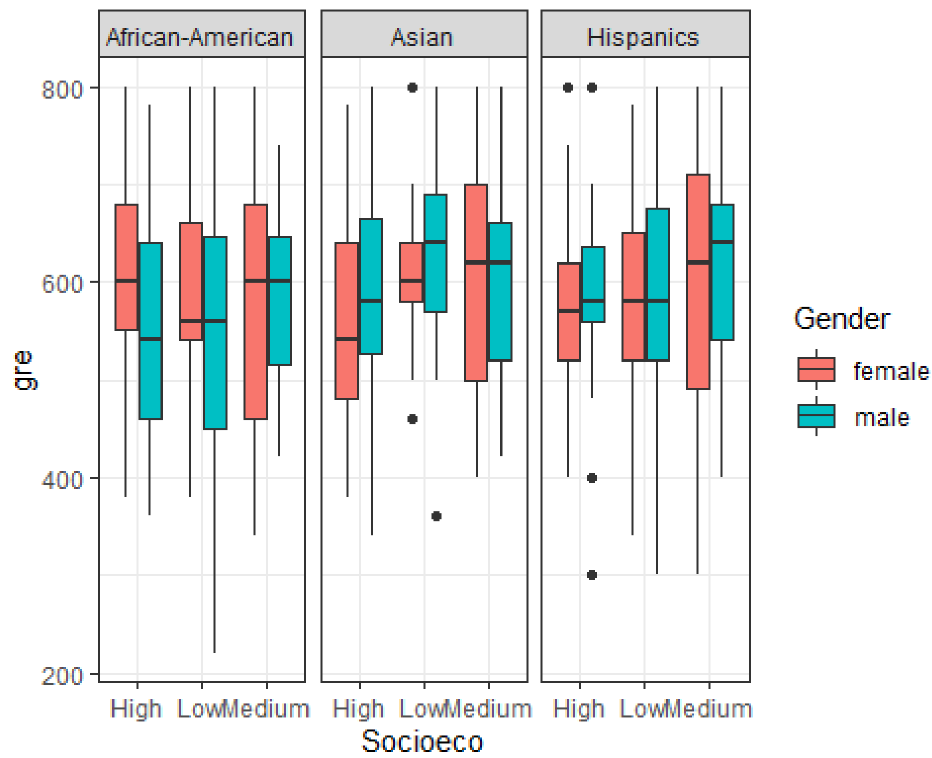
```
College_clean %>%
  ggplot(aes(Gender,gre, fill = Gender))+
  geom_boxplot()+
  facet_grid(~Demo)
```



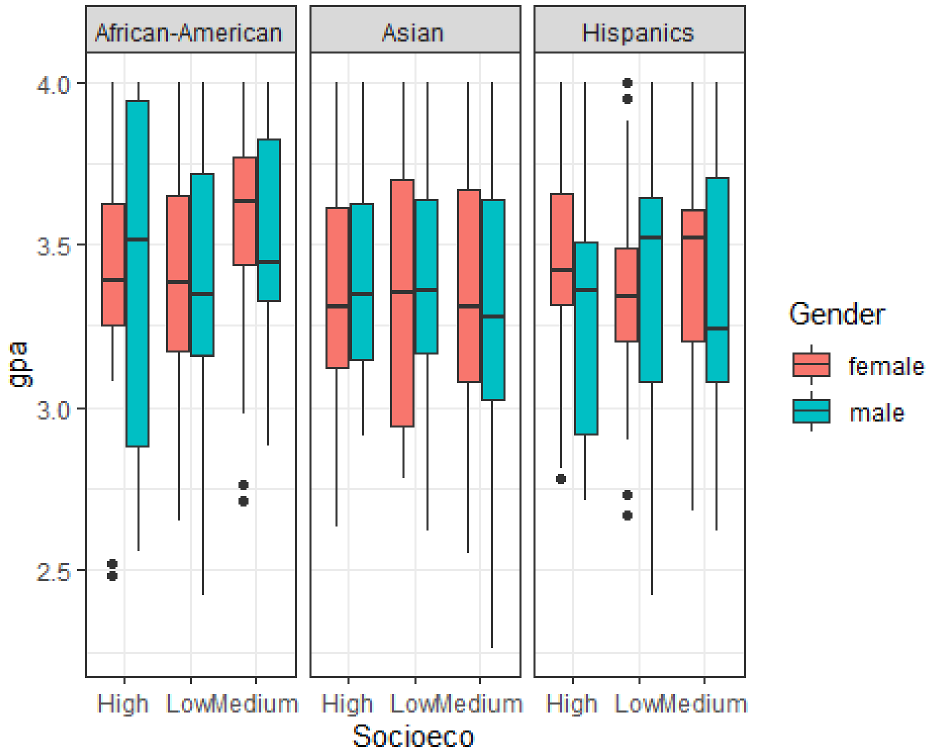

```
College_clean %>%
  ggplot(aes(Gender,gpa, fill = Gender))+
  geom_boxplot()+
  facet_grid(~Demo)
```




```
College_clean %>%
  ggplot(aes(Socioeco, gre, fill = Gender))+
  #geom_density(alpha = 0.5)+
  geom_boxplot()+
  facet_wrap(~Demo)+
  theme_bw()
```

