

CAB220 Portfolio 2

KA LONG LEE (N9845097)

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CAB220 Portfolio2

Overview This portfolio accounts for 20% of overall grade of CAB220. Full mark of this portfolio is 20. The tasks in this portfolio are designed to assess your knowledge and skills in

- Descriptive statistical data analysis and visualisation
- Statistical hypothesis testing
- Linear regression
- Logistic regression

Data:

The fictitious data set for this portfolio includes the records of 2,550 first-year students of an Australian university in terms of case ID, Attrition, Degree Type, Achieved Credit Points, Attendance Type, Age, Failed Credit Points, International student, First in family in university, Gender, GPA, OP Score, Socio Economic Status, Teaching Period Admitted, and Faculty.

Working Environment Configuration:

```
# Import Library
library(ggplot2)
library(dplyr)

# Setting up the working directory
# So that It can import external file
# Warning!!! -- Disable the next line, if you need to export the pdf report
#                               Otherwise, you will need the next line to generates diagram later on

# setwd(dirname(rstudioapi::getActiveDocumentContext())$path))

# Import external files
# Most of the visualization function is stored in this file
# Please check it if you are interested in the code
source("data_visualization.R")

# Import Data
uniData <- read.csv("datasets/Portfolio_2_data.csv", header = TRUE) %>%
  select(2:15)
```

Task 1 Summarise the information in each variable (except case ID) using a table or an appropriate statistical graph

Summary each variables using a table

```
summary(uniData)
```

```
##           Attrition      Degree_Type    Achieved_Credit_Points  Attendance_Type
## Not Retained: 448      Double: 169      Min.       : 0.00              Full Time:2308
## Retained      :2102    Single:2381      1st Qu.: 60.00              Part Time: 242
##                                           Median : 96.00
##                                           Mean   : 92.97
##                                           3rd Qu.:108.00
```

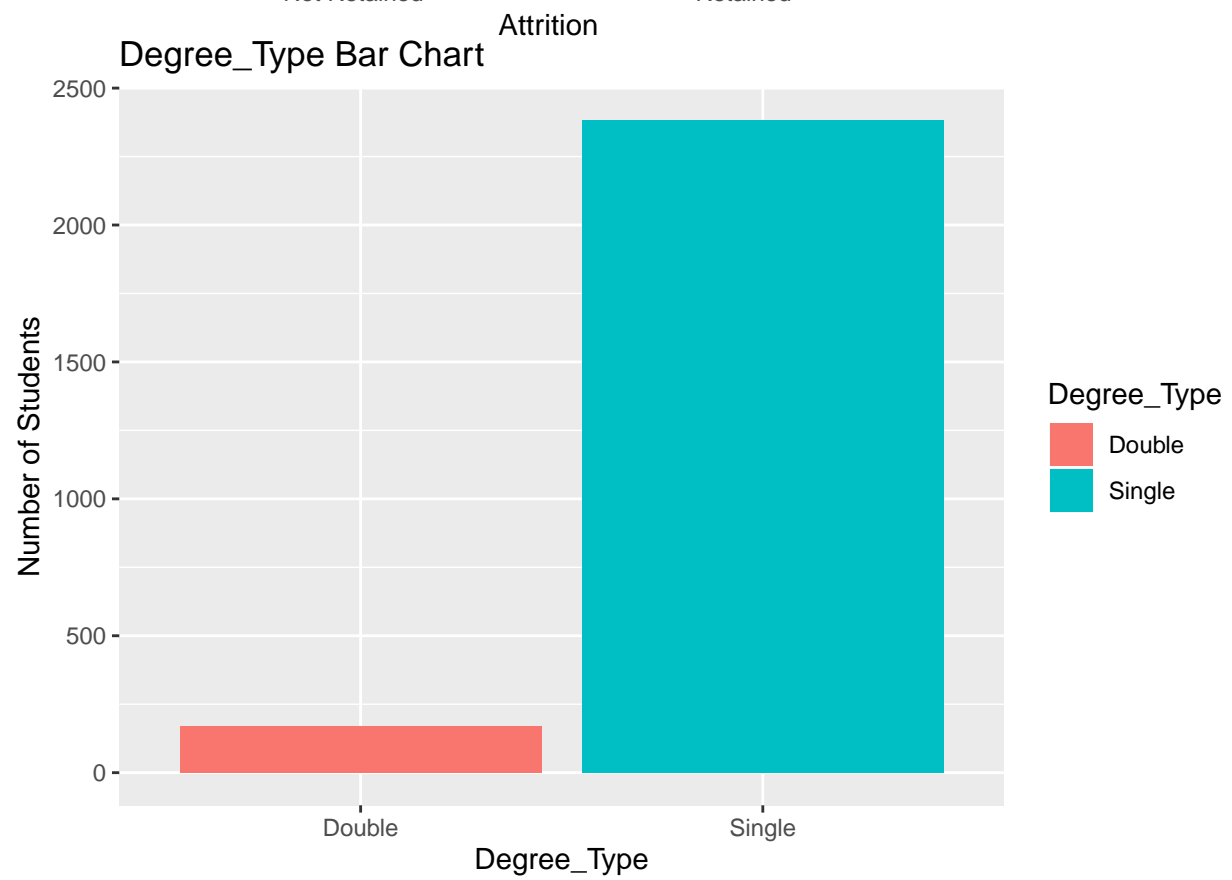
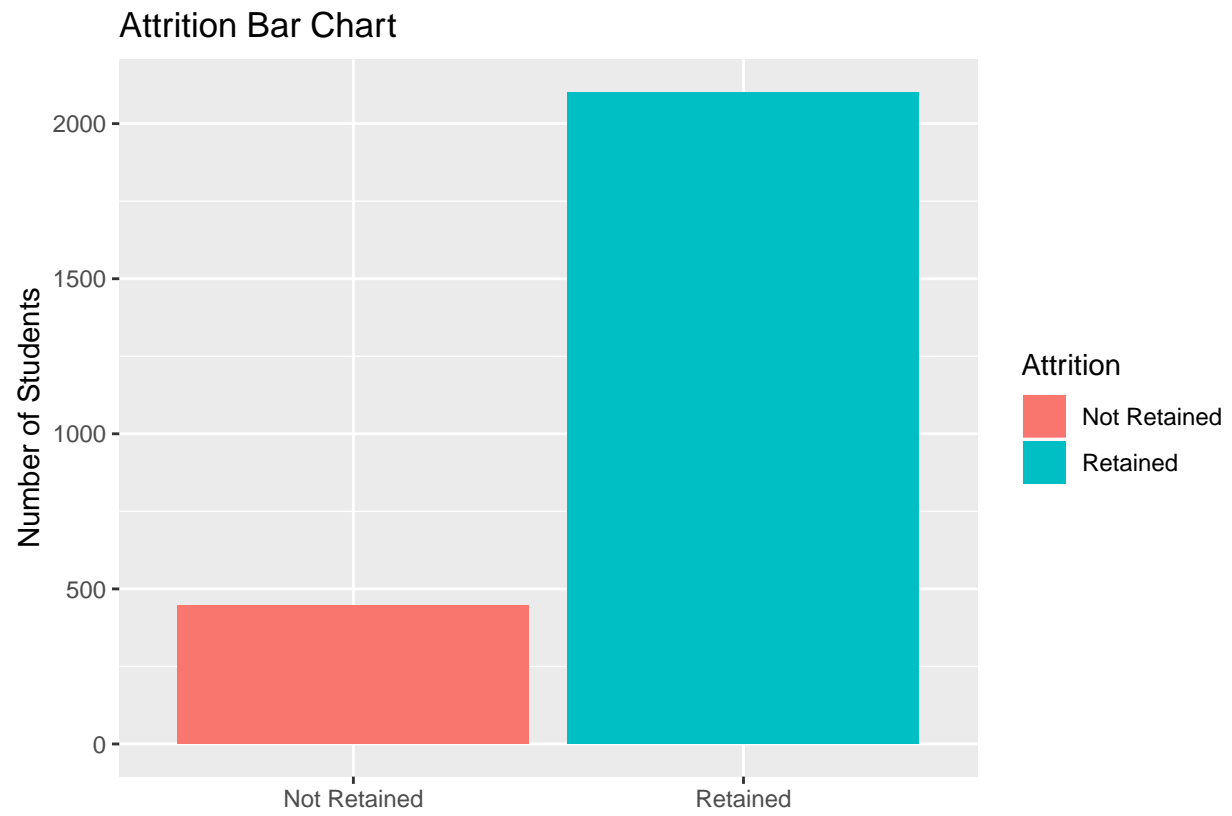
```

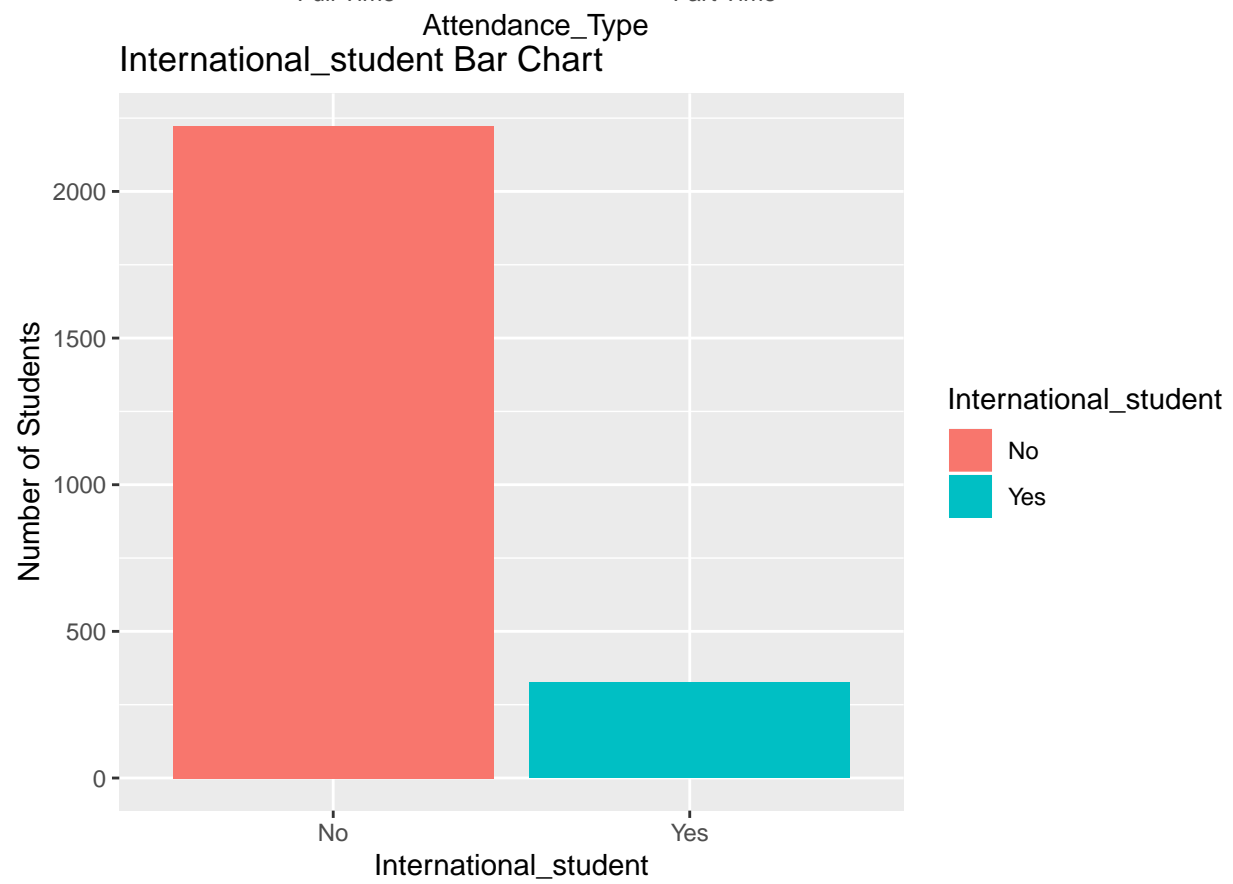
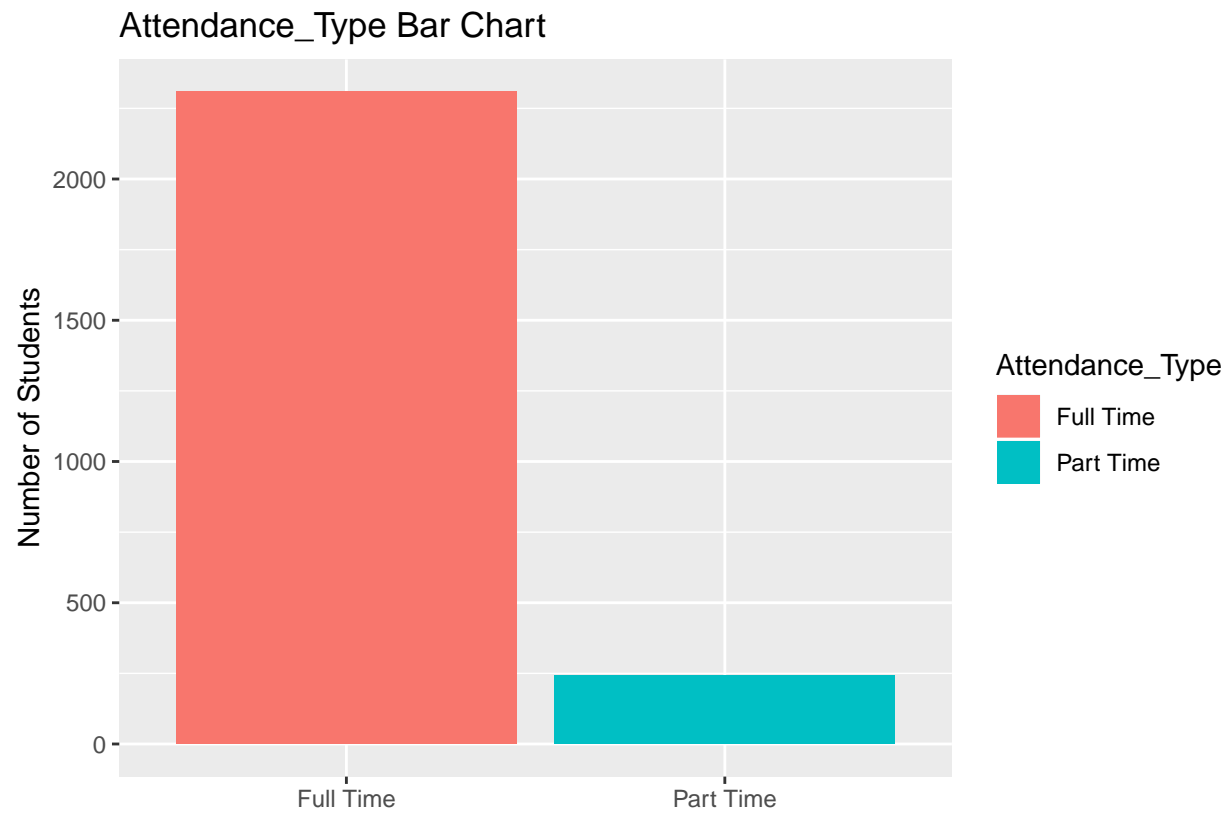
##                                     Max.    :372.00
##      Age      Failed_Credit_Points International_student
## Min.    :18.00 Min.    : 0.000      No :2223
## 1st Qu.:19.00 1st Qu.: 0.000      Yes: 327
## Median :20.00 Median : 0.000
## Mean    :22.74 Mean    : 8.033
## 3rd Qu.:23.00 3rd Qu.:12.000
## Max.    :86.00 Max.    :108.000
## First_in_family Gender      GPA      OP_Score
## No :1580      F:1254 Min.    :0.000 Min.    : 1.00
## Yes: 970      M:1296 1st Qu.:4.130 1st Qu.: 6.00
##                                     Median :4.880 Median : 9.00
##                                     Mean    :4.549 Mean    :10.74
##                                     3rd Qu.:5.630 3rd Qu.:15.00
##                                     Max.    :7.000 Max.    :25.00
## Socio_Economic_Status Teaching_Period_Admitted
## High : 771      SEM-1:2107
## Low  : 463      SEM-2: 443
## Medium:1316
##
##
##
##      Faculty
## CI Faculty      :430
## Faculty of Education:158
## Faculty of Health :677
## Faculty of Law    :244
## QUT Business School :385
## Sci and Eng Faculty :656

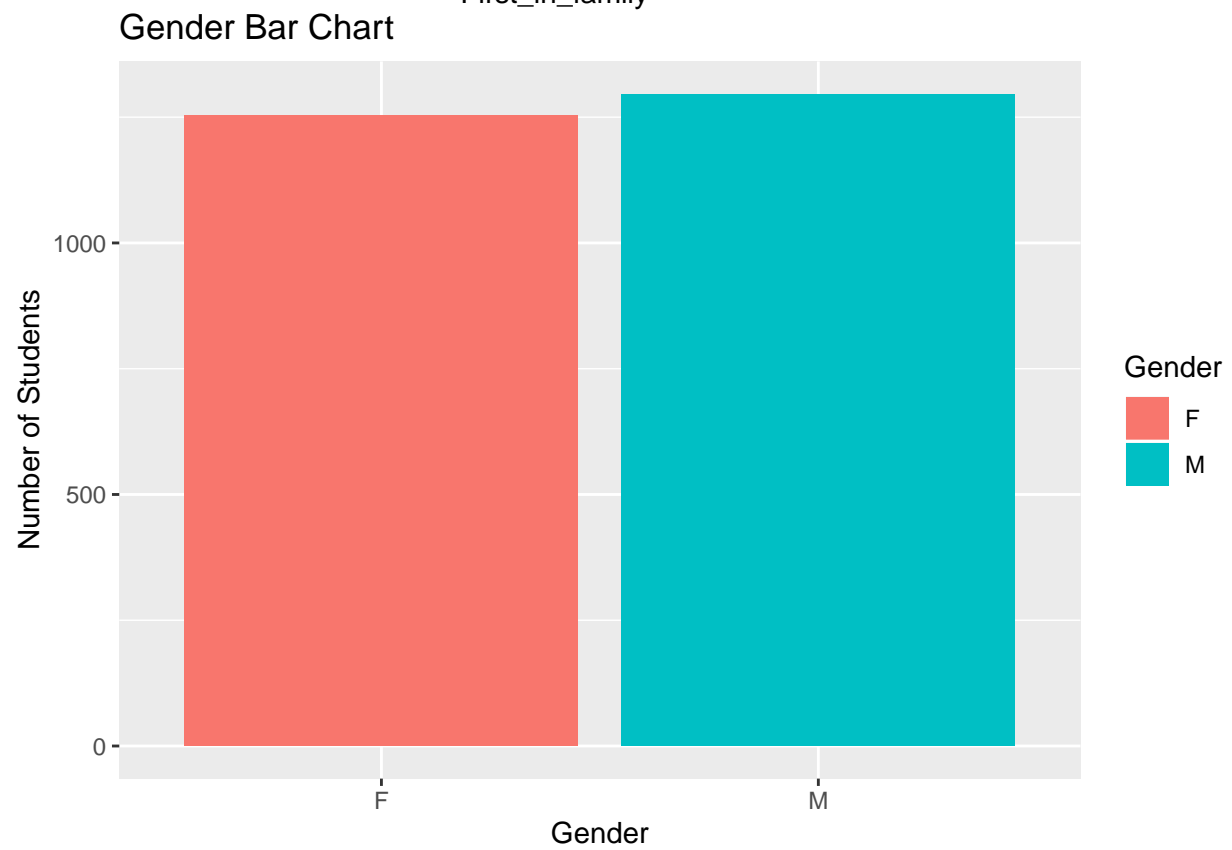
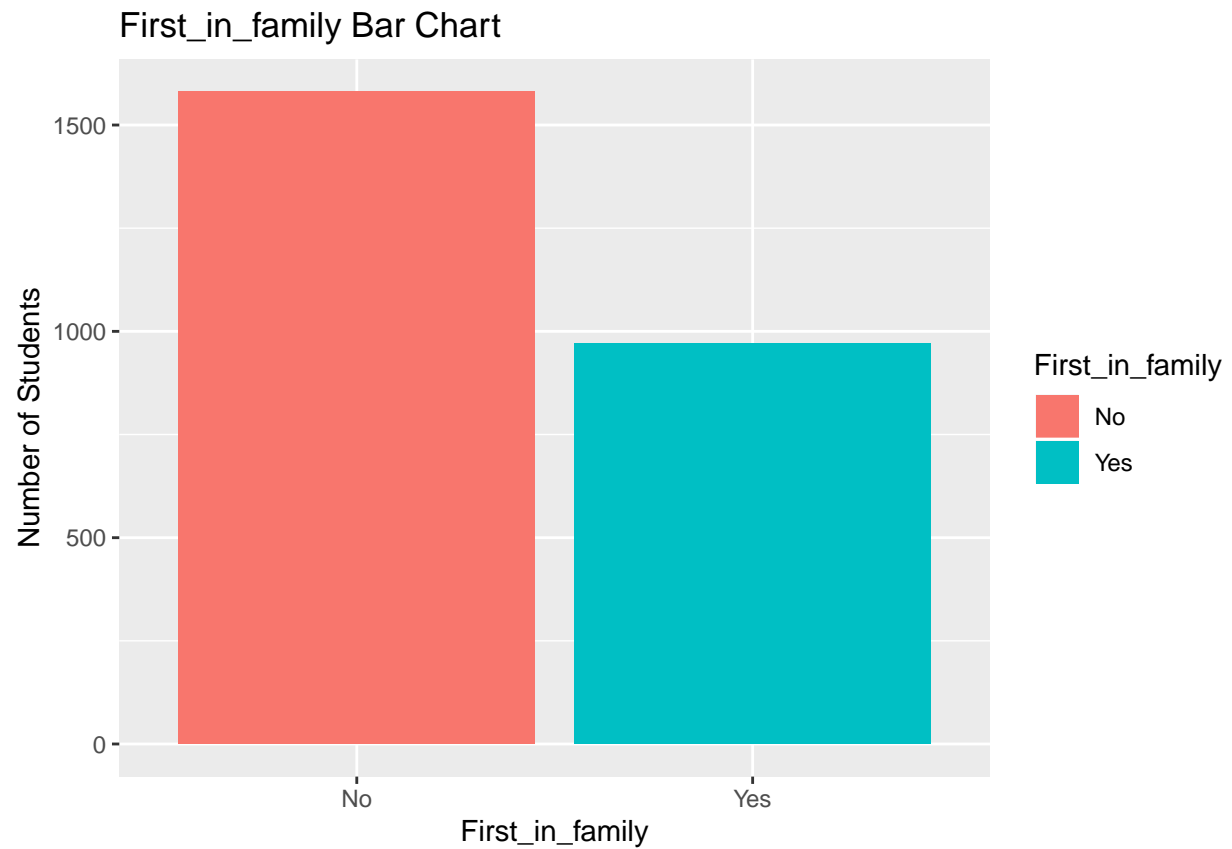
```

