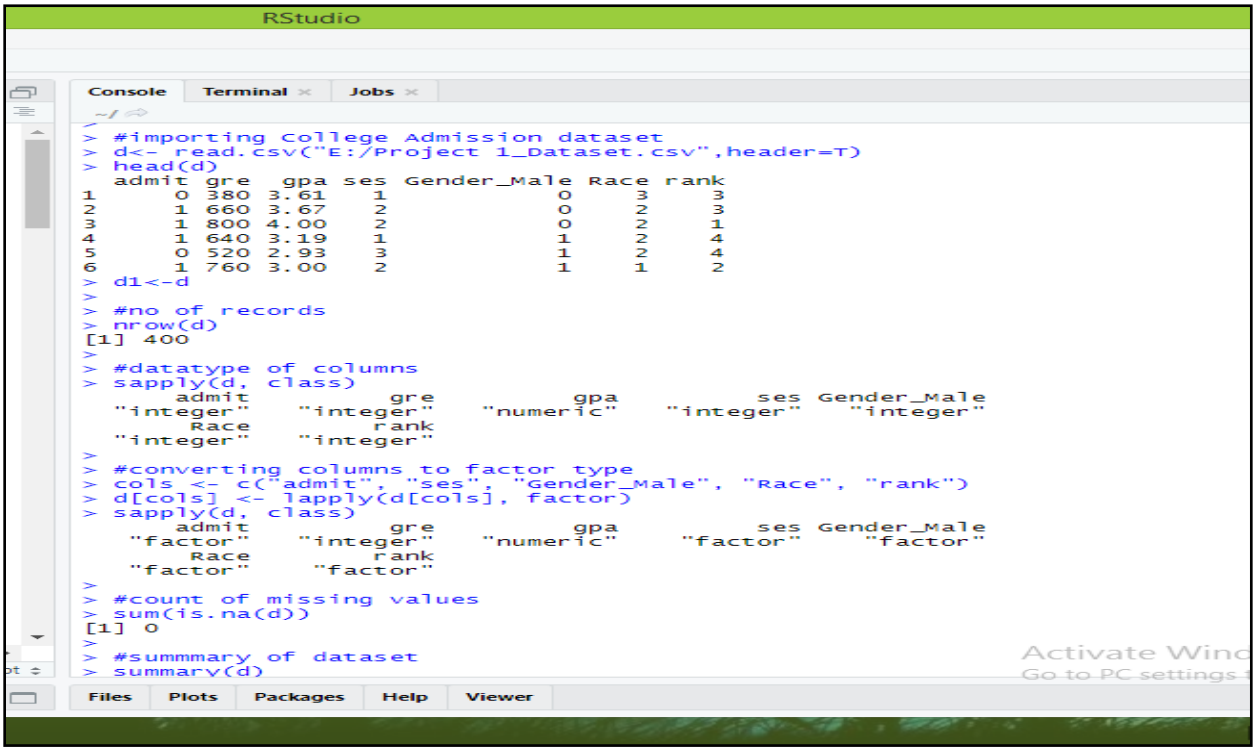
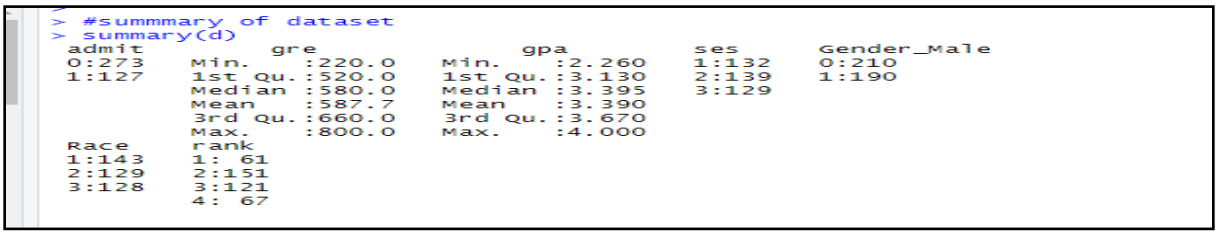
Exploring dataset