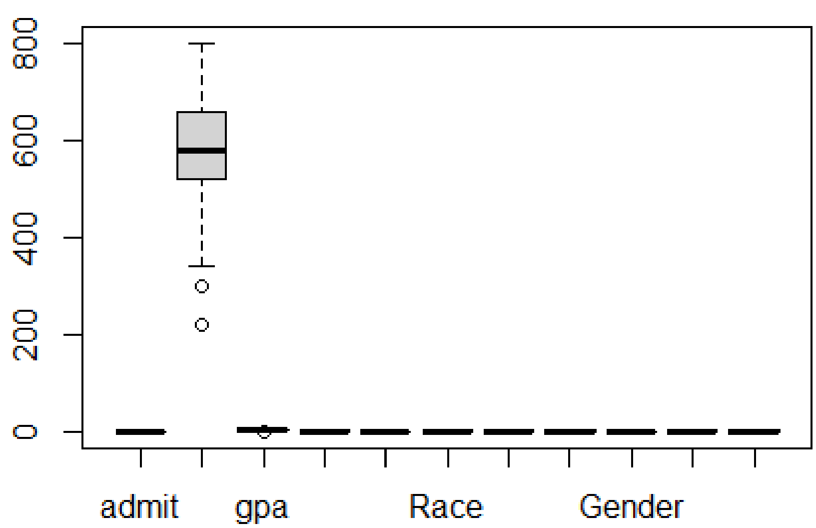



```
College_clean %>%
  ggplot(aes(Socioeco, gpa, fill = Gender))+
  #geom_density(alpha = 0.5)+
  geom_boxplot()+
  facet_wrap(~Demo)+
  theme_bw()
```