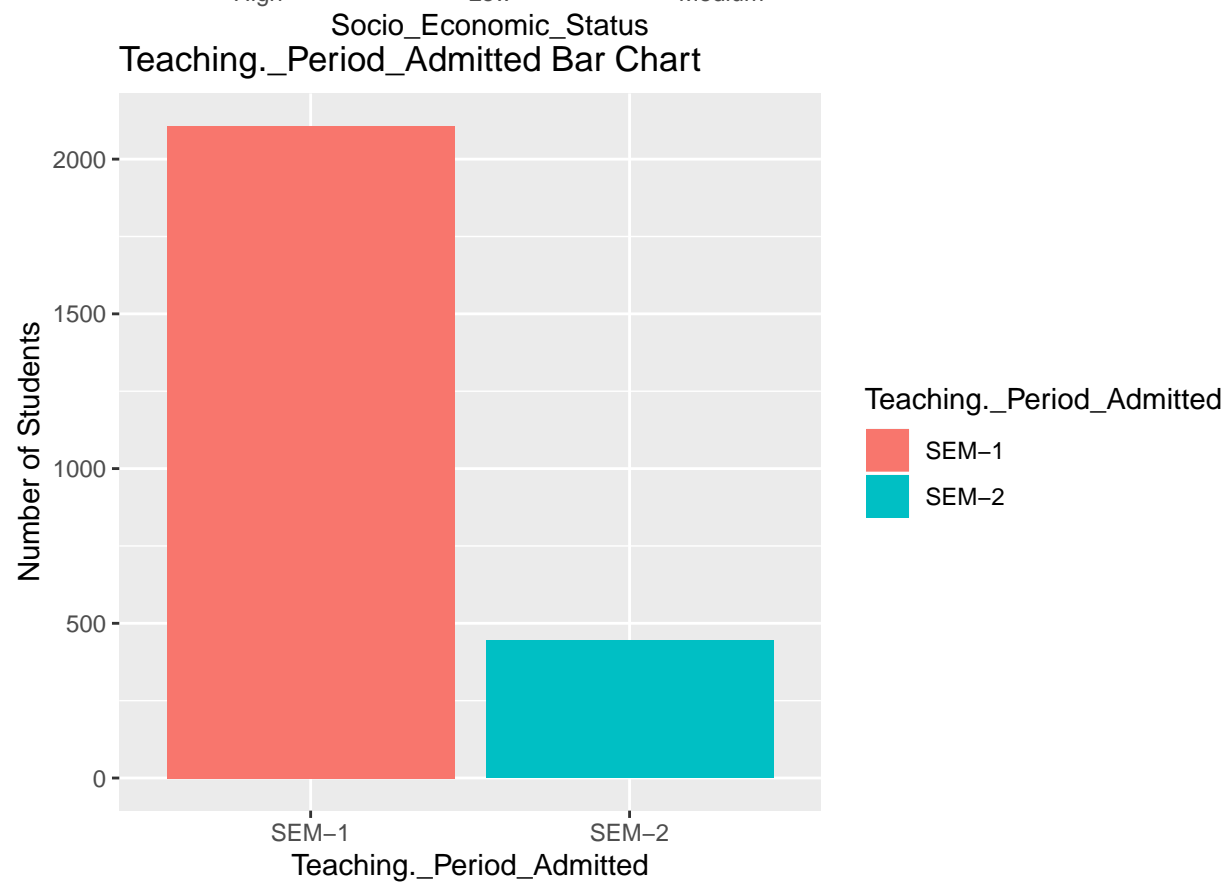
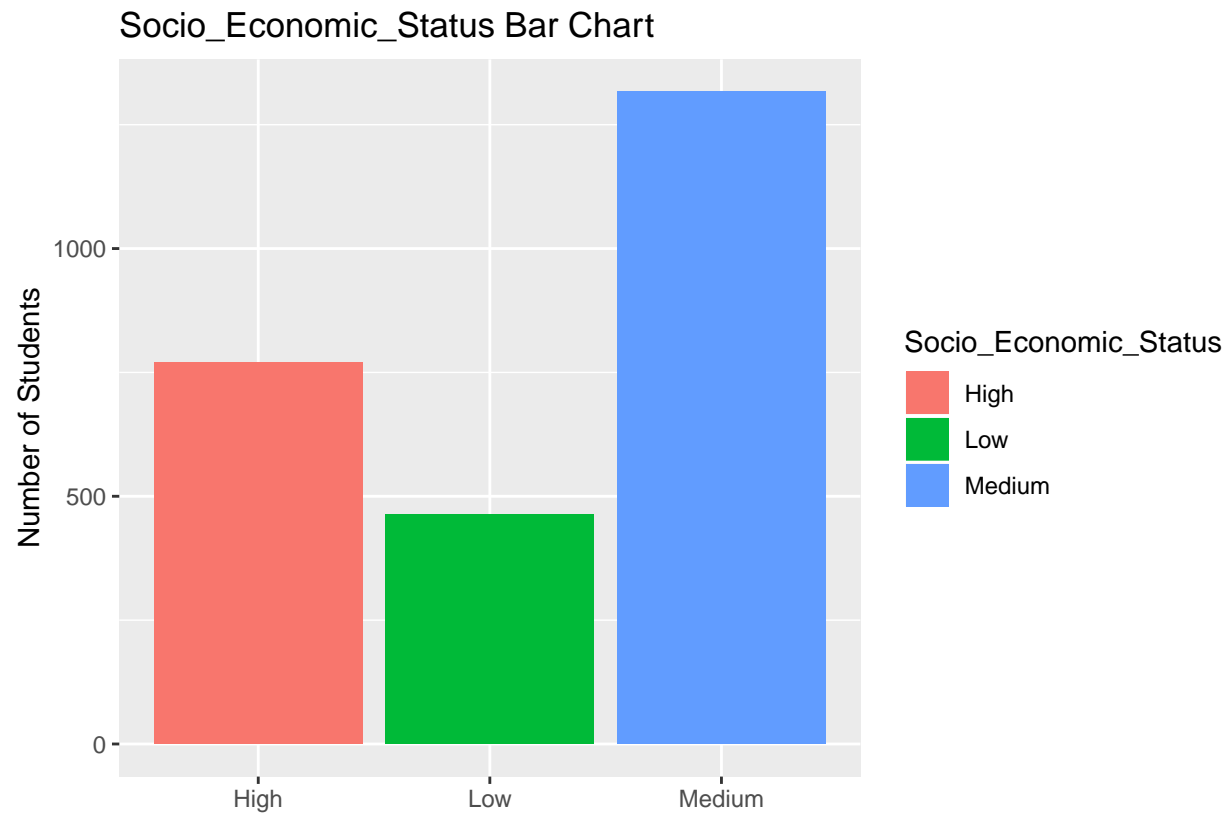
Summary each categorical data in uni dataframe using appropriate graphs

