CAR

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OBJECTIVE OF THE PROJECT:

This project requires you to understand what mode of transport employees prefers to commute to their office. The attached data 'Cars.csv' includes employee information about their mode of transport as well as their personal and professional details like age, salary, work exp.

We need to predict whether or not an employee will use Car as a mode of transport. Also, which variables are a significant predictor behind this decision.

Following is expected out of the candidate in this assessment.

1. EDA (15 Marks) - Perform an EDA on the data

2. Illustrate the insights based on EDA

3. Check for Multicollinearity - Plot the graph based on Multicollinearity & treat it

4. Data Preparation

5. Prepare the data for analysis (SMOTE)

6. Modeling - Create multiple models and explore how each model perform using appropriate model performance metrics

7. KNN

8. Naive Bayes (is it applicable here? comment and if it is not applicable, how can you build an NB model in this case?

9. Logistic Regression

10. Apply both bagging and boosting modeling procedures to create 2 models and compare its accuracy with the best model of the above step.

11. Actionable Insights & Recommendations

12. Summarize your findings from the exercise in a concise yet actionable note

Importing the Dataset

```
setwd("D:/Great Lakes/Projects/Machine Learning")
getwd()

## [1] "D:/Great Lakes/Projects/Machine Learning"

cars <- read.csv("cars.csv",header = TRUE)
```

Understanding the data

Data Description

The dataset has details on 418 employees' details with 9 Variables.

Structure of Data

```
str(cars)

## 'data.frame':    418 obs. of  9 variables:
##  $ Age      : int  28 24 27 25 25 21 23 23 24 28 ...
##  $ Gender   : Factor w/ 2 levels "Female","Male": 2 2 1 2 1 2 2 2 2 2 ...
##  $ Engineer : int  1 1 1 0 0 0 1 0 1 1 ...
##  $ MBA      : int  0 0 0 0 0 0 1 0 0 0 ...
##  $ Work.Exp : int  5 6 9 1 3 3 3 0 4 6 ...
##  $ Salary   : num  14.4 10.6 15.5 7.6 9.6 9.5 11.7 6.5 8.5 13.7 ...
##  $ Distance : num  5.1 6.1 6.1 6.3 6.7 7.1 7.2 7.3 7.5 7.5 ...
##  $ license  : int  0 0 0 0 0 0 0 0 0 1 ...
##  $ Transport: Factor w/ 3 levels "2Wheeler","Car",..: 1 1 1 1 1 1 1 1 1 1 ...
```

We see that License,Engineer,MBA Variables are taken as numerical variable. We need to convert it to categorical variable.

```
cars$license <- as.factor(cars$license)
cars$Engineer <- as.factor(cars$Engineer)
cars$MBA <- as.factor(cars$MBA)
```

Now lets look at the Structure of our Dataset

```
str(cars)
```

```
## 'data.frame':    418 obs. of  9 variables:
##  $ Age      : int  28 24 27 25 25 21 23 23 24 28 ...
##  $ Gender   : Factor w/ 2 levels "Female","Male": 2 2 1 2 1 2 2 2 2 2 ...
##  $ Engineer : Factor w/ 2 levels "0","1": 2 2 2 1 1 1 2 1 2 2 ...
##  $ MBA      : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 2 1 1 1 ...
##  $ Work.Exp : int  5 6 9 1 3 3 3 0 4 6 ...
##  $ Salary   : num  14.4 10.6 15.5 7.6 9.6 9.5 11.7 6.5 8.5 13.7 ...
##  $ Distance : num  5.1 6.1 6.1 6.3 6.7 7.1 7.2 7.3 7.5 7.5 ...
##  $ license  : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 2 ...
##  $ Transport: Factor w/ 3 levels "2Wheeler","Car",..: 1 1 1 1 1 1 1 1 1 1 ...
```

Summary

```
summary(cars)

##       Age           Gender    Engineer   MBA        Work.Exp
##  Min.   :18.00   Female:121   0:105    0   :308   Min.   : 0.000
##  1st Qu.:25.00   Male  :297   1:313    1   :109   1st Qu.: 3.000
##  Median :27.00                         NA's:  1   Median : 5.000
##  Mean   :27.33                                    Mean   : 5.873
##  3rd Qu.:29.00                                    3rd Qu.: 8.000
##  Max.   :43.00                                    Max.   :24.000
##      Salary         Distance     license          Transport
##  Min.   : 6.500   Min.   : 3.20   0:333   2Wheeler        : 83
##  1st Qu.: 9.625   1st Qu.: 8.60   1: 85   Car             : 35
##  Median :13.000   Median :10.90           Public Transport:300
##  Mean   :15.418   Mean   :11.29
##  3rd Qu.:14.900   3rd Qu.:13.57
##  Max.   :57.000   Max.   :23.40
```

We have 19 % of Employees who commute via thier own two wheelers and 8 % of employees via own car and 71 % of employees via Public Transport

Checking NA Values/ Missing Values

```
colsums(is.na(cars))

##       Age    Gender  Engineer       MBA  Work.Exp    Salary  Distance
##         0         0         0         1         0         0         0
##   license Transport
##         0         0
```

We have only 1 Na value in our Entire dataset. So removing it won’t affect our dataset.

```
cars<- na.omit(cars)
colSums(is.na(cars))

##       Age    Gender  Engineer       MBA  Work.Exp    Salary  Distance
##         0         0         0         0         0         0         0
##   license Transport
##         0         0
```

Since, we need to predict whether an employee will use Car as a mode of transport We need to convert the employees who use Public Transport and 2-Wheeler into one Category and car users into one category.

```
cars$Transport <- ifelse(cars$Transport == "Car",1,0)
cars$Transport <- as.factor(cars$Transport)
```