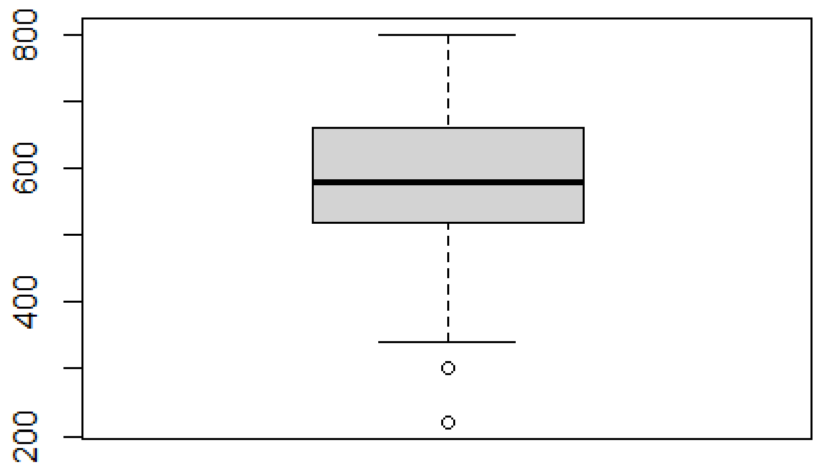


#Find outliers in data set

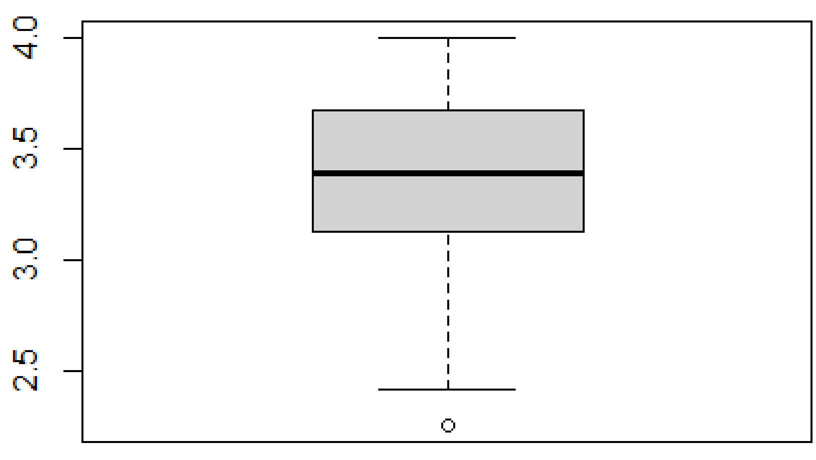
```
boxplot(College_clean)
```



```
boxplot(College_clean$gre)
```




```
boxplot(College_clean$gpa)
```



#Identifying of outliers

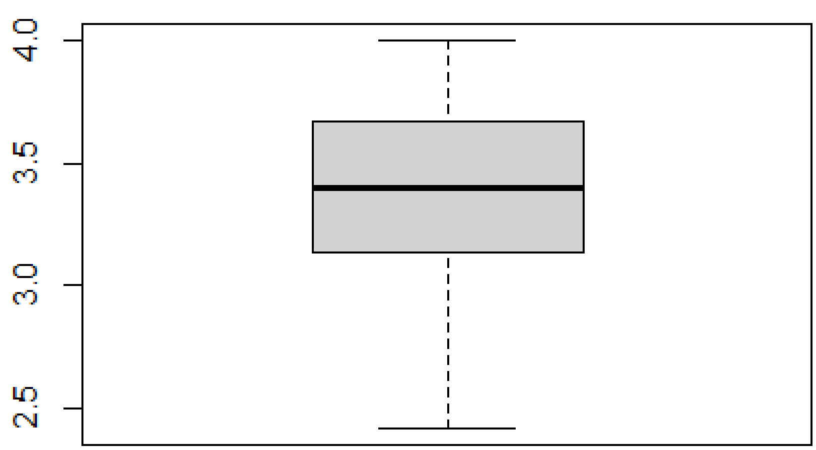
```
boxplot.stats(College_clean$gpa)$out

## [1] 2.26

boxplot.stats(College_clean$gre)$out

## [1] 300 300 220 300

#GPA outlier is 2.26
#GRE outlier are 300 300 220 300
```

#Removing outliers

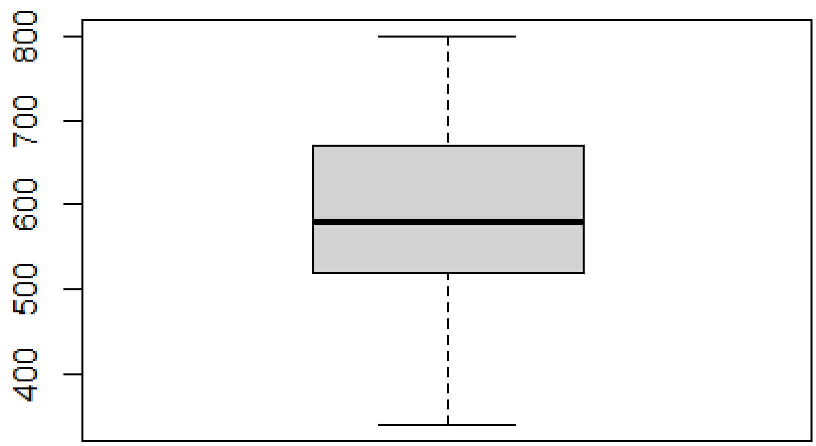
```
College_clean <- subset(College_clean, gpa != 2.26)
College_clean <- subset(College_clean, gre != 300 & gre !=220)
```