Outlier Detection and Removal

```
> 
> #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 
> 
> max1 <- 660+1.5*iqr1
> max1
[1] 870
> min1 <- 520-1.5*iqr1
> min1
[1] 310
> 
> # all the points above the upperInner Fence
> print(which(d$gre > max1))              #no outlier
integer(0)
> 
> # all the points below the LowerInner Fence
> print(which(d$gre < min1))              #4 outliers()
[1]  72 180 305 316
> 
> 
> #for gpa variable
> 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 <- 3.130-1.5*iqr2
```

```
> 
> #for gpa variable
> 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 <- 3.130-1.5*iqr2
> min2
[1] 2.32
> 
> # all the points above the upperInner Fence
> print(which(d$gpa > max2))              #no outlier
integer(0)
> 
> # all the points below the LowerInner Fence
> print(which(d$gpa < min2))              #1 outlier()
[1] 290
> 
> # Removing outliers
> d <- d[-c(72, 180, 290, 305, 316),]
> nrow(d)
[1] 395
> 
> #splitting of dataset into train and test
```

Data Splitting

```
> nrow(d)
[1] 395
> 
> #splitting of dataset into train and test
> 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)
> 
> 
```

Logistic Regression

```
> 
> ####logistic regression
> logit1<-glm(admit~.,train,family='binomial') # all variable -.
> summary(logit1)

Call:
glm(formula = admit ~ ., family = "binomial", data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8458  -0.8294  -0.5794   0.9459   2.1850

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   1.03714    0.45482   2.280  0.02259 *
gre           0.27452    0.15262   1.799  0.07206 .
gpa           0.51793    0.16125   3.212  0.00132 **
ses2         -0.38459    0.33468  -1.149  0.25050
ses3         -0.40768    0.34356  -1.187  0.23538
Gender_Male1 -0.09887    0.27541  -0.359  0.71959
Race2        -0.34389    0.33981  -1.012  0.31153
Race3        -0.43592    0.33303  -1.309  0.19054
rank2        -1.29613    0.40854  -3.173  0.00151 **
rank3        -1.70399    0.43413  -3.925 8.67e-05 ***
rank4        -2.05159    0.51218  -4.006 6.19e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 370.01  on 295  degrees of freedom
Residual deviance: 319.50  on 285  degrees of freedom
AIC: 341.5

Number of Fisher Scoring iterations: 4

> 
> #in the above model gre,ses,gender_male and race variable are
> #not significant
```

Second logistic model by removing insignificant variables

```
> 
> #in the above model gre,ses,gender_male and race variable are
> #not significant .
> #building new model with only gpa and rank variables
> 
> logit2<-glm(admit~gpa+rank,train,family='binomial') # all variable -.
> summary(logit2)

Call:
glm(formula = admit ~ gpa + rank, family = "binomial", data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8203  -0.8527  -0.5997   1.0019   2.2480

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4765     0.3386   1.407  0.15931
gpa           0.6037     0.1479   4.081 4.49e-05 ***
rank2        -1.2261     0.3978  -3.082  0.00205 **
rank3        -1.7363     0.4248  -4.087 4.37e-05 ***
rank4        -2.0552     0.5038  -4.079 4.52e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 370.01  on 295  degrees of freedom
Residual deviance: 326.90  on 291  degrees of freedom
AIC: 336.9

Number of Fisher Scoring iterations: 4
```

Here residual deviation increases so we will use first model

Accuracy of Logistic model

```
> 
> predicted_val1 <- predict(logit1,test,type="response")
> 
> test$pred_admit1 <- ifelse(predicted_val1>0.5,1,0)
> 
> #confusion matrix
> conf_mat1<-table(predicted=test$pred_admit1,actual=test$admit)
> conf_mat1
         actual
predicted  0  1
        0 55 26
        1 12  6
> 
> #accuracy
> accuracy1<-sum(diag(conf_mat1))/sum(conf_mat1)
> accuracy1     #0.6161616
[1] 0.6161616
> 
> 
> 
```

SVM model

```
> accuracy1     #0.6161616
[1] 0.6161616
>
>
>
> ####svm
>
> library(e1071)
>
> svm_clf = svm(admit ~ .  ,train, type = 'C-classification', kernel = 'linear')
> summary(svm_clf)

Call:
svm(formula = admit ~ ., data = train, type = "C-classification",
    kernel = "linear")


Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  linear
       cost:  1
      gamma:  0.09090909

Number of Support Vectors:  202

 ( 94 108 )


Number of Classes:  2

Levels:
 0 1
```