Exploratory Data Analysis

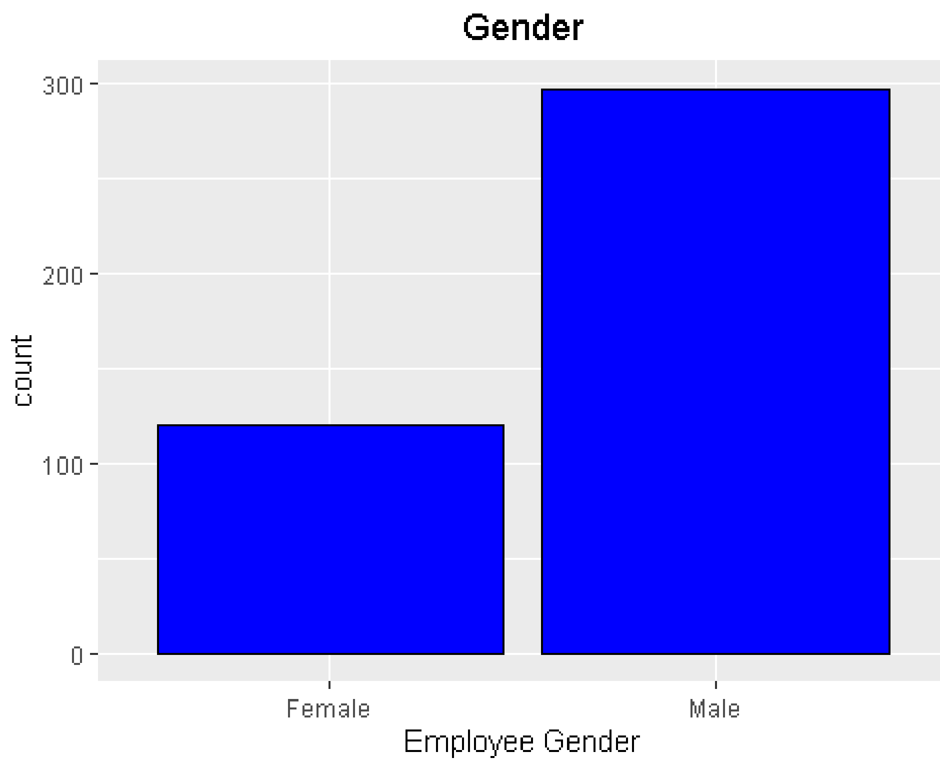
Univariate Analysis

Frequency Distribution of each Independent numerical Variable

```
library(ggplot2)
ggplot(cars,aes(x=Age))+geom_histogram(fill = "#FF9999",colour = "Black")+ggtitle("Age")+t
heme(plot.title = element_text(hjust = 0.5))+xlab("Employee Age")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

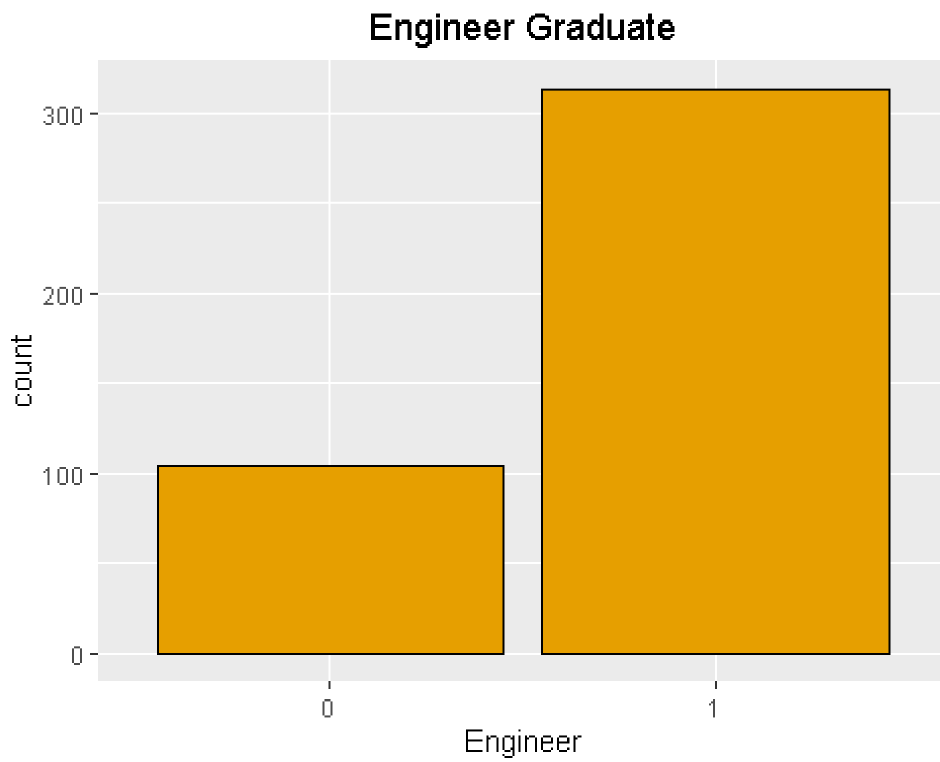
Age - Most of our Employee are younger as thier average age is around 27.

```
ggplot(cars,aes(x=Gender))+geom_bar(bins = 50,fill = "Blue",colour = "Black")+ggtitle("Gende
r")+theme(plot.title = element_text(hjust = 0.5))+xlab("Employee Gender")

## Warning: Ignoring unknown parameters: bins
```



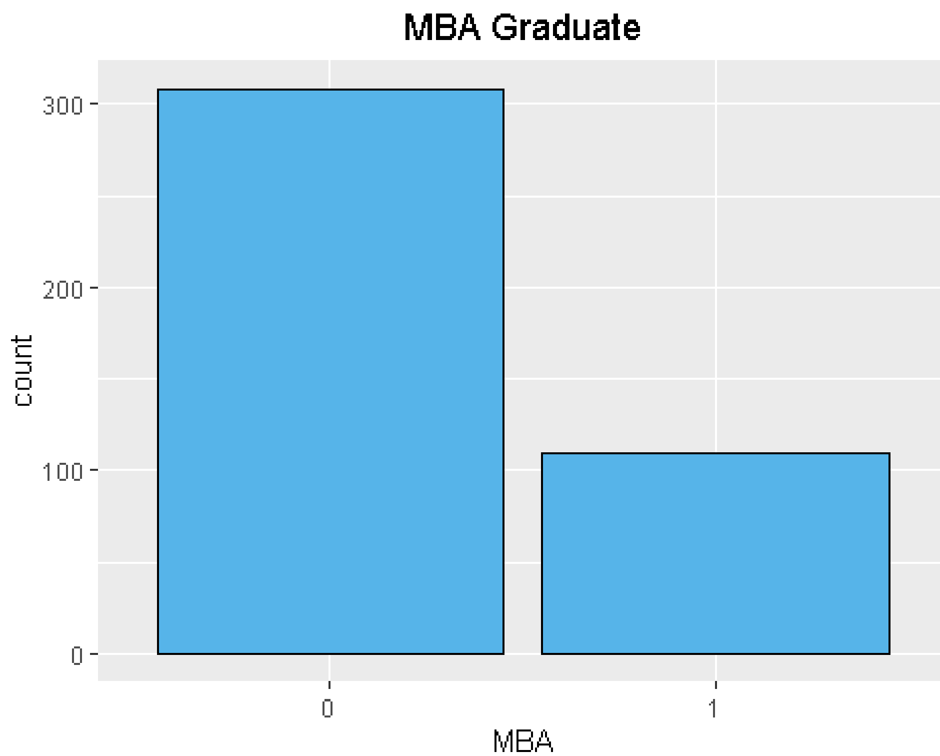
Gender - Our Employee base has lot of Males(71%) than Females (29%)

```
ggplot(cars,aes(x=Engineer))+geom_bar(fill = "#E69F00",colour = "Black")+ggtitle("Engineer Graduate")+theme(plot.title = element_text(hjust = 0.5))+xlab("Engineer")
```



Engineer - Around 75% of our Employee are engineer graduates and only 25% Employee are non- engineers

```
ggplot(cars,aes(x=MBA))+geom_bar(fill = "#56B4E9",colour = "Black")+ggtitle("MBA Graduat
e")+theme(plot.title = element_text(hjust = 0.5))+xlab("MBA")
```



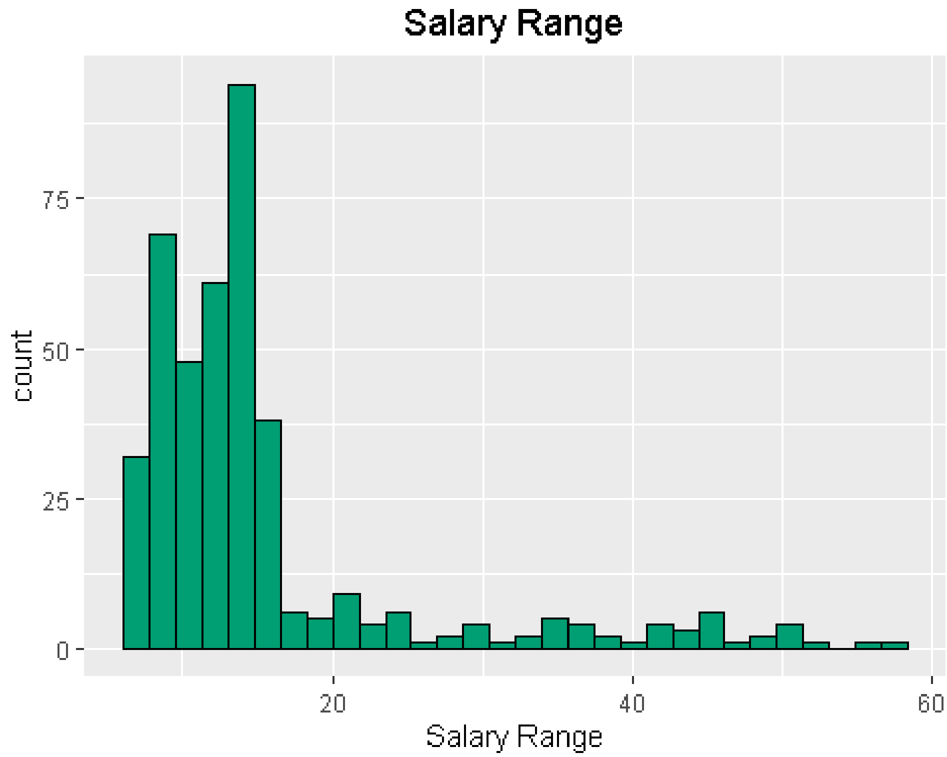
MBA - Though,we have lot of Engineer graduates as our Employees but we have only 27% of MBA Graduates in our company.