#Confirmation outliers removed

```
boxplot(College_clean$gpa)
```




```
boxplot(College_clean$gre)
```



#Creating train and test sets

```
set.seed(42, sample.kind = "Rounding")

## Warning in set.seed(42, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used

test_index <- createDataPartition(College_clean$admit, times = 1, p = 0.2,
list = FALSE)
College_test <- College_clean[test_index,]
College_train <- College_clean[-test_index,]

nrow(College_train)

## [1] 315

nrow(College_test)

## [1] 80
```

#Proportion of individuals in the training set admitted

```
mean(College_train$admit == 1)

## [1] 0.317
```

#Accuracy of guessing method

```
set.seed(3, sample.kind = "Rounding")
```

```
## Warning in set.seed(3, sample.kind = "Rounding"): non-uniform 'Rounding'
sampler
## used

guess <- sample(c(0,1), nrow(College_test), replace = TRUE)
mean(guess == College_test$admit)

## [1] 0.425
```

#Proportion of females admitted

```
College_train %>%
  group_by(Gender_Male) %>%
  summarize(Admit = mean(admit == 1)) %>%
  filter(Gender_Male == "0") %>%
  pull(Admit)

## [1] 0.327
```

#Proportion of males admitted

```
College_train %>%
  group_by(Gender_Male) %>%
  summarize(Admit = mean(admit == 1)) %>%
  filter(Gender_Male == "1") %>%
  pull(Admit)

## [1] 0.307
```

#Predicting admission by sex # predict admission = 1 if male, 0 if female

```
sex_model <- ifelse(College_test$Gender == "female", 0, 1)
```

#Calculate accuracy

```
mean(sex_model == College_test$admit)

## [1] 0.5
```

#Predicting admission by socioeconomic class

```
College_train %>%
  group_by(Socioeco) %>%
  summarize(Admit = mean(admit == 1))

## # A tibble: 3 × 2
##   Socioeco Admit
##   <fct>    <dbl>
## 1 High     0.287
## 2 Low      0.343
## 3 Medium   0.321
```

#Accuracy of class-based prediction method # predict admission only if socioeconomic class is low

```
class_model <- ifelse(College_test$ses == 1, 1, 0)
```

#Calculate accuracy

```
mean(class_model == College_test$admit)

## [1] 0.625
```

#Prediction of admission based on class and sex

```
College_train %>%
  group_by(Gender, Socioeco) %>%
  summarize(admit = mean(admit == 1))

## `summarise()` has grouped output by 'Gender'. You can override using the
## `.groups` argument.

## # A tibble: 6 × 3
## # Groups:   Gender [2]
##   Gender Socioeco admit
##   <fct>  <fct>    <dbl>
## 1 female High     0.263
## 2 female Low      0.368
## 3 female Medium   0.353
## 4 male   High     0.318
## 5 male   Low      0.314
## 6 male   Medium   0.291

  #filter(admit > 0.5)
```

#Prediction of admission based on class and sex

```
College_train %>%
  group_by(Gender, Race) %>%
  summarize(admit = mean(admit == 1))

## `summarise()` has grouped output by 'Gender'. You can override using the
## `.groups` argument.

## # A tibble: 6 × 3
## # Groups:   Gender [2]
##   Gender Race  admit
##   <fct>  <fct> <dbl>
## 1 female 1     0.321
## 2 female 2     0.283
## 3 female 3     0.385
## 4 male   1     0.406
## 5 male   2     0.25
## 6 male   3     0.217
```