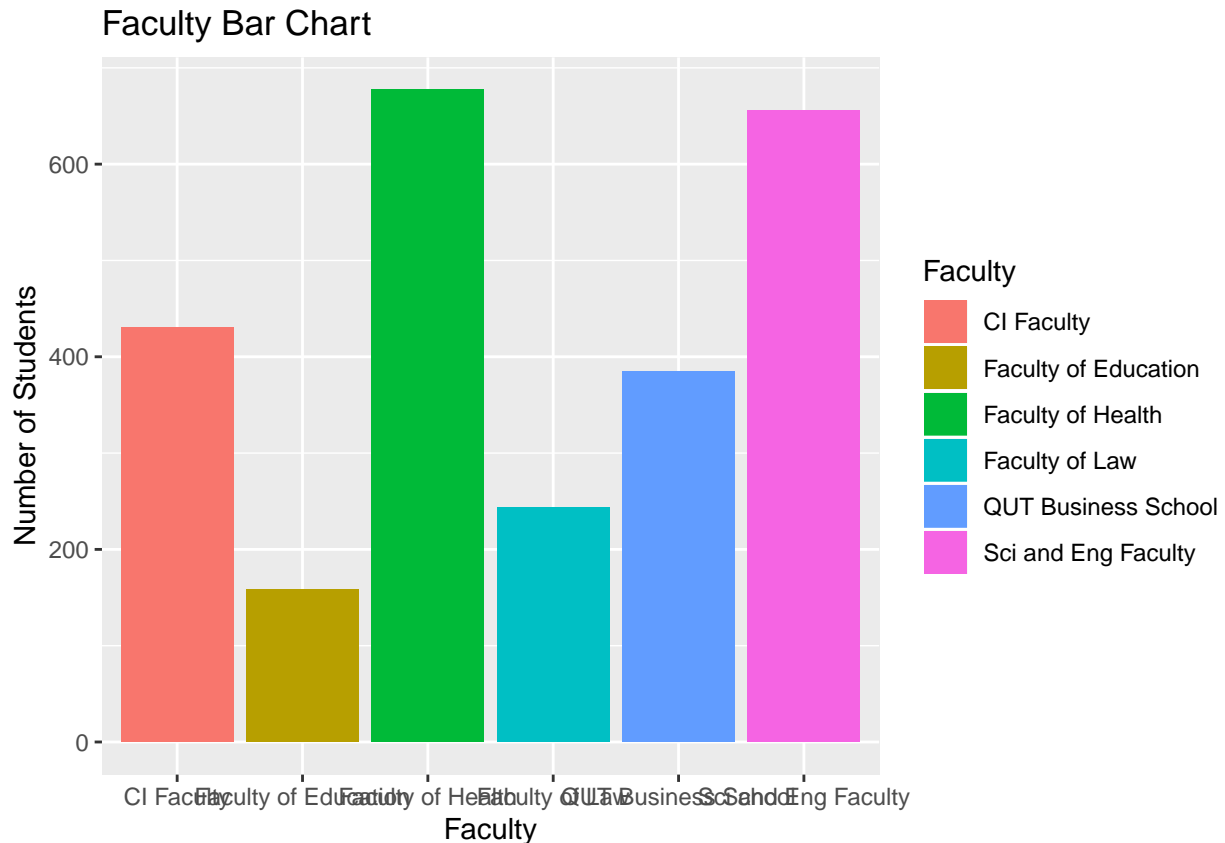
```
visualize_categorical_data(uniData)
```











The function operated above generates 9 bar charts illustrating the distribution of each categorical variables in the data frame. The summaries of each chart are listed below.

1. The distribution of the attrition of the students

It is evident that students in retained attrition are approximately four times more than students in not retained attrition.

2. The distribution of degree type among students

Almost 93% of students are doing a single degree, while the rest are doing a double degree.

3. The attendance type distribution among students

Not surprisingly, most of the students are studying full-time at university. On the other hand, around ten per cent of students is a part-time student.

4. The distribution of first in family in all the students

There are approximately 95% of students are local students in the university, while the remainder is international students.

5. The distribution of gender among students

It is interesting that gender in the university is evenly distributed. It doesn't have a huge statistical outlier.

6. The economic status of each students.

Half proportion of the students are in medium-income families. Approximately 30 per cent of students are in high-income families, while around 18% of students were heavily concerning their economic status.

7. The distribution of the period students admitted to university

The chart shows that approximately 80 per cent of the students joined the university in semester 1, while only 20 per cent of students admitted by the university in semester 2.

8. The distribution of students in each faculty

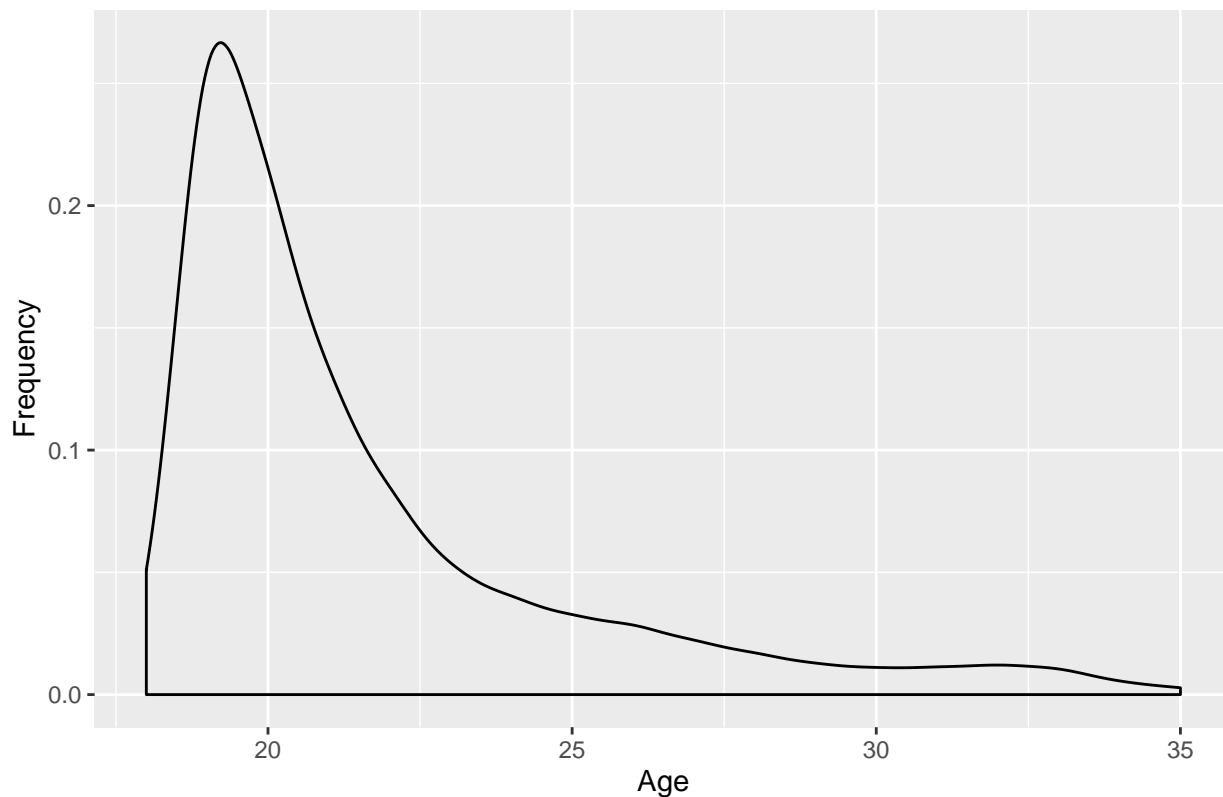
Both Faculty of Health, Science and Engineering contain the most amount of student, while CI Faculty and Business School contain the second most amount of student. Faculty of Education, however, has the least amount of student enrolled in the recorded period.