```
ggplot(cars,aes(x=Work.Exp))+geom_histogram(bins = 50,fill = "Blue",colour = "Black")+ggtitle("Work Experience")+theme(plot.title = element_text(hjust = 0.5))+xlab("Work Experience")
```

Work Experience - Employee Work Experience varies from 0 - 25years and on an average our employees have 5 years of work experience

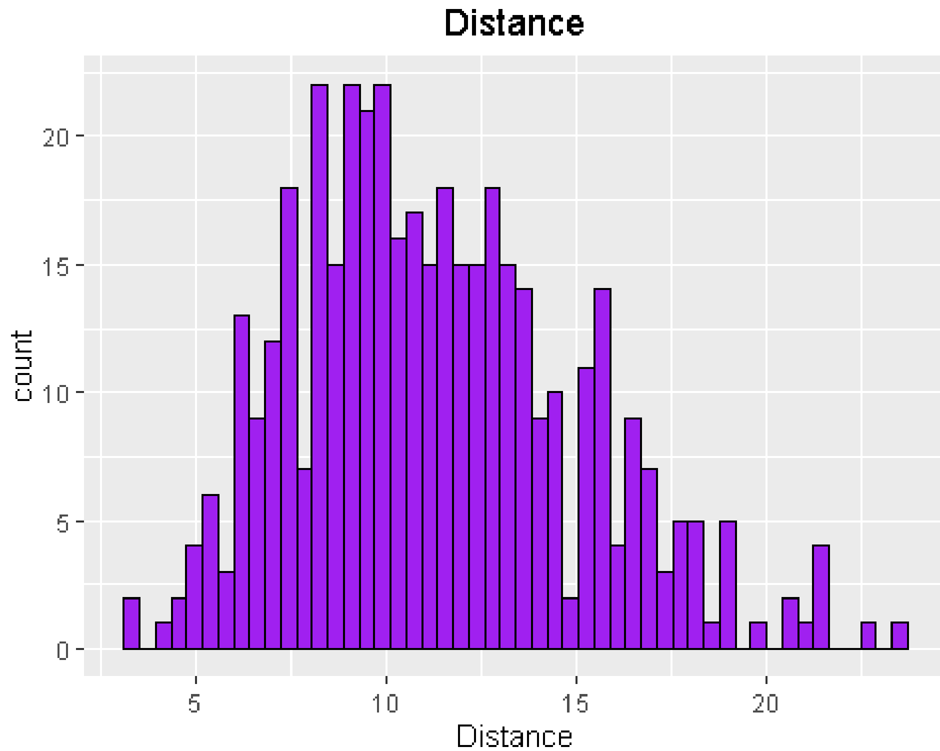
```
ggplot(cars,aes(x = Salary))+ geom_histogram(fill = "#009E73",colour = "Black")+ ggtitle("Salary Range") + theme(plot.title = element_text(hjust = 0.5))+xlab("Salary Range")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



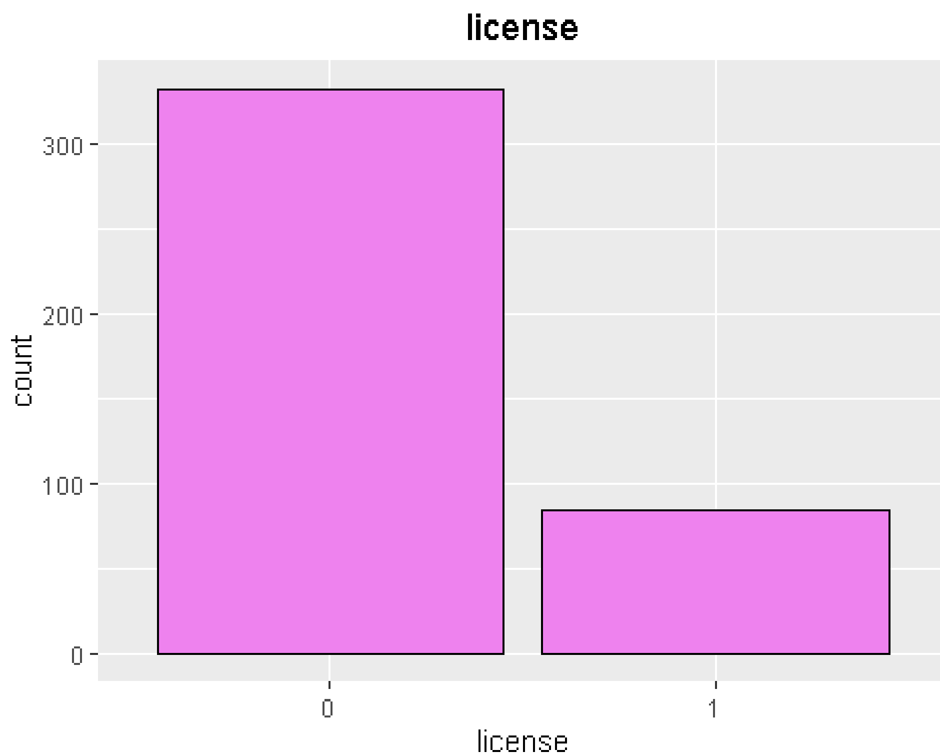
Salary - Employee Salary ranges from 6.50 to 57 and on an Average our Employee get's a salary of 15.42.

```
ggplot(cars,aes(x=Distance))+geom_histogram(bins = 50,fill = "purple",colour = "Black")+ggtitle("Distance")+theme(plot.title = element_text(hjust = 0.5))+xlab("Distance")
```