Accuracy of SVM

```
>
> predicted_val2 <- predict(svm_clf,test[-1])
> predicted_val2
  1  11  14  16  26  29  31  35  37  38  52  60  61  63  68  70  74
  0   0   0   0   1   0   0   1   1   0   0   0   0   0   1   1   0
 82  94  95 102 104 109 113 114 116 118 121 126 127 137 138 139 144
  0   0   0   0   0   0   1   0   0   0   0   1   0   0   0   0   0
150 151 159 161 172 176 179 192 197 198 202 203 205 206 212 214 215
  1   1   0   0   0   0   0   0   0   0   0   1   1   0   0   0   0
216 223 233 236 238 243 247 248 251 253 256 260 266 269 270 274 276
  0   1   0   0   0   0   0   0   0   0   0   0   0   0   0   1   0
277 279 285 286 288 294 296 304 312 315 317 320 321 324 325 332 339
  0   0   0   0   0   1   0   0   0   0   0   1   0   0   0   0   1
342 358 359 369 370 373 375 382 385 386 391 394 396 400
  0   1   0   1   0   1   0   0   0   1   0   0   0   0
Levels: 0 1
>
> #confusion matrix
> conf_mat2<-table(predicted=predicted_val2,actual=test$admit)
> conf_mat2
         actual
predicted  0  1
        0 54 25
        1 13  7
>
> #accuracy
> accuracy2<-sum(diag(conf_mat2))/sum(conf_mat2)
> accuracy2     # 0.6161616
[1] 0.6161616
>
>
>
> ####decision tree
```

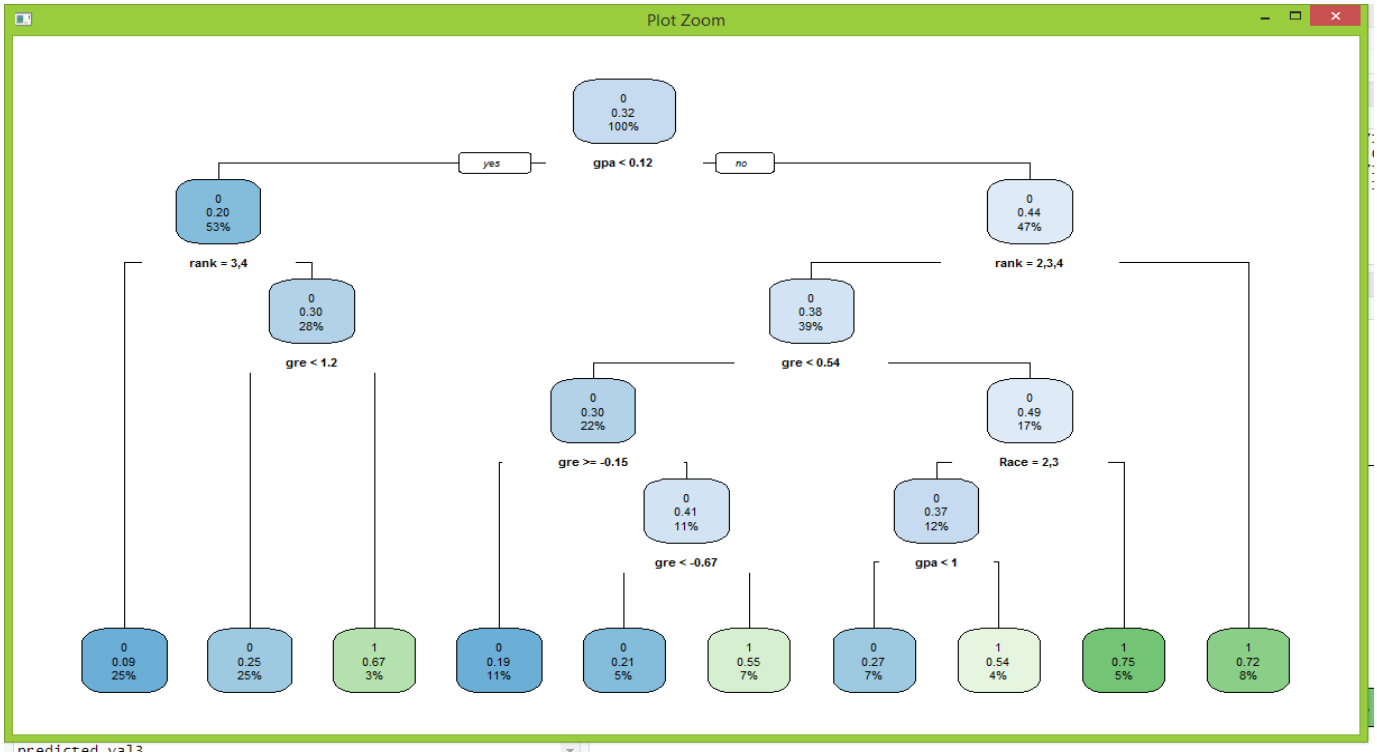
Decision tree model

```
>
>
> ####decision tree
>
> library("rpart")
> library("rpart.plot")
> nrow(train)
[1] 296
> nrow(test)
[1] 99
> 0.03*nrow(train)   #8.88
[1] 8.88
> 0.03*nrow(train)*3    #26.64
[1] 26.64
> r.cntrl<-rpart.control(minsplit = 26,minbucket=9 ,xval = 5)
> dec_clf<-rpart(admit~.,control =r.cntrl, data=train)
>
> rpart.plot(dec_clf)
>
> summary(dec_clf)
Call:
rpart(formula = admit ~ ., data = train, control = r.cntrl)
  n= 296

          CP nsplit rel error    xerror       xstd
1 0.11702128      0 1.0000000 1.0000000 0.08520516
2 0.05319149      1 0.8829787 0.9255319 0.08337946
3 0.02127660      2 0.8297872 1.0319149 0.08590901
4 0.01063830      6 0.7446809 1.0531915 0.08635291
5 0.01000000      8 0.7234043 1.0531915 0.08635291

Variable importance
      gpa      rank       gre      Race Gender_Male
       46        28        17         4         3
      ses
        2

Node number 1: 296 observations,    complexity param=0.1170213
```