#Prediction of admission based on race and sex

```
College_train %>%
  group_by(Gender, Race) %>%
  summarize(admit = mean(admit == 1))

## `summarise()` has grouped output by 'Gender'. You can override using the
## `.groups` argument.

## # A tibble: 6 × 3
## # Groups:   Gender [2]
##   Gender Race  admit
##   <fct>  <fct> <dbl>
## 1 female 1     0.321
## 2 female 2     0.283
## 3 female 3     0.385
## 4 male   1     0.406
## 5 male   2     0.25
## 6 male   3     0.217

#filter(admit > 0.5)
```

#Confusion matrix

```
confusionMatrix(data = factor(sex_model), reference =
factor(College_test$admit))

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 29 15
##          1 25 11
##
##                Accuracy : 0.5
##                  95% CI : (0.386, 0.614)
##     No Information Rate : 0.675
##     P-Value [Acc > NIR] : 1.000
##
##                   Kappa : -0.036
##
##  Mcnemar's Test P-Value : 0.155
##
##             Sensitivity : 0.537
##             Specificity : 0.423
##          Pos Pred Value : 0.659
##          Neg Pred Value : 0.306
##              Prevalence : 0.675
##          Detection Rate : 0.362
##    Detection Prevalence : 0.550
##       Balanced Accuracy : 0.480
```

```
##
##        'Positive' Class : 0
##
```

```
confusionMatrix(data = factor(class_model), reference =
factor(College_test$admit))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 41 17
##          1 13  9
##
##                Accuracy : 0.625
##                  95% CI : (0.51, 0.731)
##     No Information Rate : 0.675
##     P-Value [Acc > NIR] : 0.858
##
##                   Kappa : 0.11
##
##  Mcnemar's Test P-Value : 0.584
##
##             Sensitivity : 0.759
##             Specificity : 0.346
##          Pos Pred Value : 0.707
##          Neg Pred Value : 0.409
##              Prevalence : 0.675
##          Detection Rate : 0.512
##    Detection Prevalence : 0.725
##       Balanced Accuracy : 0.553
##
##        'Positive' Class : 0
##
```

#F means score

```
F_meas(data = factor(sex_model), reference = College_test$admit)

## [1] 0.592

F_meas(data = factor(class_model), reference = College_test$admit)

## [1] 0.732
```

#Admission by gre and gpa using LDA and QDA #The accuracy on the test set for the LDA model

```
set.seed(1, sample.kind = "Rounding")
```

```
## Warning in set.seed(1, sample.kind = "Rounding"): non-uniform 'Rounding'
sampler
## used
```

```
train_lda <- train(admit ~ gpa, method = "lda", data = College_train)
lda_preds <- predict(train_lda, College_test)
mean(lda_preds == College_test$admit)
```

```
## [1] 0.675
```

```
train_lda_a <- train(admit ~ gre, method = "lda", data = College_train)
lda_preds_a <- predict(train_lda_a, College_test)
mean(lda_preds_a == College_test$admit)
```

```
## [1] 0.675
```

#The accuracy on the test set for the QDA model

```
train_qda <- train(admit ~ gpa, method = "qda", data = College_train)
qda_preds <- predict(train_qda, College_test)
mean(qda_preds == College_test$admit)
```

```
## [1] 0.675
```

```
train_qda_a <- train(admit ~ gre, method = "qda", data = College_train)
qda_preds_a <- predict(train_qda_a, College_test)
mean(qda_preds_a == College_test$admit)
```

```
## [1] 0.675
```

#The accuracy of your model (using gre as the only predictor) on the test set

```
train_glm_gre <- train(admit ~ gre, method = "glm", data = College_train)
glm_preds_gre <- predict(train_glm_gre, College_test)
mean(glm_preds_gre == College_test$admit)
```

```
## [1] 0.675
```