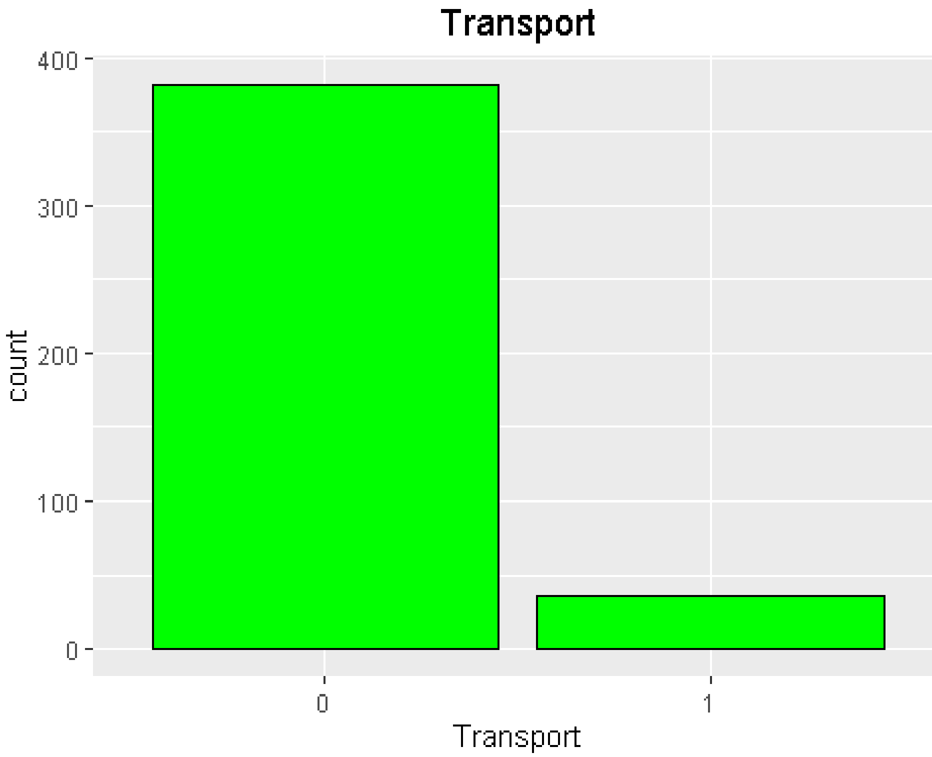
Distance - Employee commute Distance ranges from 3.2 to 23.4 kilometers and on an average our Employee commutes a distance of 11.3 kilometers

```
ggplot(cars,aes(x=license))+geom_bar(fill = "violet",colour = "Black")+ggtitle("license")+theme
(plot.title = element_text(hjust = 0.5))+xlab("license")
```



License - Only 20% of our Employee has License, which is quite surprising.

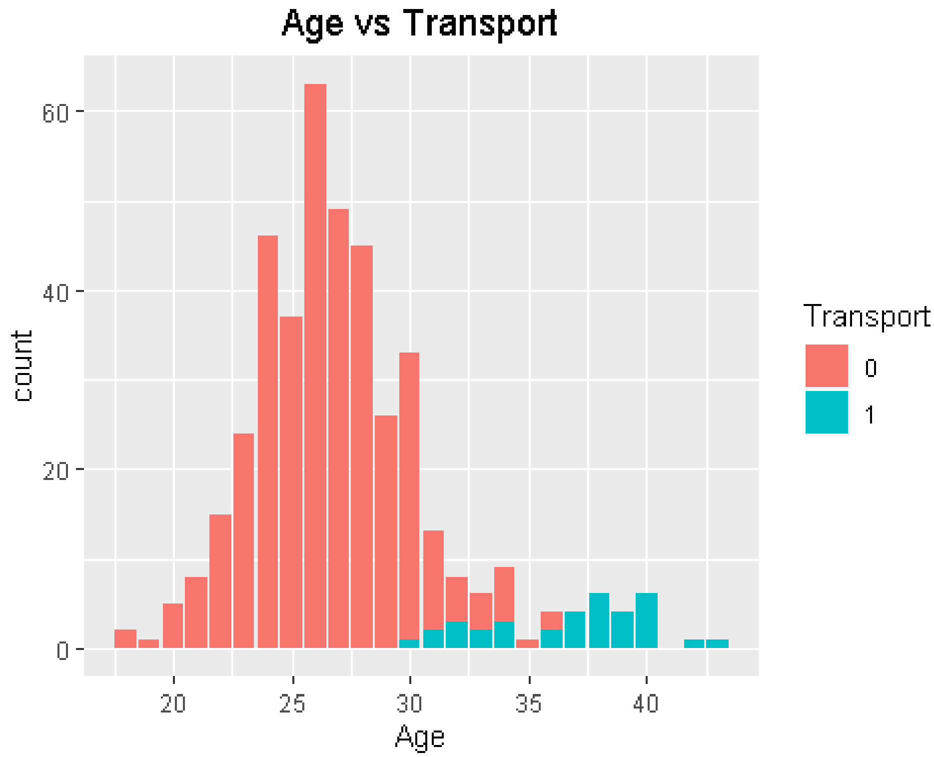
```
ggplot(cars,aes(x=Transport))+geom_bar(fill = "green",colour = "Black")+ggtitle("Transport")+t
heme(plot.title = element_text(hjust = 0.5))+xlab("Transport")
```



Transport - We have 19 % of Employees who commute via thier own two wheelers and 8 % of employees via own car and 71 % of employees via Public Transport

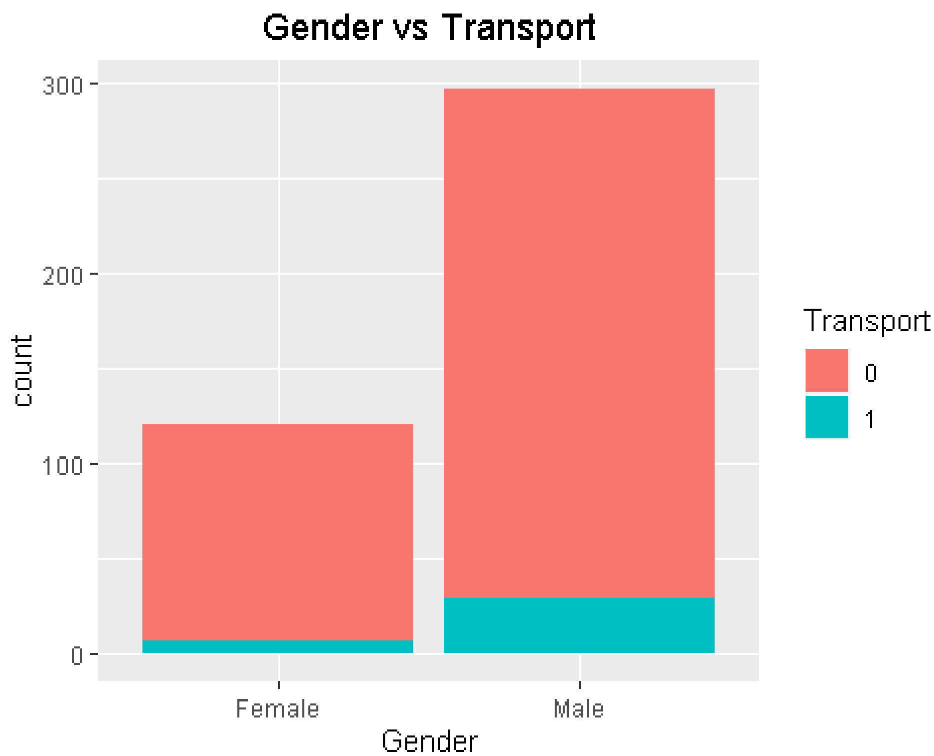
Bi Variable analysis

```
ggplot(cars,aes(Age,fill = Transport))+geom_bar()+ggtitle("Age vs Transport")+ theme(plot.title = element_text(hjust = 0.5))+ xlab("Age")
```



