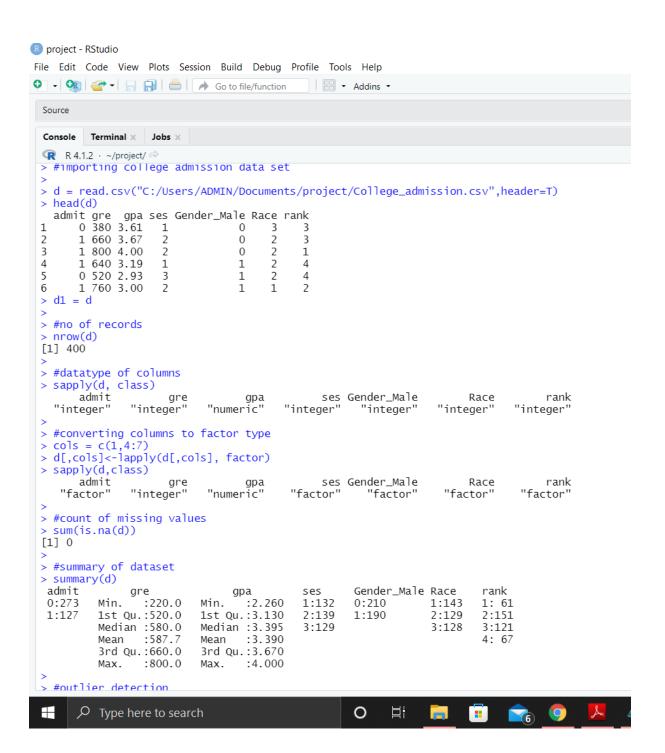
Find the missing values. (if any, perform missing value treatment)



Find outliers (if any, then perform outlier treatment)

```
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 Source
 Console Terminal X Jobs X
 Max.
                 :800.0
                          Max.
                                 :4.000
 > #outlier detection
 > #for gre variable
 > iqr1=IQR(d$gre)
 > iqr1
 [1] 140
 > quantile(d$gre,na.rm=TRUE)
  0% 25% 50% 75% 100%
  220 520 580 660 800
 > maz1 = 660+1.5*iqr1
 > maz1
 [1] 870
 > min1 = 520 - 1.5*iqr1
 > min1
 [1] 310
 > #all the pointers above the upperinner fence
 > print(which(d$gre > maz1))
                                           #no outliers
 integer(0)
 > # all the pointers below the lowerinner fence
 > print(which(d$gre < min1))</pre>
                                           #4 outliers
 [1] 72 180 305 316
 > # for gpa variables
 > iqr2= IQR(d$gpa)
 > iqr2
 [1] 0.54
 > quantile(d$gpa,na.rm=TRUE)
   0% 25% 50% 75% 100%
 2.260 3.130 3.395 3.670 4.000
 > max2 = 3.67+1.5*iqr2
 > max2
 [1] 4.48
 > min2 = 3.13-1.5*iqr2
 > min2
 Γ11 2.32
                                                        ≓<del>i</del> 🔚
       7 Type here to search
```

```
Console Terminal x Jobs x

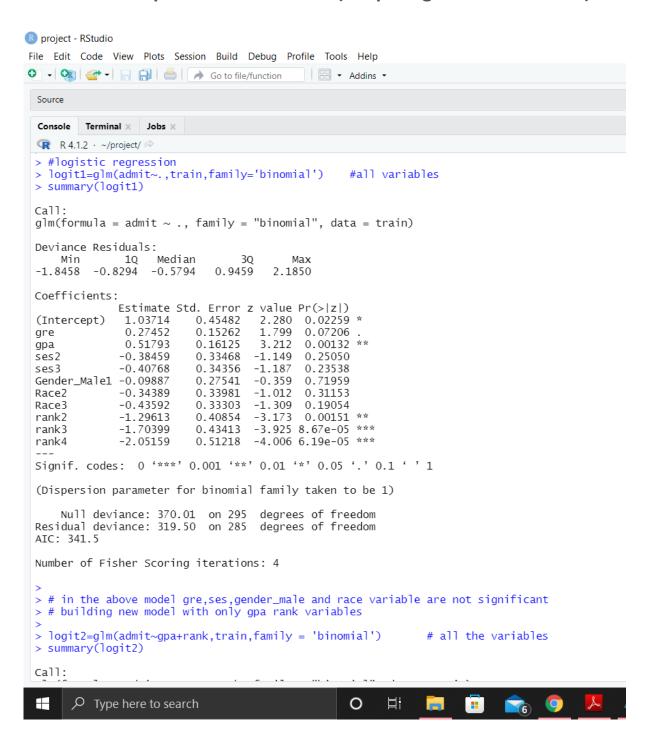
R 4.1.2 · ~/project/ →

> # all the pointers above the upperinner fence
> print(which(d$gpa > max2))  # no outlier
integer(0)
>
> print(which(d$gpa < min2))  # 1 outlier
[1] 290
>
> #removing outliers
> d=d[-c(72, 180, 290, 305, 316),]
> nrow(d)
[1] 395
```