Summary each numerical data using appropriate graphs

```
# A function print out each appropriate graphs  
visualize_numerical_data(uniData)
```

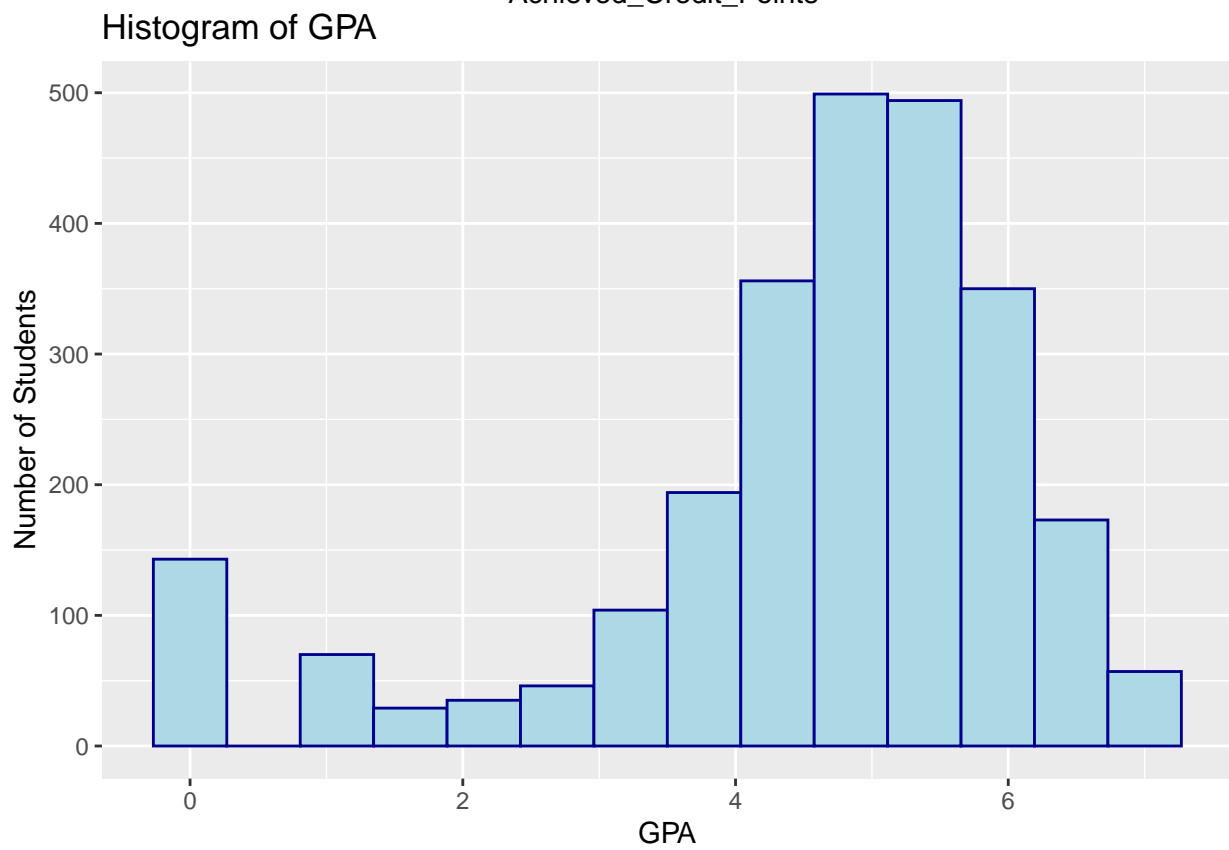
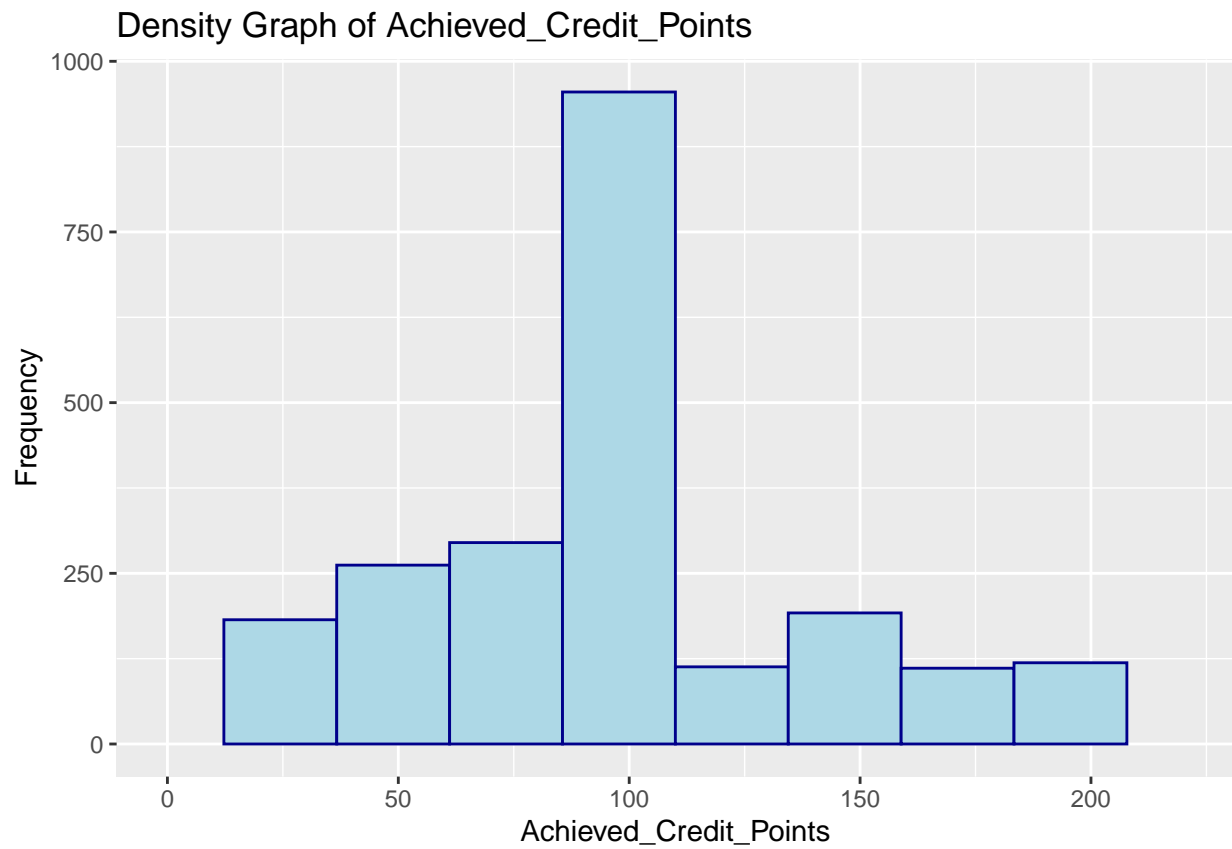
```
## Warning: Removed 132 rows containing non-finite values (stat_density).
```

Density Graph of Age

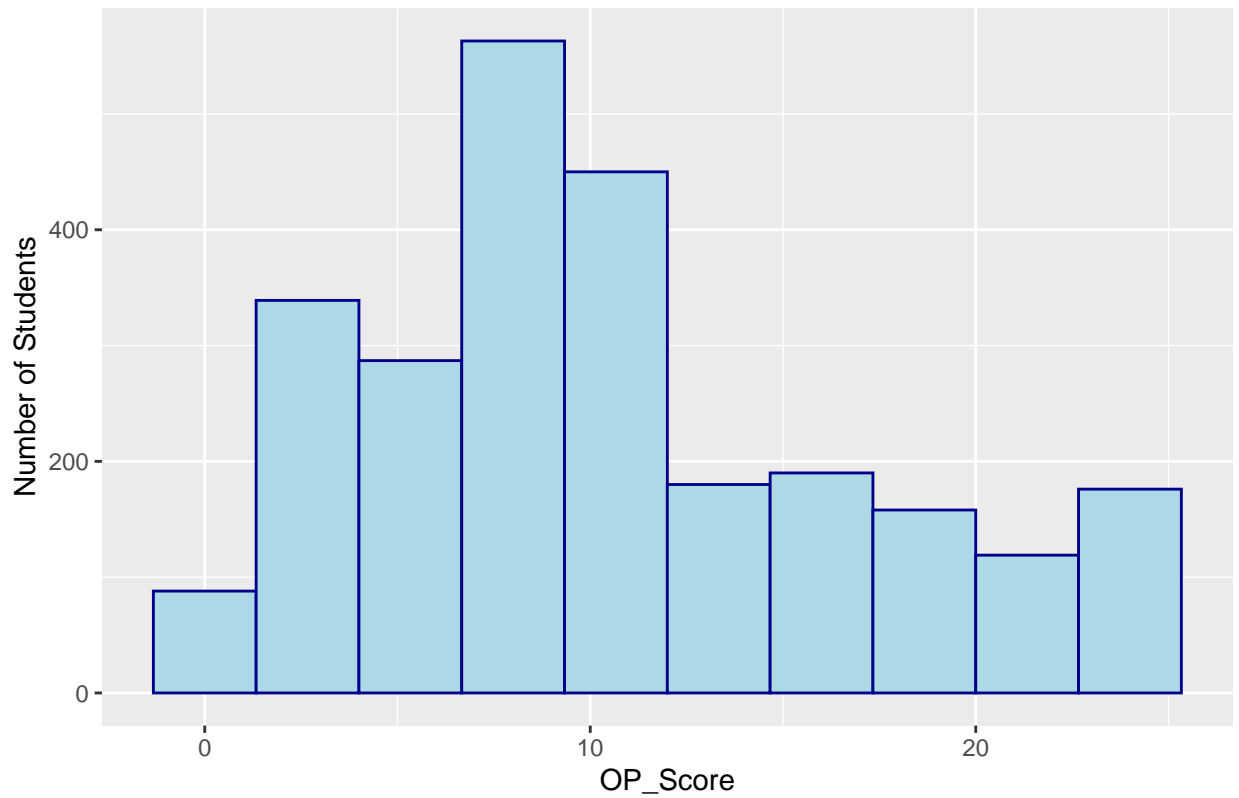


```
## Warning: Removed 46 rows containing non-finite values (stat_bin).
```

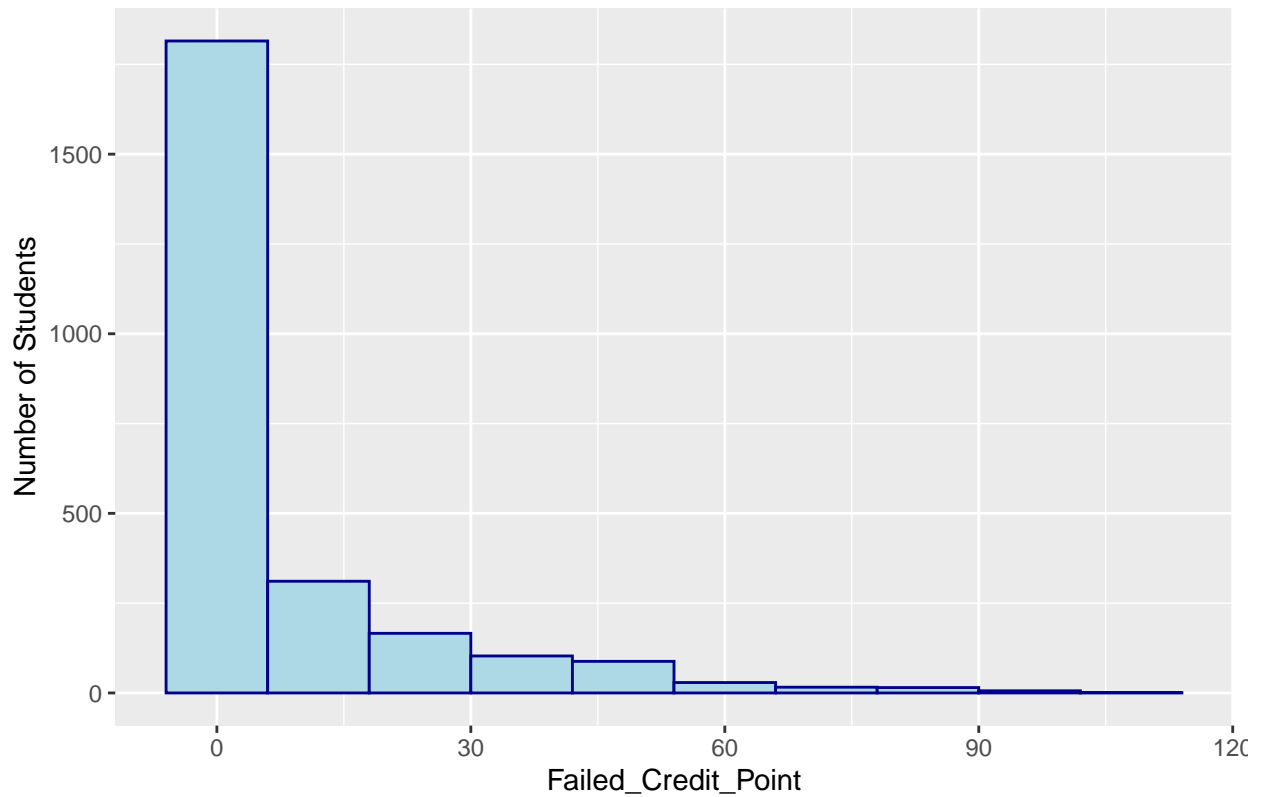
```
## Warning: Removed 2 rows containing missing values (geom_bar).
```

Histogram of OP Score



Histogram of Failed_Credit_Point



The function operated above generates one density graphs and four histogram illustrating the distribution of

each numerical variables in the data frame. The summaries of each chart are listed below.