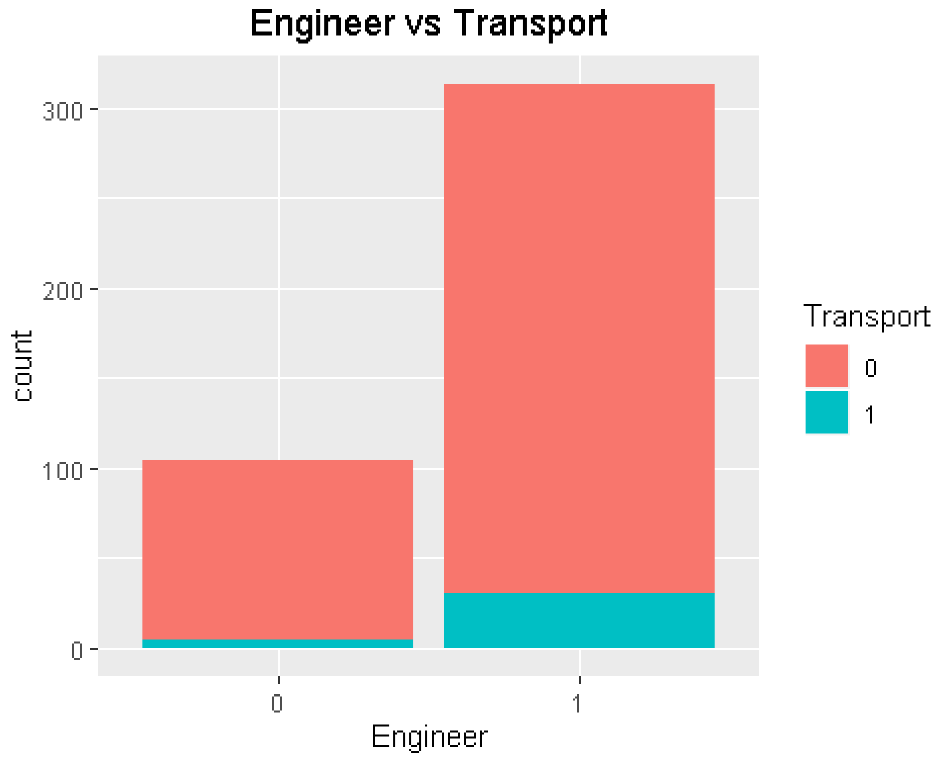
From the plot, it’s evident that employee whose age above 30 are the ones who use car as a mode of transport and most employees are using public transport only.

```
ggplot(cars,aes(Gender,fill = Transport))+geom_bar()+ggtitle("Gender vs Transport")+ theme(
plot.title = element_text(hjust = 0.5))+ xlab("Gender")
```



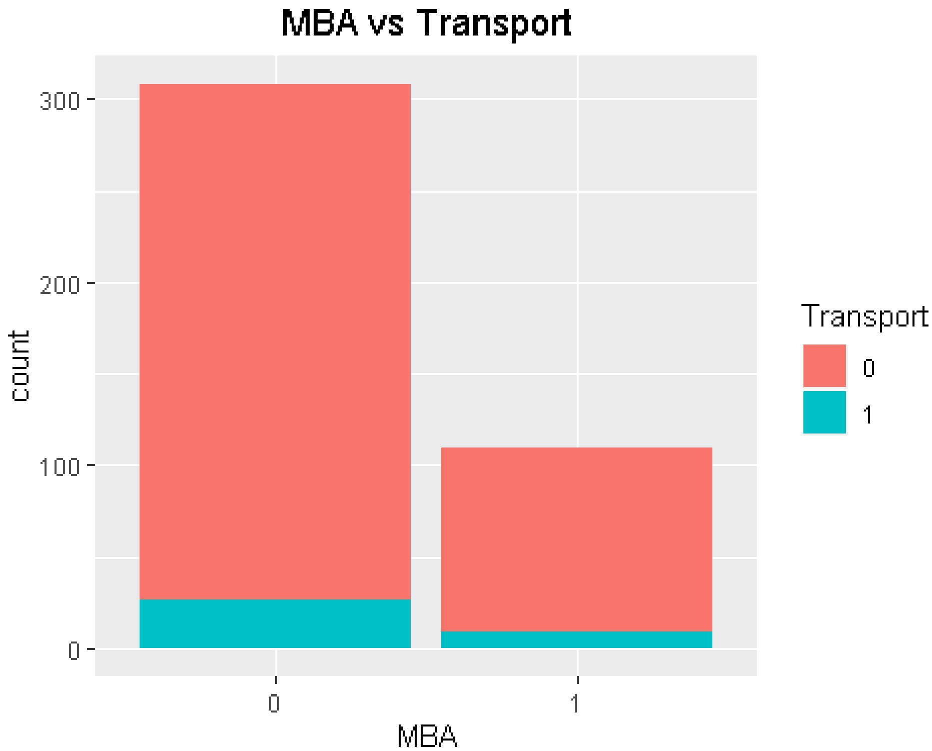
Out of 297 Male employees only 29 Male employees are driving Car and out of 120 Female employees only 6 Females are commuting via car to the office.

```
ggplot(cars,aes(Engineer,fill = Transport))+geom_bar()+ggtitle("Engineer vs Transport")+ the
me(plot.title = element_text(hjust = 0.5))+ xlab("Engineer")
```



Out of 313 Engineer graduates, only 30 graduates are commuting to the office via car and only 5 out of 104 non engineers own a car

```
ggplot(cars,aes(MBA,fill = Transport))+geom_bar()+ggtitle("MBA vs Transport")+ theme(plot.title = element_text(hjust = 0.5))+ xlab("MBA")
```

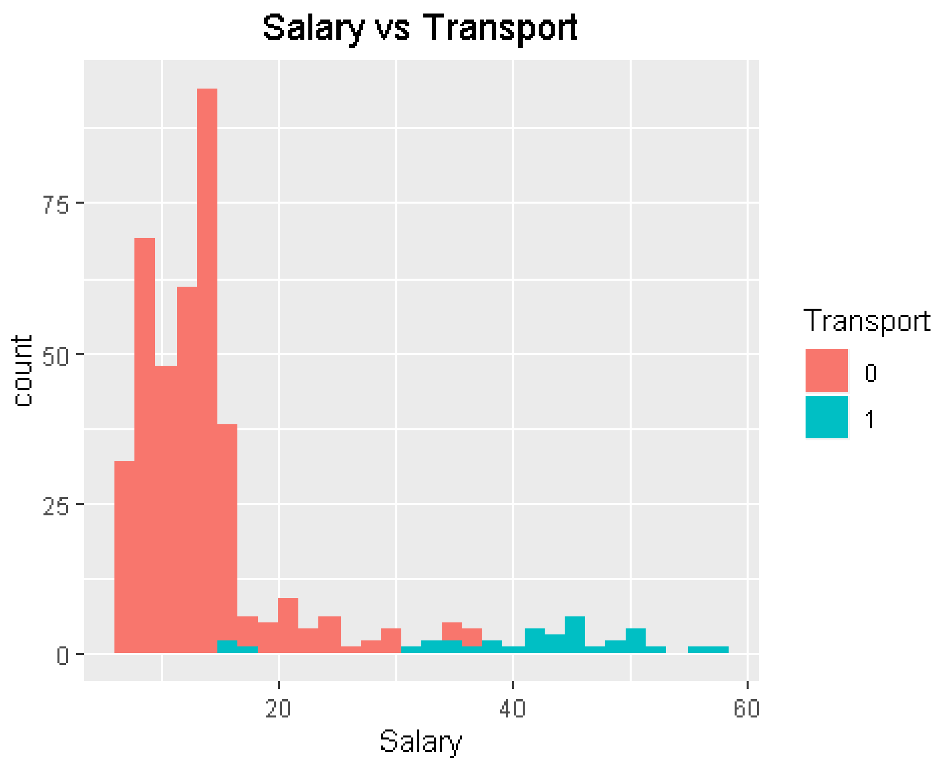


Out of 109 MBA graduates, only 9 graduates are commuting to the office via car and 26 out of 308 no- MBA graduates own a car

```
ggplot(cars,aes(Work.Exp,fill = Transport))+geom_histogram(bins = 30)+ggtitle("Work Exp vs Transport")+ theme(plot.title = element_text(hjust = 0.5))+ xlab("Work Exp")
```