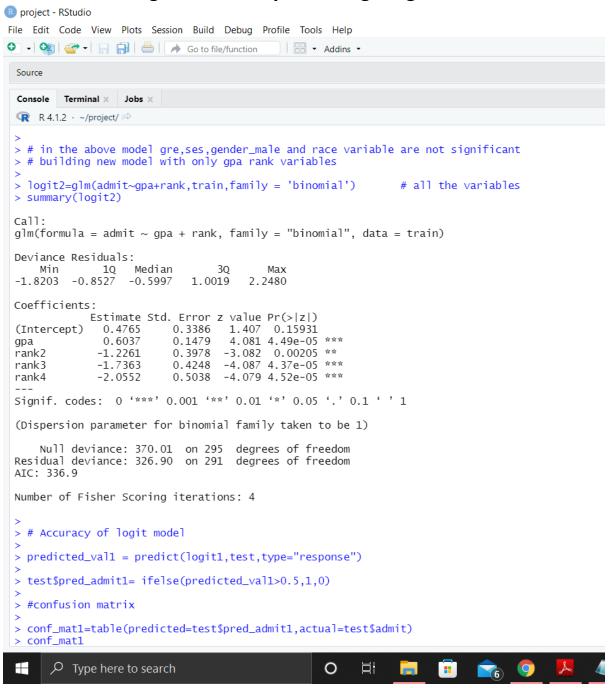
Splitting the data into train and test

```
> #splitting of data set into train and test
>
> set.seed(0)
> library("caTools")
>
> set.seed(0)
> library("caTools")
> d[,2:3]=scale(d[,2:3])
> split=sample.split(d$admit,SplitRatio = .75)
> train=subset(d,split==T)
> test=subset(d,split==F)
```

Run logistic model to determine the factors that influence the admission process of a student (Drop insignificant variables)



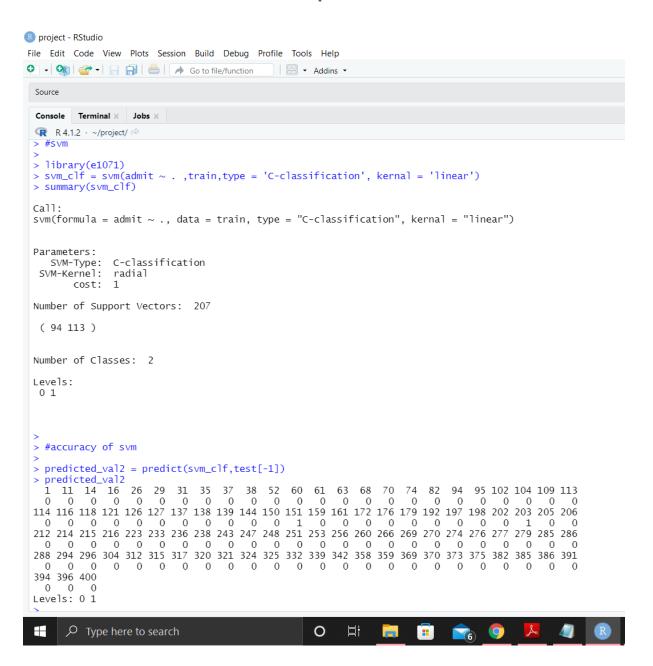
Second logistic model by removing insignificant variables