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
  1   1   0   0   1   0   1   0   0   0   0   0   0   0   0   1   1
 82  94  95 102 104 109 113 114 116 118 121 126 127 137 138 139 144
  0   0   1   0   1   0   0   0   1   0   1   0   1   0   1   0   0
150 151 159 161 172 176 179 192 197 198 202 203 205 206 212 214 215
  0   1   1   0   0   0   0   1   0   0   0   1   1   0   0   0   0
216 223 233 236 238 243 247 248 251 253 256 260 266 269 270 274 276
  0   0   0   0   1   0   0   0   0   1   0   0   0   1   0   0   0
277 279 285 286 288 294 296 304 312 315 317 320 321 324 325 332 339
  1   0   0   0   0   1   0   1   1   0   0   0   0   0   0   1   0
342 358 359 369 370 373 375 382 385 386 391 394 396 400
  0   0   0   1   0   0   0   0   0   0   0   0   1   0
Levels: 0 1
>
> #confusion matrix
> conf_mat3<-table(predicted=predicted_val3,actaul=test$admit)
> conf_mat3
         actaul
predicted  0  1
        0 50 22
        1 17 10
>
> #accuracy
> accuracy3<-sum(diag(conf_mat3))/sum(conf_mat3)
> accuracy3       # 0.6060606
[1] 0.6060606
>
>
>
```

KNN and its Accuracy

```
>
>
> ####knn
>
> library("class")
> knn = knn(train, test[-1], train$admit,  k=19)
> knn
 [1] 0 1 1 0 1 1 0 0 0 0 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 1 1 0 0 0 0 1
[33] 1 1 1 1 0 1 1 1 1 1 0 0 1 0 0 1 1 1 1 1 0 0 1 0 1 1 0 1 0 0 0 0
[65] 1 0 1 0 0 1 0 0 1 1 1 1 1 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 1 0 0 1
[97] 0 0 0
Levels: 0 1
>
> #confusion matrix
> conf_mat4<-table(predicted=knn,actaul=test$admit)
> conf_mat4
         actaul
predicted  0  1
        0 41 15
        1 26 17
>
> #accuracy
> accuracy4<-sum(diag(conf_mat4))/sum(conf_mat4)
> accuracy4       #0.5858586
[1] 0.5858586
>
>
```

Naïve Bayes