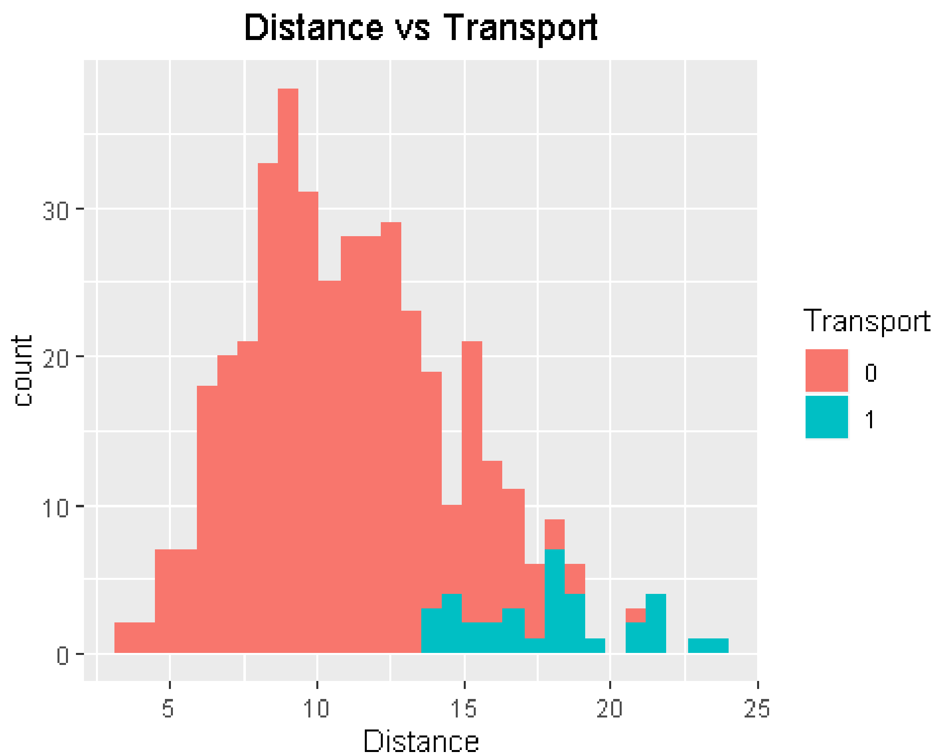
As expected, Higher the work experience higher the chance of commuting to the office via car.

```
ggplot(cars,aes(Salary,fill = Transport))+geom_histogram(bins = 30)+ggtitle("Salary vs Trans
port")+ theme(plot.title = element_text(hjust = 0.5))+ xlab("Salary")
```



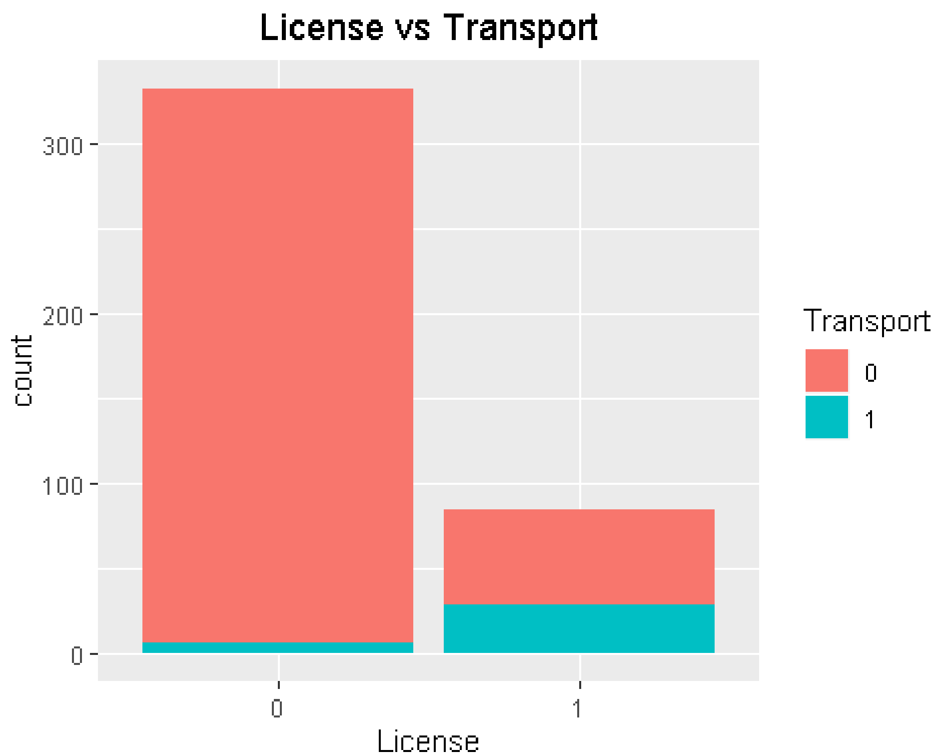
As expected, Higher the Salary higher the chance of commuting to the office via car.

```
ggplot(cars,aes(Distance,fill = Transport))+geom_histogram(bins = 30)+ggtitle("Distance vs T
ransport")+ theme(plot.title = element_text(hjust = 0.5))+ xlab("Distance")
```



Higher the distance, more the possibility of commuting to the office via car.

```
ggplot(cars,aes(license,fill = Transport))+geom_bar()+ggtitle("License vs Transport")+ theme(
plot.title = element_text(hjust = 0.5))+ xlab("License")
```