Here residual deviation increases so we will use first model

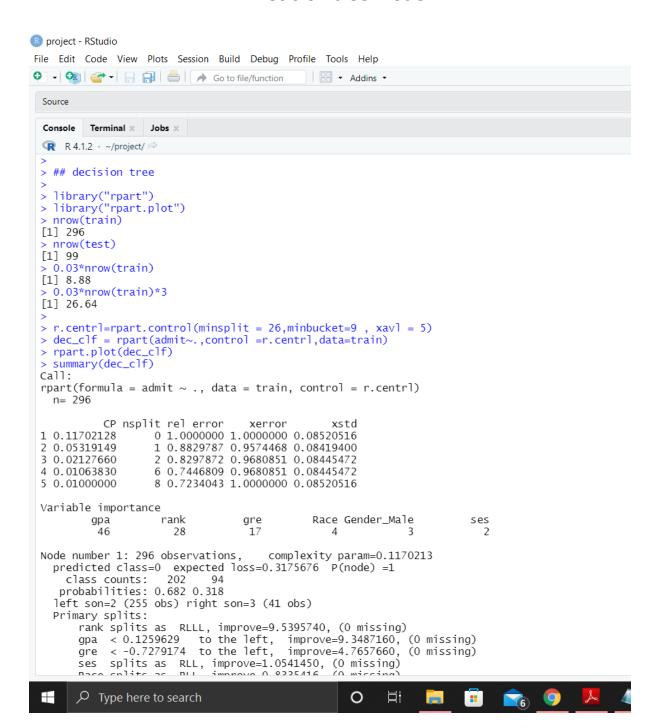
Accuracy of Logistic model

Try other modelling techniques like decision tree and SVM and select a champion model