1. The distribution of the age of the students

Not surprisingly, most of the students are around 17 and 19 years old. They normally enrolled in the university after graduated from high school. However, also some students are over 20 years old. It could be some students enrolled in the university after finishing a lower education, such as a diploma or certificate IV.

2. The distribution of achieved credit points among students

The histogram does not show any interesting fact to be noted. Most of the students in the record are in second year of their study.

3. The GPA distribution among students

Most of the student average around a GPA of 4 to 6. It can be summarised that there are approximately 80% of student with a GPA higher than 3.5, while the remainders are with a lower GPA less than 3.5.

4. The OP Score distribution among students

Clearly, most of the students get OP score around 5 to 10. The diagram occurs right-skewed.

5. The distribution of failed credit points among students

Not surprisingly, most of the students are highly possible that never fail any unit (0 point) or one single unit (12 point). It makes the diagrams tend to be frequent on the left-hand side.

Task 2 Compare average GPA between male and female students using a graph, conduct a statistical test, and interpret its results

Summary GPA for male

```
male_data <- uniData %>%
  filter(Gender == "M")

summary(male_data$GPA)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	0.000	4.000	4.750	4.472	5.500	7.000

Summary GPA for Female

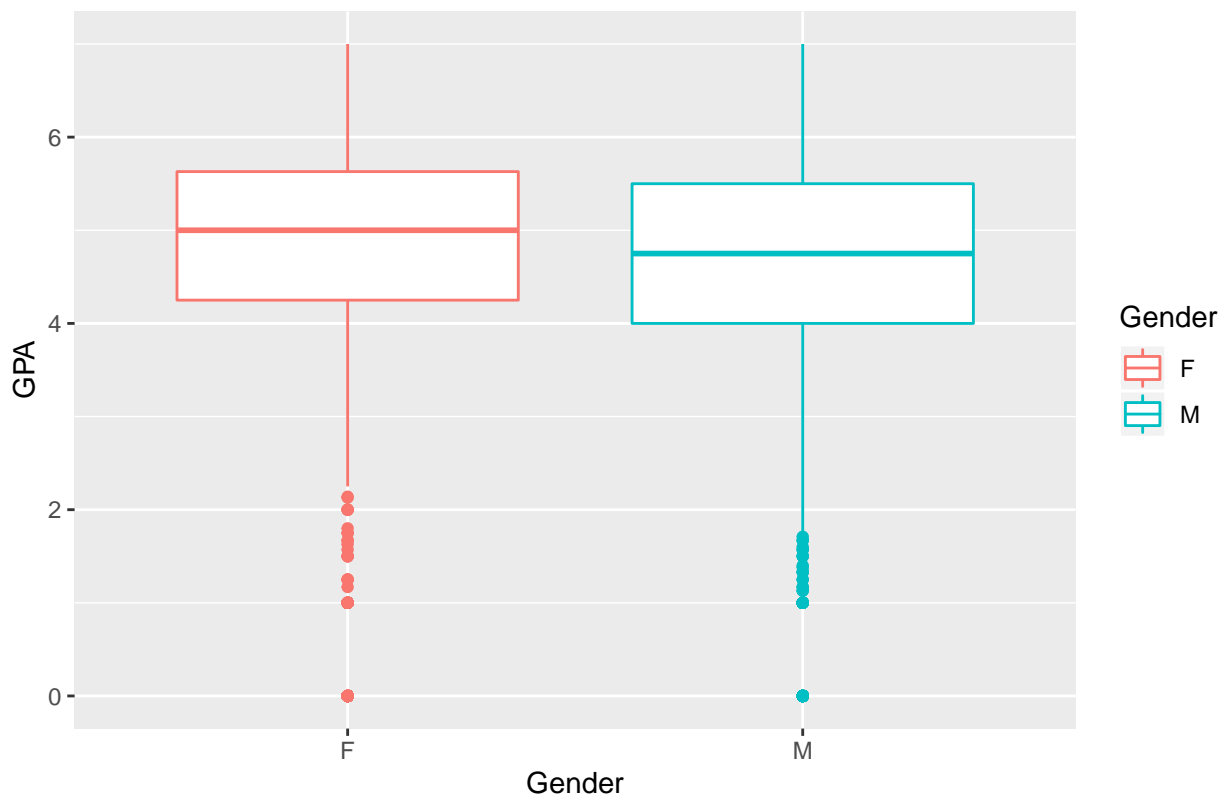
```
female_data <- uniData %>%
  filter(Gender == "F")

summary(female_data$GPA)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	0.000	4.250	5.000	4.629	5.630	7.000

```
# Compare average GPA between Male and Female
# Conduct a statistical Test
# Interpret its results
visualize_boxplot_gpa_vs_gender(uniData)
```

BoxPlot (GPA vs Gender)



T-Test & Variance

```
# T Test
t.test(uniData$GPA ~ uniData$Gender)

##
## Welch Two Sample t-test
##
## data: uniData$GPA by uniData$Gender
## t = 2.4454, df = 2539.7, p-value = 0.01453
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.03111718 0.28297210
## sample estimates:
## mean in group F mean in group M
##      4.629282      4.472238

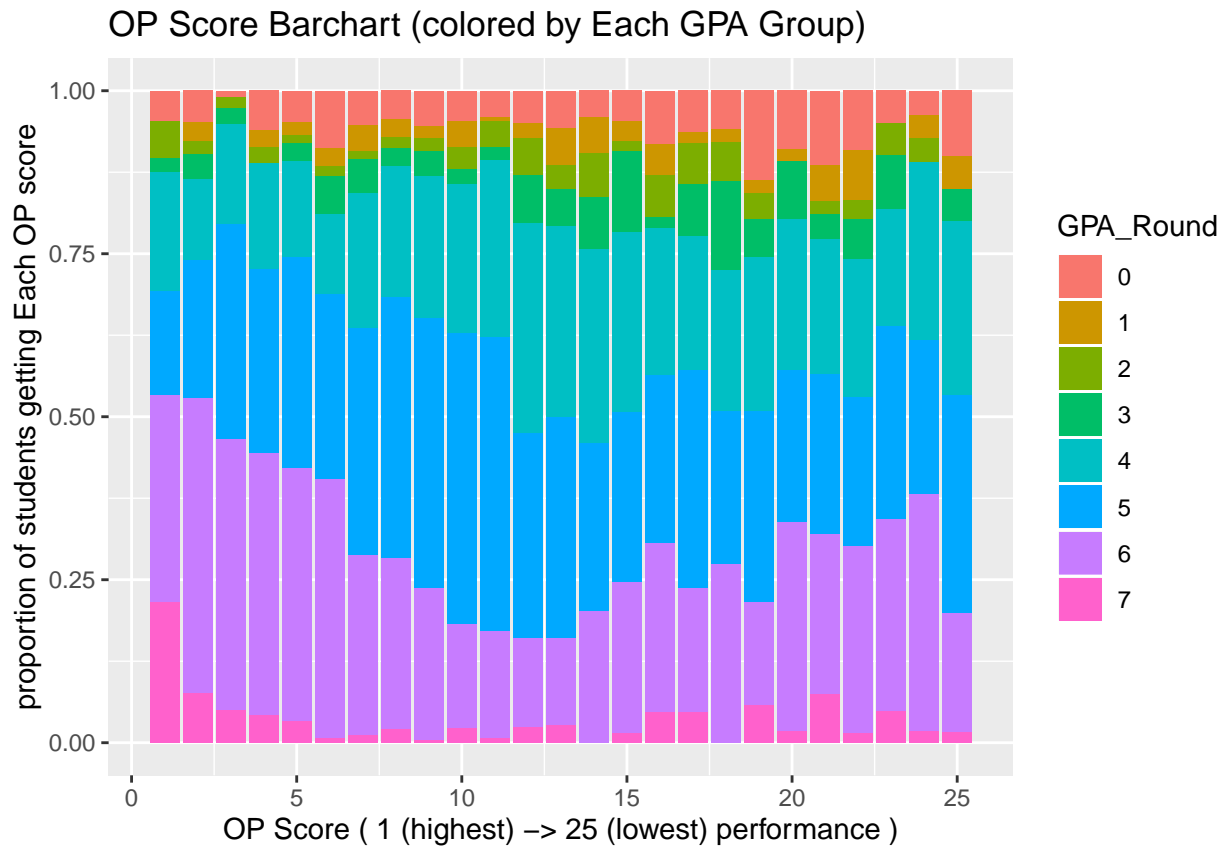
# Variance
var.test(uniData$GPA ~ uniData$Gender)

##
## F test to compare two variances
##
## data: uniData$GPA by uniData$Gender
## F = 1.0496, num df = 1253, denom df = 1295, p-value = 0.3873
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.9404454 1.1716026
```

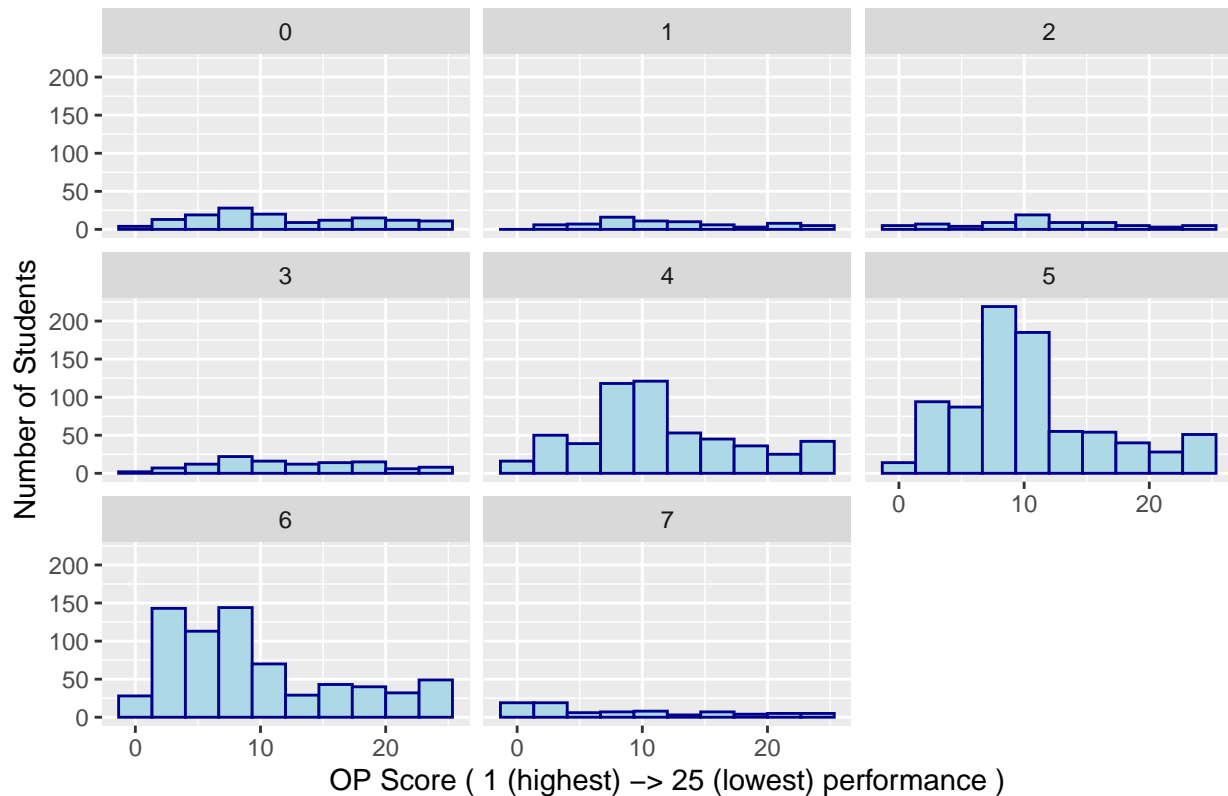
```
## sample estimates:
## ratio of variances
##          1.049627
```

Task3 Explore the relationship between OP Score and GPA using a graph, describe the relationship

```
visualize_relationship_op_and_gpa(uniData)
```



OP Score histogram (Divided by Each GPA Group)



Bar chart (OP Score VS GPA)

The first bar chart displayed the relationship between OP score and GPA. Each bar indicates every student achieves in the OP exam, while each bar is filled with 8 different colours which indicate how these students perform in the university. The GPA score is rounded to the nearest integer, for instance, 3.67 will be rounded to 4 and 6.18 will be rounded to 6.

Most of the students, who get the lowerest OP exam, tend to perform better in the university. Approximately 50% of students, who get 1 OP score, archived above GPA 6 when they are studying in university. In contrast, about 40% of students, who get 25 OP score, archived below GPA 4 which means failed the study in university.