#The accuracy of your model (using these four predictors) on the test

```
train_glm <- train(admit ~ gre + gpa + ses + Race, method = "glm", data =
College_train)
glm_preds <- predict(train_glm, College_test)
mean(glm_preds == College_test$admit)
```

```
## [1] 0.725
```

#The accuracy of your model (using all predictors) on the test set

```
str(College_train)
```

```
## 'data.frame':    315 obs. of  11 variables:
##  $ admit      : Factor w/ 2 levels "0","1": 2 2 2 1 2 1 1 1 2 1 ...
##  $ gre        : int  800 640 760 400 540 700 800 440 760 700 ...
```

```
##  $ gpa        : num  4 3.19 3 3.08 3.39 3.92 4 3.22 4 3.08 ...
##  $ ses        : Factor w/ 3 levels "1","2","3": 2 1 2 2 1 1 1 3 3 2 ...
##  $ Gender_Male: Factor w/ 2 levels "0","1": 1 2 2 1 2 1 2 1 2 1 ...
##  $ Race       : Factor w/ 3 levels "1","2","3": 2 2 1 2 1 2 1 2 2 2 ...
##  $ rank       : Factor w/ 4 levels "1","2","3","4": 1 4 2 2 3 2 4 1 1 2
...
##  $ GreLevels  : Factor w/ 3 levels "High","Low","Medium": 1 1 1 2 3 1 1 3
1 1 ...
##  $ Gender     : Factor w/ 2 levels "female","male": 1 2 2 1 2 1 2 1 2 1
...
##  $ Demo       : Factor w/ 3 levels "African-American",..: 2 2 3 2 3 2 3 2
2 2 ...
##  $ Socioeco   : Factor w/ 3 levels "High","Low","Medium": 3 2 3 3 2 2 2 1
1 3 ...
```

```
college_train_all <- College_train %>% select (admit:rank)
college_test_all <- College_test %>% select (admit:rank)

train_glm_all <- train(admit ~ ., method = "glm", data = college_train_all)
train_glm_all
```

```
## Generalized Linear Model
##
## 315 samples
##   6 predictor
##   2 classes: '0', '1'
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 315, 315, 315, 315, 315, 315, ...
## Resampling results:
##
##   Accuracy  Kappa
##   0.692     0.17
```

```
glm_all_preds <- predict(train_glm_all, college_test_all)
glm_all_preds
```

```
##  [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
## [39] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0
1 1 0
## [77] 1 0 0 0
## Levels: 0 1
```

```
mean(glm_all_preds == college_test_all$admit)
```

```
## [1] 0.7
```

#kNN model

```r
set.seed(6, sample.kind = "Rounding")
```

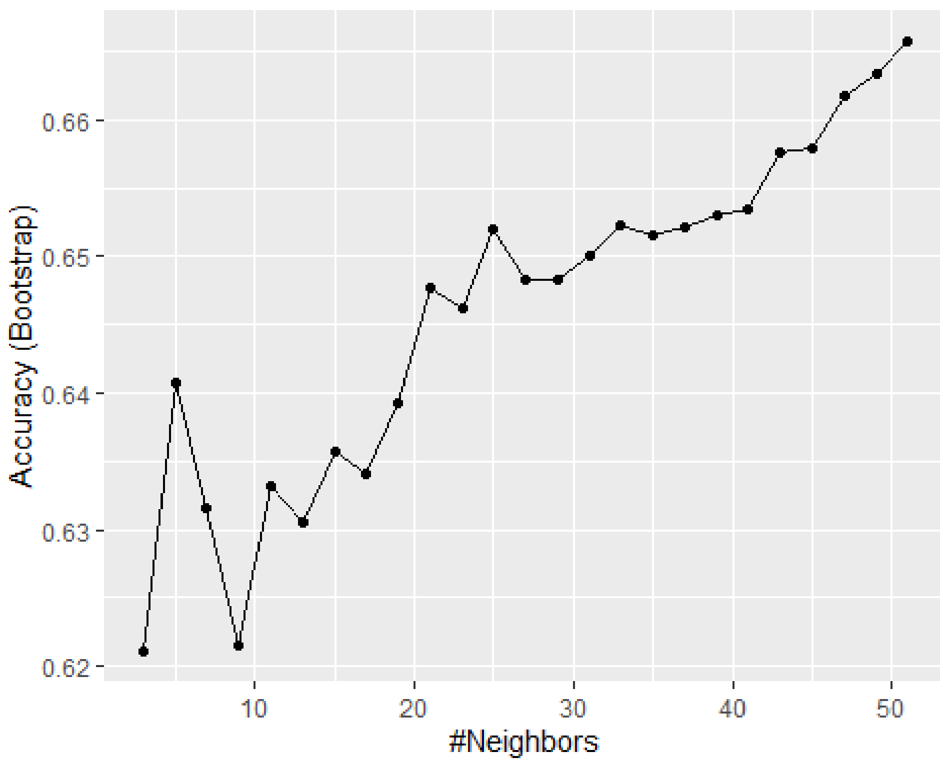
```
## Warning in set.seed(6, sample.kind = "Rounding"): non-uniform 'Rounding'
sampler
## used
```

```r
train_knn <- train(admit ~ .,
                   method = "knn",
                   data = college_train_all,
                   tuneGrid = data.frame(k = seq(3, 51, 2)))
train_knn$bestTune
```

```
##     k
## 25 51
```