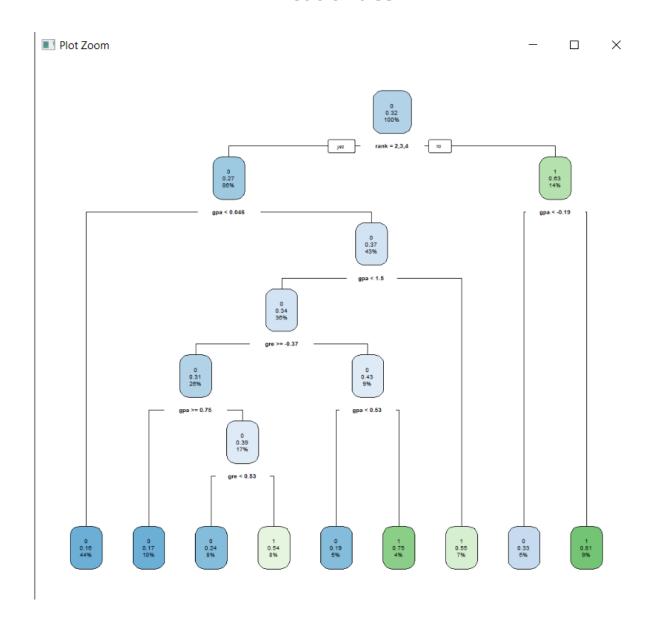


Accuracy of SVM Model

Decision tree model



Decision tree



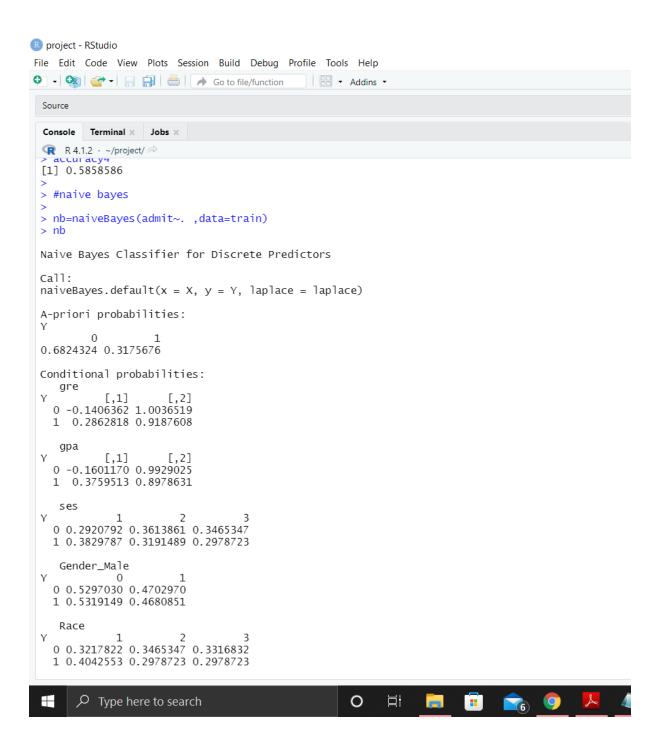
Accuracy of Decision Tree

```
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Console Terminal × Jobs ×
 probabilities: 0.458 0.542
 > #accuracy of decision tree
 > predicted_val3 = predict(dec_clf,test[-1],type="class")
 > predicted_val3
 1 11 14 16 26 29 31 35 37 38 52 60 61 63 68 70 74 82 94 95 102 104 109 113
1 1 0 0 1 0 1 0 0 0 0 0 0 0 0 1 1 0 0 1 0 1 0 0
 114 116 118 121 126 127 137 138 139 144 150 151 159 161 172 176 179 192 197 198 202 203 205 206
 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 288 294 296 304 312 315 317 320 321 324 325 332 339 342 358 359 369 370 373 375 382 385 386 391
  394 396 400
  0 1
 Levels: 0 1
 > #confusion matrix
 > conf_mat3 = table(predicted=predicted_val3,actual=test$admit)
 actual
predicted 0 1
0 50 22
       1 17 10
 > #accuracy
 > accuracy3= sum(diag(conf_mat3))/sum(conf_mat3)
 [1] 0.6060606
```

KNN and its Accuracy

```
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File Edit Code View Plots Session Build Debug Profile Tools Help
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 accuracy3
 [1] 0.6060606
 > #KNN and its accuracy
 > library("class")
 > knn = knn(train, test[-1],train$admit, k=19)
 > knn
 Levels: 0 1
 > #confussion matrix
 > conf_mat4=table(predicted=knn,actual=test$admit)
 > conf_mat4
actual
predicted 0 1
0 41 15
       1 26 17
 > # accuracy
 > accuracy4= sum(diag(conf_mat4))/sum(conf_mat4)
 > accuracy4
[1] 0.5858586
```

Naïve Bayes

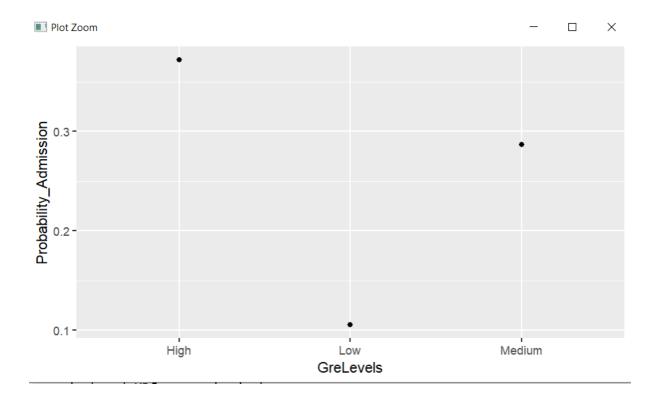


Accuracy of Naïve Bayes

Categorize the average of grade point into High, Medium, and Low (with admission probability percentages) and plot it on a point chart.

```
> #Descriptiven Categorize the average of grade point into High, Medium, and Low
> Descriptive = transform(d1,GreLevels=ifelse(gre<440,"Low",ifelse(gre<580,"Medium","High")))
> View(Descriptive)
> Sum_Desc=aggregate(admit~GreLevels,Descriptive,FUN=sum)
> length_Desc=aggregate(admit~GreLevels,Descriptive,FUN=length)
> Probability_table = cbind(Sum_Desc,Recs=length_Desc[,2])
> Probability_table_final = transform(Probability_table,Probability_Admission=admit/Recs)
 > Probability_table_final
  GreLevels admit Recs Probability_Admission
               84 226
4 38
        High
1
                                          0.3716814
                                          0.1052632
         Low
3
                39 136
      Medium
                                          0.2867647
 > library("ggplot2")
 > ggplot(Probability_table_final,aes(x=GreLevels , y=Probability_Admission))+geom_point()
 > #Cross grid for admission variable with GRE categorized
 > table(Descriptive$admit,Descriptive$GreLevels)
   High Low Medium
0 142 34 97
                     39
       84
             4
```

Point Chart



Descriptive showing GreLevels