In conclusion, if students get the lower OP scores tends to performs better in the university.

Task 4 Linear Regression

Develop a linear regression model of GPA using the given data. You need to describe your choice of predictors, examine your model's assumptions, assess model fit, and interpret the final model's regression coefficients.

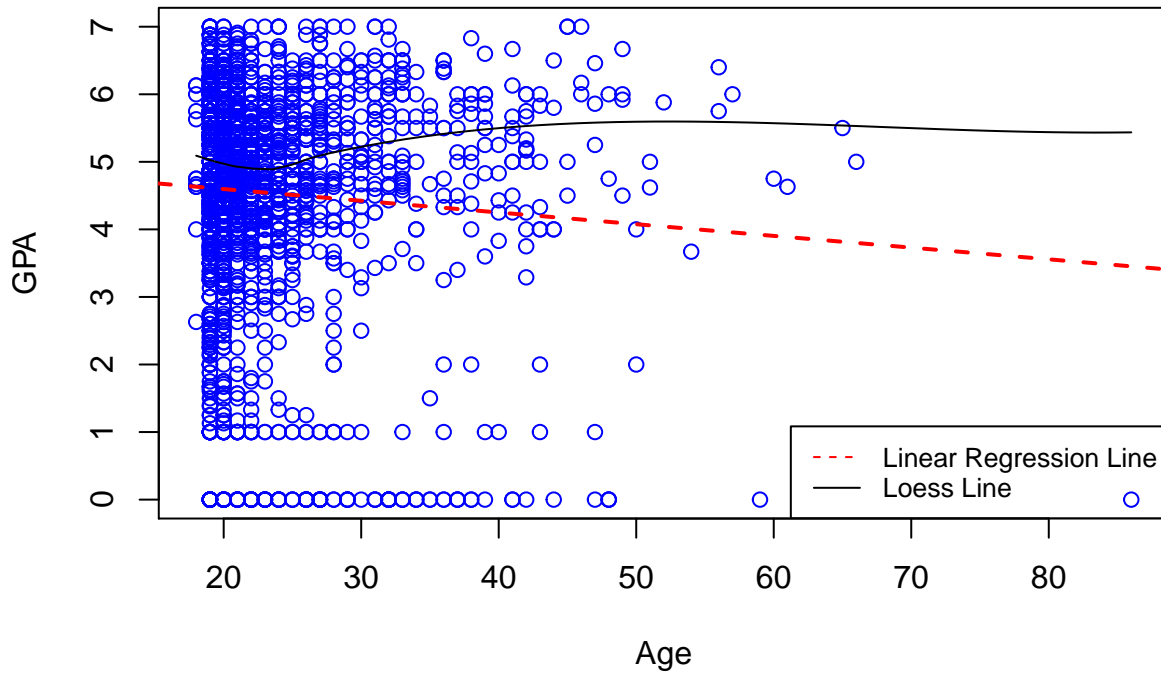
Analyse Each numerical data its relation related to GPA

Correlation between each numerical data and GPA

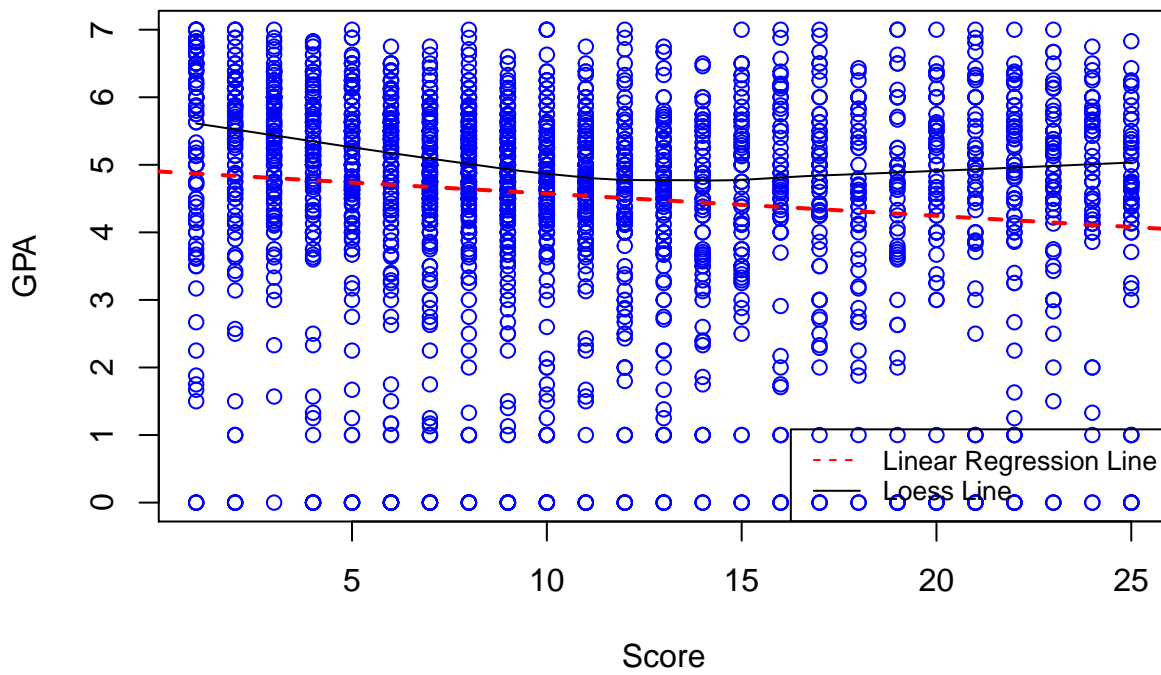
1. Age : -0.0641342
2. OP_Score : -0.129619
3. Achieved_Credit_Points : 0.4920035
4. Failed_Credit_Points : -0.473419

```
visualize_scatterplots_Vs_GPA(uniData)
```

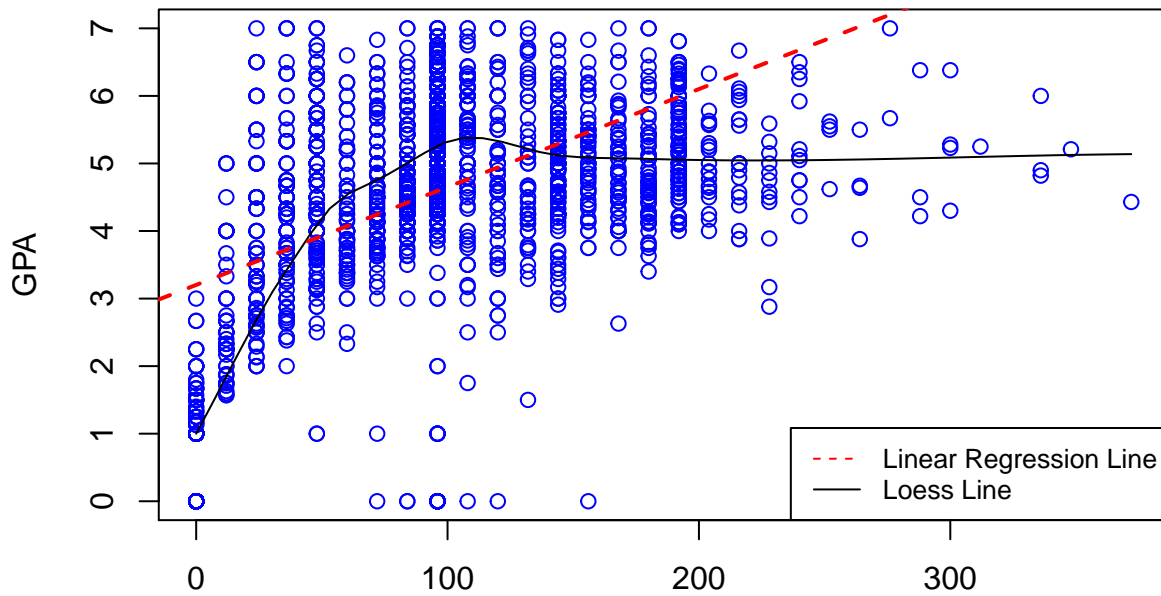
Age vs GPA



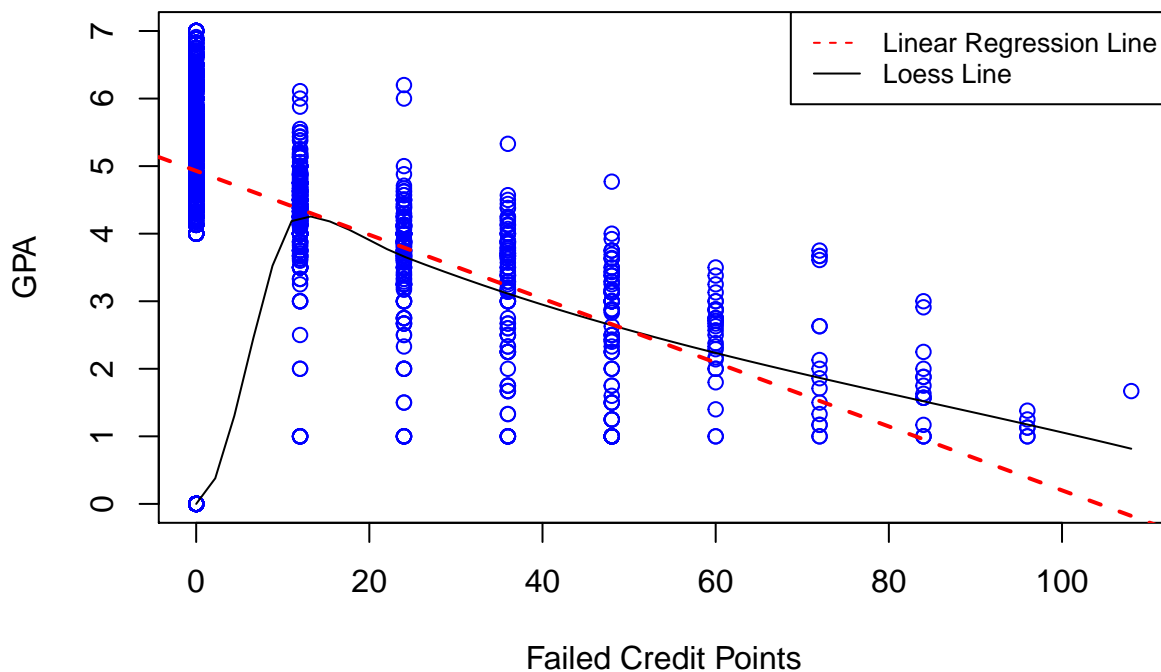
OP_Score vs GPA



Achieved_Credit_Points vs OP_Score



Failed_Credit_Points vs OP_Score



The chosen predictors

It is evident that GPA will always be selected to be Y-axis which is classified as quantitative value. The predictor will need to be a strong data value that could have a significant impact on the analysis. From the correlation coefficient and scatterplot we got above, Achieved Credit Point seems to be a biased and

homoscedastic graph. It provides a good fit for the linear regression model as it has a positive linear relationship and a positive moderate correlation coefficient. It also achieves the highest correlation coefficient which indicates that it presents the strongest relationship with GPA comparing to the other three. Therefore, Achieved Credit Point is selected to train and test the simple linear regression model. From the Scatterplot (Achieved Credit Points vs GPA), we can know that people higher Achieved Credit Points (Successfully complete the unit they study) are likely to have higher GPA.

Spiting dataframe into training set and test set

```
# Data Preprocessing Library
library(caTools)
# Set Random seed
set.seed(2)
# Splitting Training and test dataset
split <- sample.split(uniData, SplitRatio = 0.7)
train <- subset(uniData, split==TRUE)
test <- subset(uniData, split==FALSE)
```

Training Linear Regression Model & Review diagnostic measures.

```
linear_model <- lm(GPA ~ Achieved_Credit_Points, data=train)
summary(linear_model)

##
## Call:
## lm(formula = GPA ~ Achieved_Credit_Points, data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.9761 -0.7239  0.2029  1.0120  3.4564
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    3.1854527  0.0688092   46.29  <2e-16 ***
## Achieved_Credit_Points 0.0149224  0.0006455   23.12  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.411 on 1637 degrees of freedom
## Multiple R-squared:  0.2461, Adjusted R-squared:  0.2457
## F-statistic: 534.4 on 1 and 1637 DF,  p-value: < 2.2e-16
```

regression function: $GPA = 3.1854527 + 0.0149224 * \text{Achieved_Credit_Points}$ that can be used for prediction

The typical difference between the Achieved Credit Points and the GPA predicted by the model is about 1.411 percentage points.

24.6% of the variability in GPA can be explained by Achieved Credit Points.