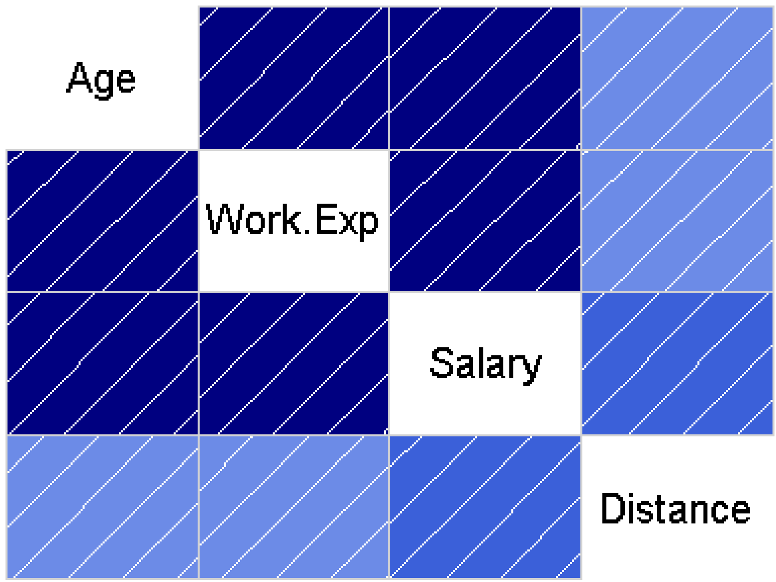


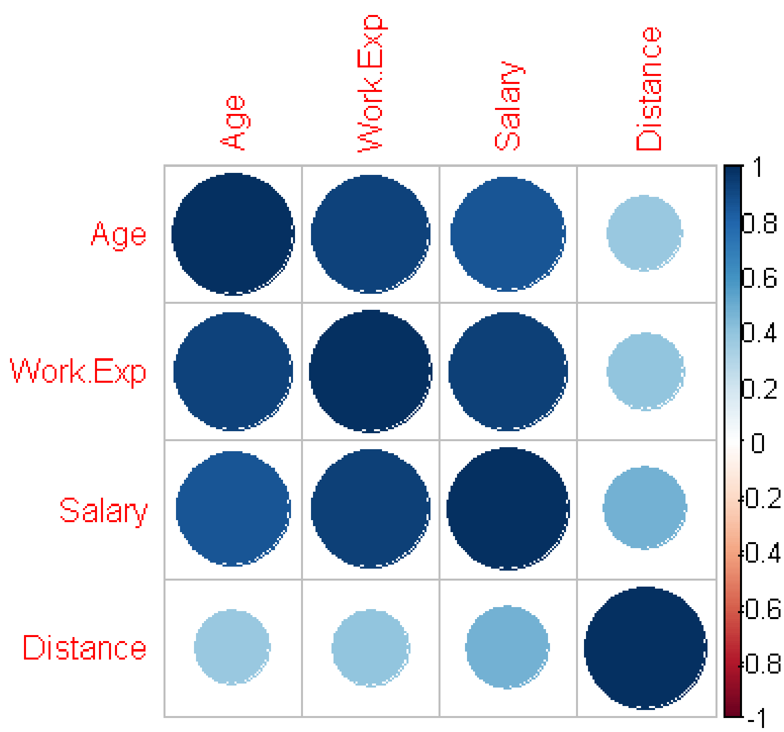
As expected, Most of the non licensed people use Public Transport as the way of commute to thier offices and 29 out of 85 licensed employee uses car as a mode of transport.

Multi-Collinearity

Let’s checkout the existence of Multi-collinearity between the Independent variables

```
library(corrgram)

## Registered S3 method overwritten by 'seriation':
##   method         from
##   reorder.hclust gclus

library(corrplot)

## corrplot 0.84 loaded

library(car)

## Loading required package: carData

corrplot::corrplot(corrgram(cars[,-c(2,3,4,8,9)]))
```






```
cor(cars[,-c(2,3,4,8,9)])

##              Age  Work.Exp    Salary  Distance
## Age      1.0000000 0.9244489 0.8579114 0.3754669
```

```
## Work.Exp 0.9244489 1.0000000 0.9318574 0.3945957
## Salary   0.8579114 0.9318574 1.0000000 0.4783049
## Distance 0.3754669 0.3945957 0.4783049 1.0000000
```

It's Evident that Multicollinearity is exist in the dataset.Now, let's calculate the VIF value and decide how to treat Multi-Collinearity

```
model <- glm(Transport~.,cars,family = "binomial")
summary(model)

##
## Call:
## glm(formula = Transport ~ ., family = "binomial", data = cars)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.84326  -0.00930  -0.00202  -0.00020   2.21440
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -61.7598    34.3933  -1.796  0.07254 .
## Age           1.5130     1.1274   1.342  0.17958
## GenderMale   -2.2754     1.7055  -1.334  0.18215
## Engineer1     0.4954     1.8071   0.274  0.78398
## MBA1         -1.9522     1.7152  -1.138  0.25505
## Work.Exp     -0.6739     0.8970  -0.751  0.45247
## Salary        0.2441     0.1827   1.336  0.18163
## Distance      0.9479     0.3487   2.718  0.00656 **
## license1      2.7683     2.0922   1.323  0.18577
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 240.42  on 416  degrees of freedom
## Residual deviance:  22.29  on 408  degrees of freedom
## AIC: 40.29
##
## Number of Fisher Scoring iterations: 11

vif(model)

##       Age    Gender  Engineer       MBA  Work.Exp    Salary  Distance
## 21.262525  2.345914  1.144534  2.458458 28.209208  9.719722  3.091251
##   license
##  3.671921
```

As a rule of thumb, a VIF value that exceeds 5 or 10 indicates a problematic amount of collinearity.

As hinted in the Correlation Matrix plot, we can clearly see that Work Experience and salary has high Vif Let’s remove the Age, Work Experience and check the VIF for other predictors

```
cars1 <- cars[,-c(1,5)]
model1 <- glm(Transport~.,cars1,family = "binomial")
vif(model1)

##   Gender Engineer      MBA   Salary Distance  license
## 1.352185 1.057026 1.140748 1.556626 1.474680 1.455595
```

The Vif of all the other variables are around 1,i.e. they are less correlated with each other.

Key-Insights From EDA

Uni-Variate Analysis:

- Age - Most of our Employee are younger as thier average age is around 27.
- Gender - Our Employee base has lot of Males (71%) than Females (29%)
- Engineer - Around 75% of our Employee are engineer graduates and only 25% Employee are non- engineers
- MBA - Though, we have lot of Engineer graduates as our Employees, but we have only 27% of MBA Graduates in our company.
- Distance - Employee commute Distance ranges from 3.2 to 23.4 kilometers and on an average our Employee commutes a distance of 11.3 kilometers
- License - Only 20% of our Employee has License, which is quite surprising.
- Transport - We have 19 % of Employees who commute via thier own two wheelers and 8 % of employees via own car and 71 % of employees via Public Transport

Bi-Variate Analysis:

- Employee whose age above 30 are the ones who use car as a mode of transport and most employees are using public transport only.
- Out of 297 Male employees only 29 Male employees are driving Car and out of 120 Female employees only 6 Females are commuting via car to the office.
- Out of 313 Engineer graduates, only 30 graduates are commuting to the office via car and only 5 out of 104 non engineers own a car
- Out of 109 MBA graduates, only 9 graduates are commuting to the office via car and 26 out of 308 non - MBA graduates own a car
- As expected, Higher the work experience higher the chance of commuting to the office via car.

- As expected, Higher the Salary higher the chance of commuting to the office via car. Higher the distance, more the possibility of commuting to the office via car.
- As expected, Most of the non licensed people use Public Transport as the way of commute to thier offices and 29 out of 85 licensed employee uses car as a mode of transport.

Multi-collinearity:

Then, we figured out that the Work Experience,Salary are highly correlated with the other variables and causing Misintepretation.So we removed them from our Data.

Data Preparation

Before building a model, let's check the imbalance of our Dataset.

```
prop.table(table(cars1$Transport))

##
##          0          1
## 0.91606715 0.08393285
```

From the above output, it's pretty evident that we have high unbalanced classifiers and we need to treat the imbalance by SMOTE Method.

SMOTE (Synthetic Minority Oversampling TEchnique)

```
library("DMwR")

## Warning: package 'DMwR' was built under R version 3.6.2

## Loading required package: lattice

##
## Attaching package: 'lattice'

## The following object is masked from 'package:corrgram':
##
##     panel.fill

## Loading required package: grid

## Registered S3 method overwritten by 'xts':
##   method     from
##   as.zoo.xts zoo

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo

smoted_data <- SMOTE(Transport~.,cars1, perc.over=100, perc.under=600, k=5)
prop.table(table(smoted_data$Transport))
```

```
##
##    0    1
## 0.75 0.25
```

After we did SMOTE we have increased our minority class level from 8% to 25%. By doing so we have made the data with more balanced classifiers.