#Highest Knn accuracy

```r
ggplot(train_knn)
```



#Accuracy of the kNN model

```r
knn_preds <- predict(train_knn, college_test_all)
mean(knn_preds == college_test_all$admit)
```

```
## [1] 0.675
```

#Cross-validation of Knn

```r
set.seed(8, sample.kind = "Rounding")
```

```
## Warning in set.seed(8, sample.kind = "Rounding"): non-uniform 'Rounding'
sampler
## used
```

```
train_knn_cv <- train(admit ~ .,
                      method = "knn",
                      data = college_train_all,
                      tuneGrid = data.frame(k = seq(3, 51, 2)),
                      trControl = trainControl(method = "cv", number = 10, p
= 0.9))
train_knn_cv$bestTune
```

```
##     k
## 25 51
```

#The accuracy of cross-validated kNN model

```
knn_cv_preds <- predict(train_knn_cv, college_test_all)
mean(knn_cv_preds == college_test_all$admit)
```

```
## [1] 0.675
```

#Classification tree model

```
set.seed(10, sample.kind = "Rounding")
```

```
## Warning in set.seed(10, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

```
train_rpart <- train(admit ~ .,
                     method = "rpart",
                     tuneGrid = data.frame(cp = seq(0, 0.05, 0.002)),
                     data = college_train_all)
train_rpart$bestTune
```

```
##       cp
## 25 0.048
```

#The accuracy of the decision tree model

```
rpart_preds <- predict(train_rpart, college_test_all)
mean(rpart_preds == college_test_all$admit)
```

```
## [1] 0.675
```

#Inspect final model

```
train_rpart$finalModel
```

```
## n= 315
##
## node), split, n, loss, yval, (yprob)
##       * denotes terminal node
```

```
##
## 1) root 315 100 0 (0.683 0.317) *
```

#Random forest model

```
set.seed(14, sample.kind = "Rounding")

## Warning in set.seed(14, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used

train_rf <- train(admit ~ .,
                  data = college_train_all,
                  method = "rf",
                  ntree = 100,
                  tuneGrid = data.frame(mtry = seq(1:7)))
train_rf$bestTune

##   mtry
## 1    1
```

#The accuracy of the random forest model

```
rf_preds <- predict(train_rf, college_test_all)
mean(rf_preds == college_test_all$admit)

## [1] 0.675
```

#The most important variable

```
varImp(train_rf)

## rf variable importance
##
##              Overall
## gpa          100.000
## gre           62.006
## rank3         10.580
## rank4          7.930
## ses3           5.980
## Race3          4.321
## rank2          2.706
## Race2          1.863
## ses2           0.688
## Gender_Male1   0.000
```