AIC / BIC

```
# two information criteria, only useful when comparing competing models
# Smaller value = better model
AIC(linear_model)
```

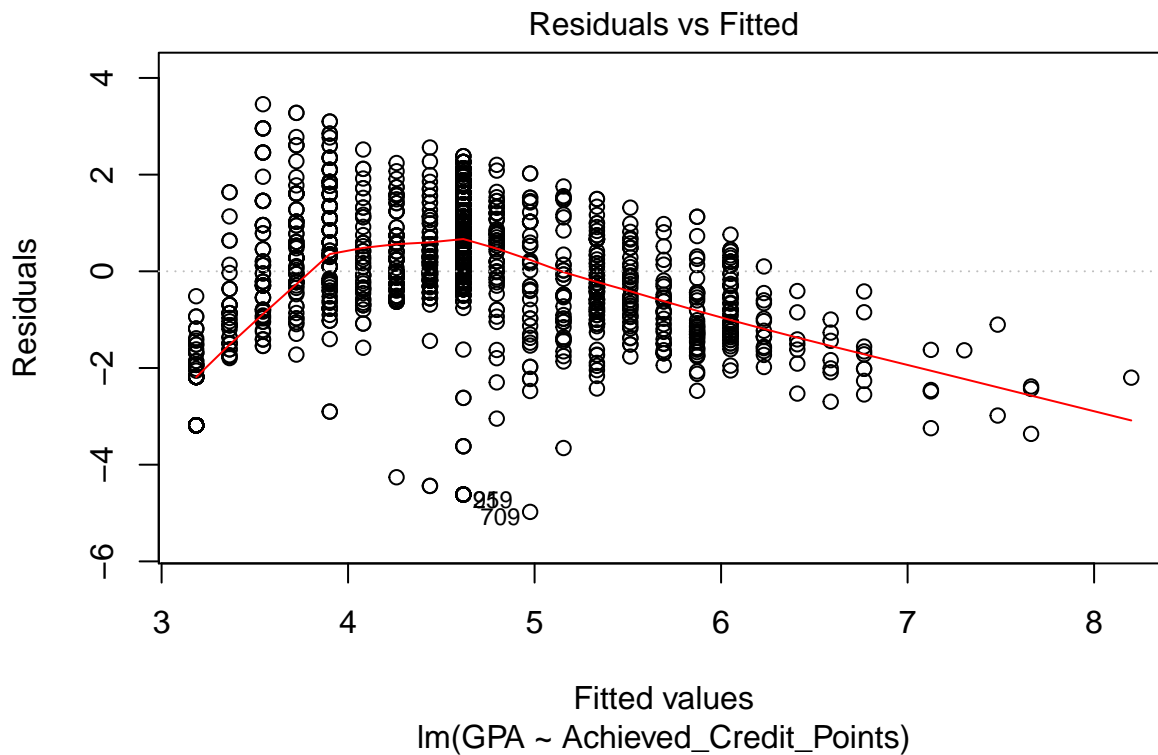
```
## [1] 5783.126
```

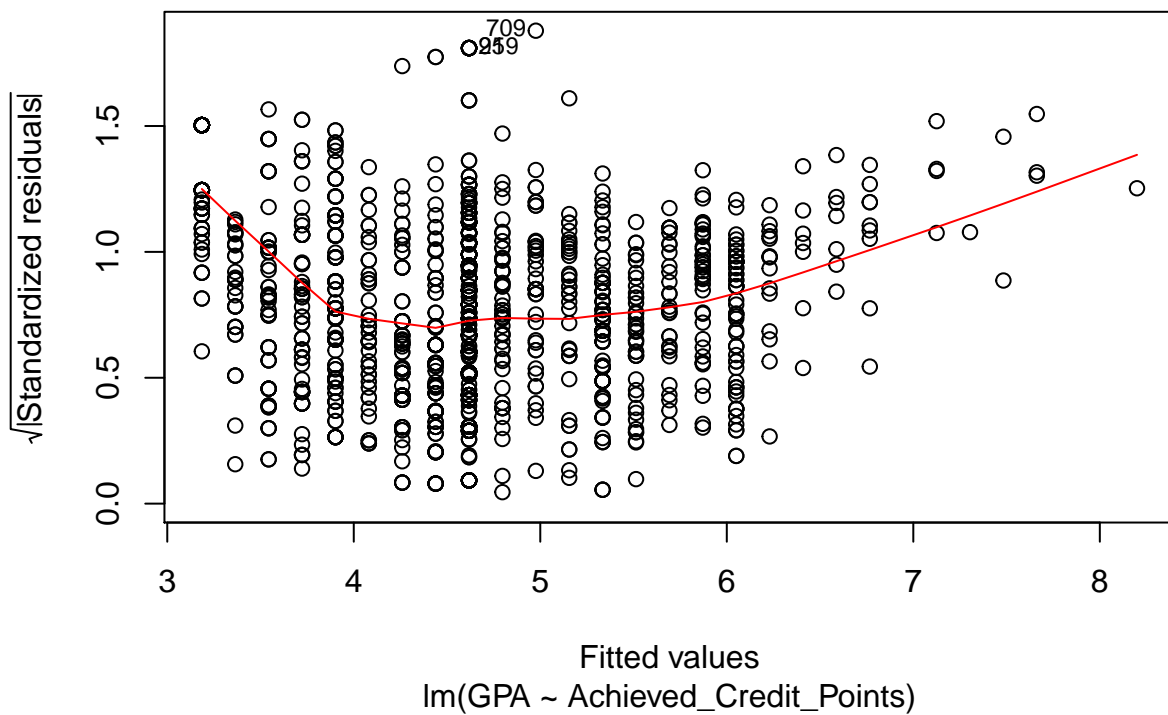
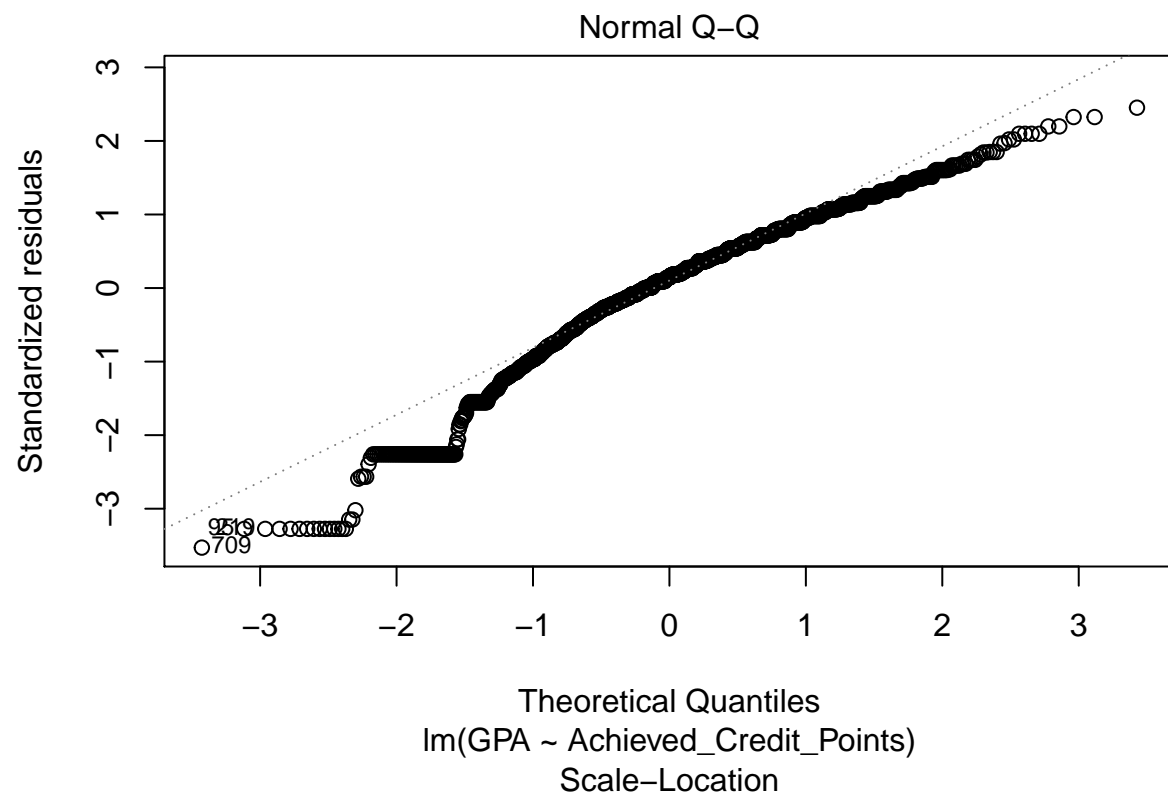
```
BIC(linear_model)
```

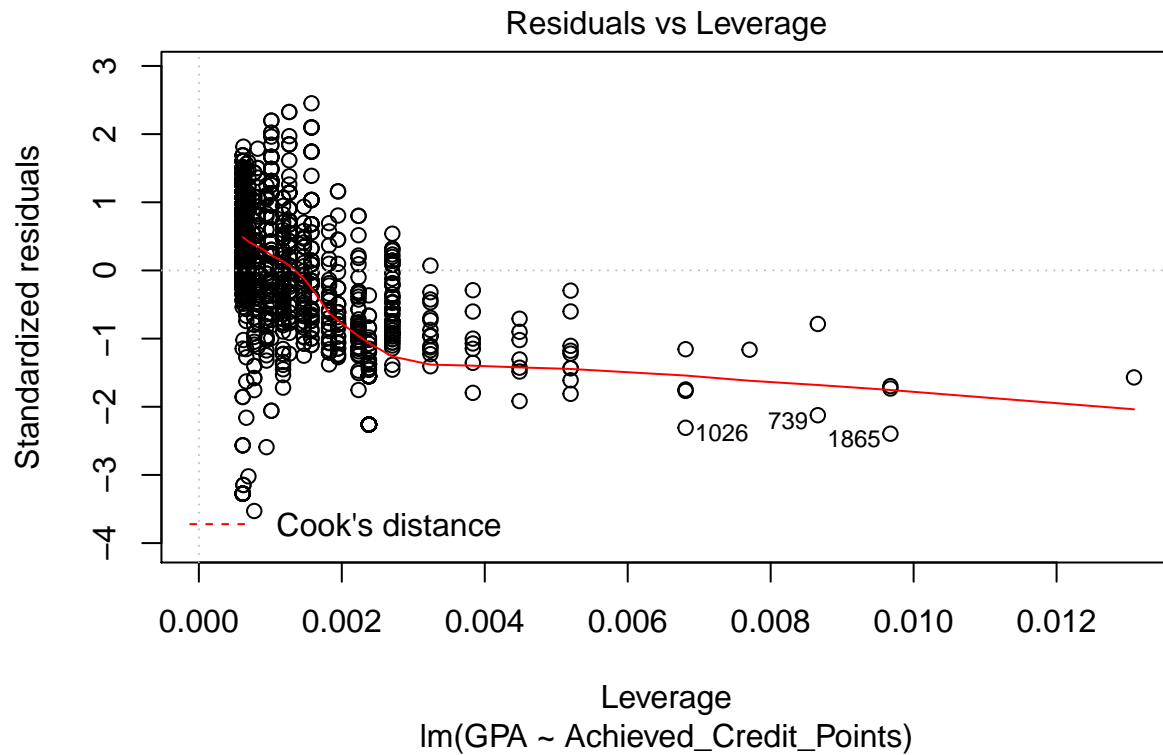
```
## [1] 5799.331
```

Plot the Linear Regression Prediction Line

```
plot(linear_model)
```







Task 5 Logistic Regression

```
# Logistic Regression Library
library(DAAG)
source("regression_helper.R")
```

Bivariate exploration

```
attach(uniData)
print(xtabs(~ Attrition + Faculty))

##              Faculty
## Attrition    CI Faculty Faculty of Education Faculty of Health
## Not Retained      97             21             112
## Retained         333            137             565
##
##              Faculty
## Attrition    Faculty of Law QUT Business School Sci and Eng Faculty
## Not Retained      53             54             111
## Retained         191            331             545

print(xtabs(~ Attrition + Socio_Economic_Status))

##              Socio_Economic_Status
## Attrition    High Low Medium
## Not Retained  135  98  215
## Retained     636 365 1101

print(xtabs(~ Attrition + Degree_Type))

##              Degree_Type
```

```
## Attrition      Double Single
## Not Retained   14    434
## Retained       155   1947
print(xtabs(~ Attrition + Attendance_Type))

##              Attendance_Type
## Attrition      Full Time Part Time
## Not Retained    428      20
## Retained       1880     222
print(xtabs(~ Attrition + First_in_family))

##              First_in_family
## Attrition      No  Yes
## Not Retained  256  192
## Retained    1324  778
print(xtabs(~ Attrition + Teaching._Period_Admitted))

##              Teaching._Period_Admitted
## Attrition      SEM-1 SEM-2
## Not Retained   382    66
## Retained      1725   377
print(xtabs(~ Attrition + Gender))

##              Gender
## Attrition      F    M
## Not Retained  224  224
## Retained    1030 1072
print(xtabs(~ Attrition + International_student))

##              International_student
## Attrition      No  Yes
## Not Retained  424   24
## Retained    1799  303
detach(uniData)
```