```
>
> ####naive bayes
>
> nb<-naiveBayes(admit~.,data=train)
> nb

Naive Bayes Classifier for Discrete Predictors

Call:
naiveBayes.default(x = X, y = Y, laplace = laplace)

A-priori probabilities:
Y
        0         1
0.6824324 0.3175676

Conditional probabilities:
   gre
Y       [,1]      [,2]
  0 -0.1406362 1.0036519
  1  0.2862818 0.9187608

   gpa
Y       [,1]      [,2]
  0 -0.1601170 0.9929025
  1  0.3759513 0.8978631

   ses
Y         1         2         3
  0 0.2920792 0.3613861 0.3465347
  1 0.3829787 0.3191489 0.2978723

   Gender_Male
Y         0         1
  0 0.5297030 0.4702970
  1 0.5319149 0.4680851

  _
```

Accuracy of Naïve Bayes

```
   0 0.5297030 0.4702970
   1 0.5319149 0.4680851

    Race
Y          1         2         3
   0 0.3217822 0.3465347 0.3316832
   1 0.4042553 0.2978723 0.2978723

    rank
Y          1         2         3         4
   0 0.07425743 0.38118812 0.32673267 0.21782178
   1 0.27659574 0.38297872 0.24468085 0.09574468

> predicted_val5 <- predict(nb,test[-1], type="class")
> predicted_val5
  [1] 0 1 0 0 1 1 0 0 1 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 1
 [33] 0 0 1 1 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 [65] 0 0 1 0 0 0 0 0 0 1 0 1 1 0 0 1 0 0 0 0 1 0 1 0 1 1 0 0 0 0 0 0
 [97] 0 0 0
Levels: 0 1
>
> #confusion matrix
> conf_mat5<-table(predicted=predicted_val5,actual=test$admit)
> conf_mat5
         actual
predicted  0  1
        0 52 25
        1 15  7
>
> #accuracy
> accuracy5<-sum(diag(conf_mat5))/sum(conf_mat5)
> accuracy5       #0.5959596
[1] 0.5959596
>
> #logistic regression and svm are the best model with accuracy=61.61%
>
>
```


logistic regression and svm are the best model with accuracy=61.61%

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

```
>
>
> #Categorize the grade point average 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
1      High    84  226             0.3716814
2       Low     4   38             0.1052632
3    Medium    39  136             0.2867647
> library("ggplot2")
Registered S3 methods overwritten by 'ggplot2':
  method         from
  [.quosures     rlang
  c.quosures     rlang
  print.quosures rlang
> 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
  1   84   4      39
> |
```

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Education.R* | r programming 4.R | Descriptive

Filter

	admit	gre	gpa	ses	Gender_Male	Race	rank	GreLevels
1	0	380	3.61	1	0	3	3	Low
2	1	660	3.67	2	0	2	3	High
3	1	800	4.00	2	0	2	1	High
4	1	640	3.19	1	1	2	4	High
5	0	520	2.93	3	1	2	4	Medium
6	1	760	3.00	2	1	1	2	High
7	1	560	2.98	2	1	2	1	Medium
8	0	400	3.08	2	0	2	2	Low
9	1	540	3.39	1	1	1	3	Medium
10	0	700	3.92	1	0	2	2	High
11	0	800	4.00	1	1	1	4	High
12	0	440	3.22	3	0	2	1	Medium
13	1	760	4.00	3	1	2	1	High
14	0	700	3.08	2	0	2	2	High
15	1	700	4.00	2	1	1	1	High
16	0	480	3.44	3	0	1	3	Medium
17	0	780	3.87	2	0	3	4	High
18	0	360	2.56	3	1	3	3	Low
19	0	800	3.75	1	1	3	2	High
20	1	540	3.81	1	0	3	1	Medium
21	0	500	3.17	3	0	2	3	Medium
22	1	660	3.63	1	0	1	2	High
23	0	600	2.82	1	0	3	4	High

Showing 1 to 23 of 400 entries, 8 total columns

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