A simple model with only one predictor

```
simple_log_model <- glm(Attrition ~ Socio_Economic_Status, data=uniData, family = "binomial")
summary(simple_log_model)

##
## Call:
## glm(formula = Attrition ~ Socio_Economic_Status, family = "binomial",
##      data = uniData)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.9035   0.5973   0.5973   0.6205   0.6897
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.54992    0.09476  16.356  <2e-16 ***
```

```
## Socio_Economic_StatusLow    -0.23499    0.14807   -1.587    0.112
## Socio_Economic_StatusMedium 0.08341    0.12058    0.692    0.489
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2370.4  on 2549  degrees of freedom
## Residual deviance: 2365.1  on 2547  degrees of freedom
## AIC: 2371.1
##
## Number of Fisher Scoring iterations: 4
```

simple model P-value & Pseudo R²

```
print_R2_and_pvalue(simple_log_model$null.deviance, simple_log_model$deviance)
```

```
## [1] "R^2 : 0.0022540272034674"
## [1] "P-value : 0.0208056460092459"
```

Summarise the predicted probabilities

```
simple.predicted.data <- data.frame(
  probability.of.Attrition = simple_log_model$fitted.values,
  Socio_Economic_Status = uniData$Socio_Economic_Status
)

xtabs(~ probability.of.Attrition + Socio_Economic_Status ,data=simple.predicted.data)
```

```
##                               Socio_Economic_Status
## probability.of.Attrition High  Low Medium
##      0.788336933045247      0  463      0
##      0.824902723735415    771      0      0
##      0.836626139817635      0      0    1316
```

Logistic Regression model with all predictors

```
# Logistic Regression with all predictors
log_model <- glm(Attrition ~ ., data=uniData, family = "binomial")
summary(log_model)
```

```
##
## Call:
## glm(formula = Attrition ~ ., family = "binomial", data = uniData)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -3.5129   0.2020   0.4329   0.5718   1.8857
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    0.961335   0.450604   2.133  0.03289 *
## Degree_TypeSingle -0.741475   0.309181  -2.398  0.01648 *
## Achieved_Credit_Points 0.016922   0.001841   9.192 < 2e-16 ***
```

```
## Attendance_TypePart Time      1.425308    0.262767    5.424 5.82e-08 ***
## Age                           -0.026512    0.009730   -2.725 0.00643 **
## Failed_Credit_Points          -0.017050    0.003407   -5.005 5.60e-07 ***
## International_studentYes       0.775607    0.247844    3.129 0.00175 **
## First_in_familyYes            0.017776    0.121154    0.147 0.88335
## GenderM                       0.105876    0.125705    0.842 0.39965
## GPA                           0.075554    0.043064    1.754 0.07935 .
## OP_Score                      -0.007203    0.009468   -0.761 0.44683
## Socio_Economic_StatusLow      -0.145242    0.169840   -0.855 0.39246
## Socio_Economic_StatusMedium   0.049286    0.135809    0.363 0.71667
## Teaching._Period_AdmittedSEM-2 0.390834    0.171037    2.285 0.02231 *
## FacultyFaculty of Education   0.596908    0.282377    2.114 0.03453 *
## FacultyFaculty of Health      0.228437    0.175987    1.298 0.19428
## FacultyFaculty of Law         -0.256680    0.230529   -1.113 0.26552
## FacultyQUT Business School    0.524731    0.215330    2.437 0.01482 *
## FacultySci and Eng Faculty    0.415301    0.184758    2.248 0.02459 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 2370.4 on 2549 degrees of freedom
## Residual deviance: 1914.3 on 2531 degrees of freedom
## AIC: 1952.3
##
## Number of Fisher Scoring iterations: 6
```

Logistic Regression model with all predictors P-value & Pseudo R²

```
print_R2_and_pvalue(log_model$null.deviance, log_model$deviance)
```

```
## [1] "R^2 : 0.192423133796394"
## [1] "P-value : 0"
```

Multicollinearity using VIF

```
vif(log_model)
```

```
## Degree_TypeSingle      Achieved_Credit_Points
##           1.0421           1.9565
## Attendance_TypePart Time      Age
##           1.0777           1.1650
## Failed_Credit_Points      International_studentYes
##           1.2924           1.0595
## First_in_familyYes      GenderM
##           1.0537           1.1668
## GPA      OP_Score
##           1.9817           1.0562
## Socio_Economic_StatusLow Socio_Economic_StatusMedium
##           1.3670           1.3618
## Teaching._Period_AdmittedSEM-2 FacultyFaculty of Education
##           1.1346           1.2050
## FacultyFaculty of Health      FacultyFaculty of Law
##           1.7609           1.4829
```

```
## FacultyQUT Business School FacultySci and Eng Faculty
## 1.4804 1.8834
```

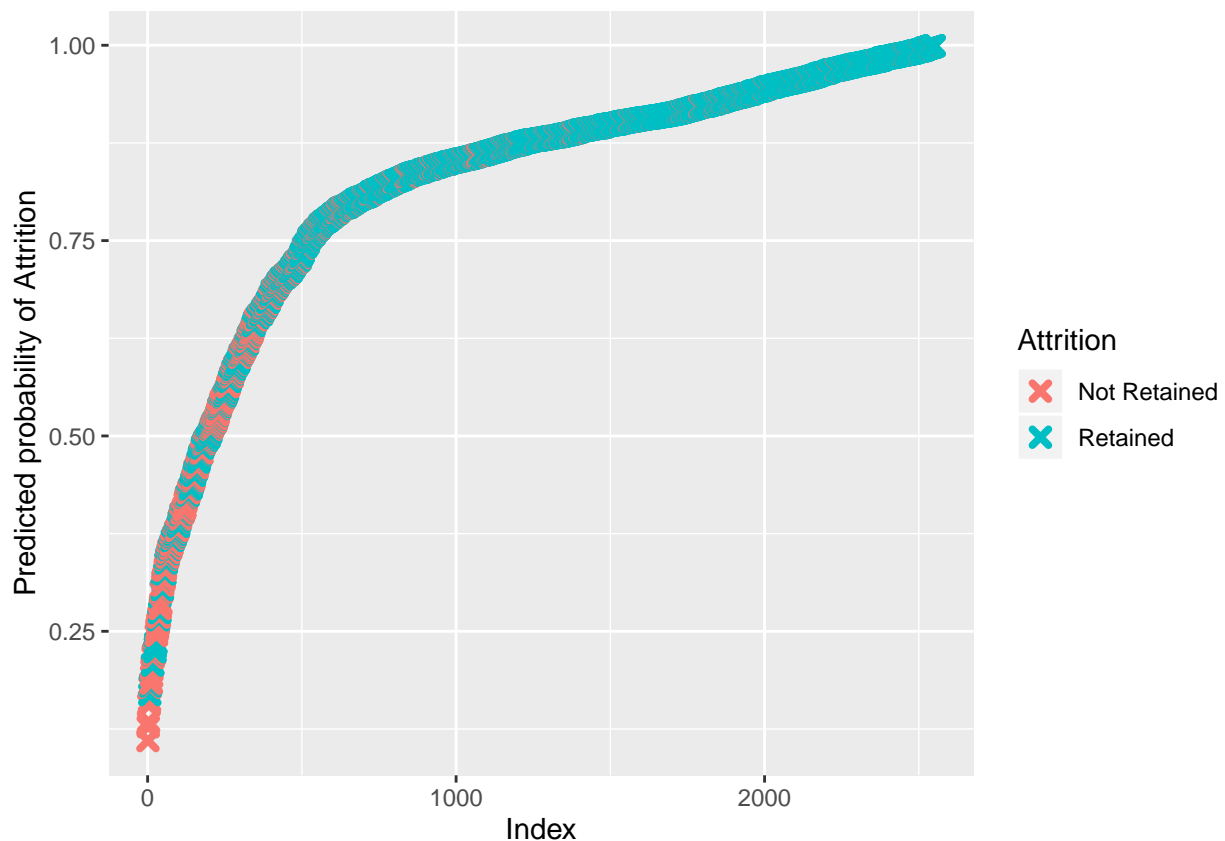
Plot Predicted Probabilities

```
predicted.data <- data.frame(
  probability.of.Attrition = log_model$fitted.values,
  Attrition = uniData$Attrition
)

# Sort predicted data by Probabilities
predicted.data <- predicted.data[order(predicted.data$probability.of.Attrition, decreasing = FALSE),]
predicted.data$rank <- 1:nrow(predicted.data)

library(ggplot2)
library(cowplot)

ggplot(data=predicted.data, aes(x=rank, y=probability.of.Attrition) ) +
  geom_point(aes(color=Attrition), alpha = 1, shape = 4, stroke = 2) +
  xlab("Index") +
  ylab("Predicted probability of Attrition")
```



ROC Curve

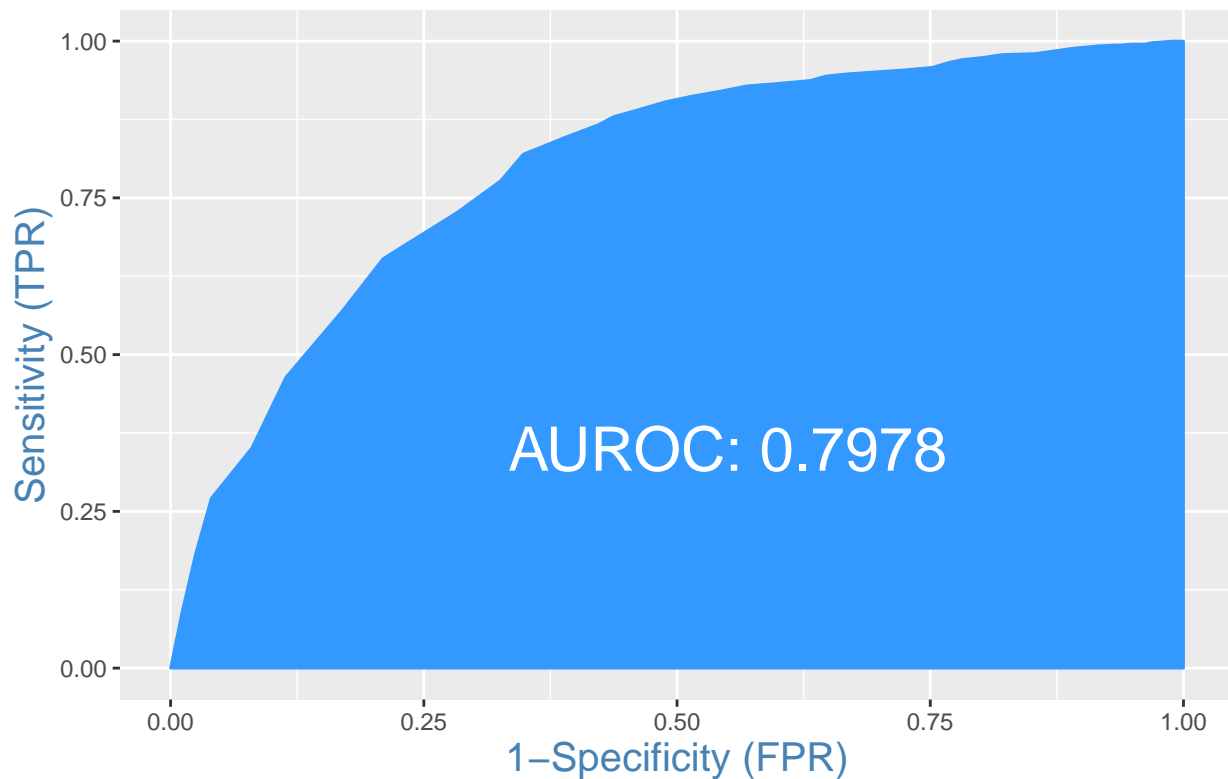
```
#
predicted.data$actuals <- factor(predicted.data$Attrition, labels = c(0,1))
```



```
# Shows ROC Curve
```

```
visualize_ROC_Curve(predicted.data$actuals, predicted.data$probability.of.Attrition)
```

ROC Curve



MisClassification Error, Sensitivity, Specificity

```
print_MCE_Sens_Spec( predicted.data$actuals, predicted.data$probability.of.Attrition)
```

```
## [1] "Optimal Cut off : 0.569423153772749"
```

```
## [1] "MisClassification Error : 0.158"
```

```
## [1] "sensitivity: 0.9476688867745"
```

```
## [1] "specificity : 0.345982142857143"
```

```
print_ConfusionMatrix( predicted.data$actuals, predicted.data$probability.of.Attrition)
```

```
##      0      1
```

```
## 0 155  110
```

```
## 1 293 1992
```