Model Building

Now,Let's Build the Model with the Smoted data and check how it performs on the training and testing dataset.

```
library(caTools)# Used for Spliting the Data
set.seed(1234)
split <- sample.split(smoted_data$Transport, SplitRatio = 0.7)
train <- subset(smoted_data,split== TRUE)
test <- subset(smoted_data,split == FALSE)
LogTrainModel <- glm(Transport~Gender+Engineer+MBA+Distance+license,train,family = "bino
mial")
summary(LogTrainModel)
```

```
##
## Call:
## glm(formula = Transport ~ Gender + Engineer + MBA + Distance +
##     license, family = "binomial", data = train)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.28911  -0.02598  -0.00209   0.00014   2.28347
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -31.0795     7.9823  -3.894 9.88e-05 ***
## GenderMale   -1.1724     0.9554  -1.227 0.219762
## Engineer1     6.9460     2.3072   3.011 0.002608 **
## MBA1         -1.9202     1.1312  -1.697 0.089613 .
## Distance      1.4797     0.3888   3.806 0.000141 ***
## license1      6.5546     1.7793   3.684 0.000230 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 220.435  on 195  degrees of freedom
## Residual deviance:  41.818  on 190  degrees of freedom
## AIC: 53.818
##
## Number of Fisher Scoring iterations: 9
```

```
vif(LogTrainModel)
```

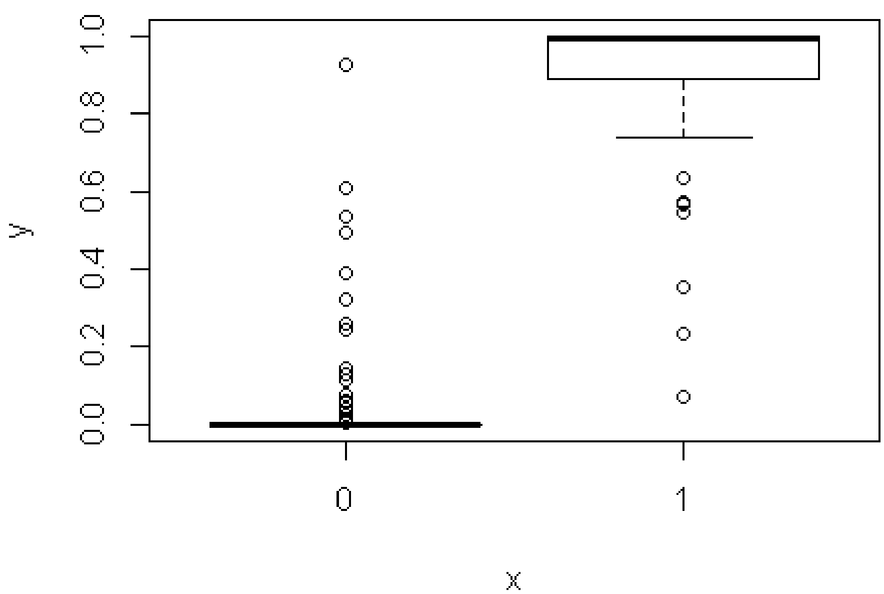
```
##   Gender Engineer      MBA Distance  license
## 1.366866 2.571031 1.496295 3.073153 4.183224
```

Now, Let’s see how our model performs on both Training and Test Dataset Logistic regression does not return directly the class of observations.

It allows us to estimate the probability (p) of class membership. The probability will range between 0 and 1.

We need to decide the threshold probability at which the category flips from one to the other.

```
Log_Prediction_Train <- predict(LogTrainModel,data = "train",type = "response")

plot(train$Transport,Log_Prediction_Train)
```



From the above Plot, we can clearly see that most employers who use Public Transport and 2-wheeler as a mode of transport lies within 0-0.4.

So, let’s take the threshold of 0.4. The Probabilty predicted by our Model above 0.4 will be taken as 1 (Employees who use car as a mode of transport)

Model Perfomance on Training Data

```
Log_model.predicted <- ifelse(Log_Prediction_Train<0.4,0,1)
Logmodel <- table(train$Transport,Log_model.predicted)
print(Logmodel)
```

```
##    Log_model.predicted
##       0   1
##   0 141   6
##   1   4  45
```

Confusion Matrix

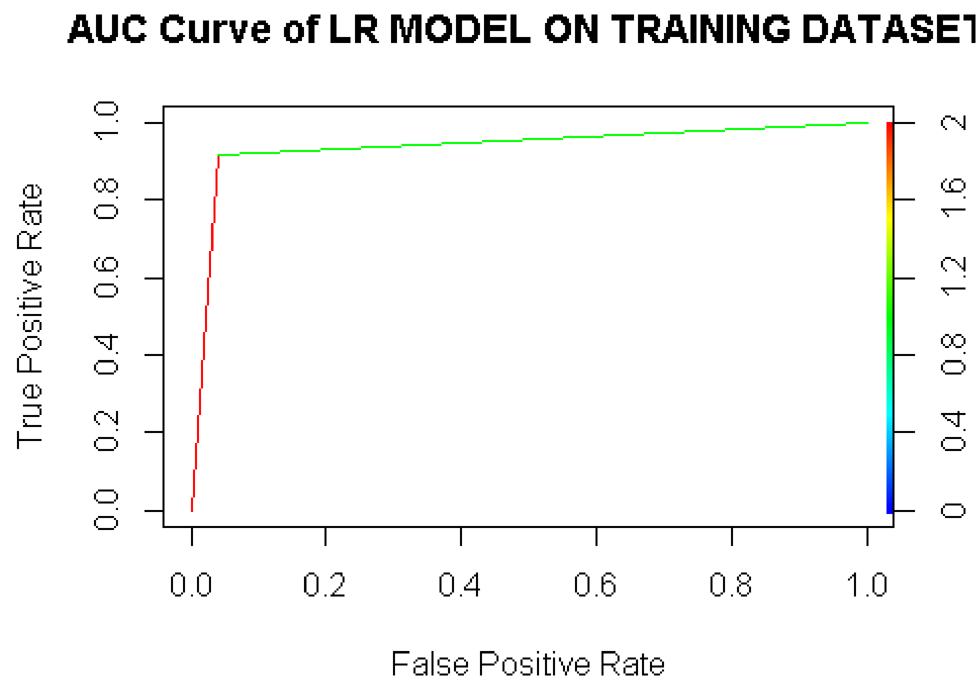
```
#Accuracy
accuracy <- round(sum(diag(Logmodel))/sum(Logmodel),2)
print(accuracy)

## [1] 0.95

# Sensitivity
sensitivity <- round(44/(44+9),2)
print(sensitivity)

## [1] 0.83

# 0.83
# Specificity
specificity <-round(138/(138 + 5),2)
print(specificity)

## [1] 0.97

#0.97
```

Based on Confusion Matrix, with 95% accuracy on the Training Dataset, Our model has done well in predicting both the 0 (0.97) (Employees who use Public Transport and 2-wheeler) and 1 (83%) (Employees who use car as a mode of transport).

Now, Let's Check Our Model with other Model Perfomance measures like AUC, Gini, KS

AUC & Gini

```
library(ROCR)

## Loading required package: gplots

##
## Attaching package: 'gplots'

## The following object is masked from 'package:stats':
##
##     lowess

ROCRpred <- prediction(Log_model.predicted, train$Transport)
ROCRperf <- performance(ROCRpred, 'tpr','fpr')
plot(ROCRperf,colorize = TRUE, text.adj = c(-0.2,1.7),main="AUC Curve of LR MODEL ON TR
AINING DATASET",xlab="False Positive Rate",ylab="True Positive Rate")
```




```
auc = performance(ROCRpred,"auc");
auc = as.numeric(auc@y.values)
print(auc)

## [1] 0.9387755

library(ineq)
gini = ineq(Log_model.predicted, type="Gini")
print(gini)

## [1] 0.7397959
```

Thumb Rule - Larger the auc and gini coefficient better the model is.

We have a auc of 92% and gini coefficient of 72% which conveys the message that our model has done a Ok Job in training datset.

KS

KS Statistic or Kolmogorov-Smirnov statistic is the maximum difference between the cumulative true positive and cumulative false positive rate.

It is often used as the deciding metric to judge the efficacy of models in credit scoring. The higher the ks_stat, the more efficient is the model at capturing the Ones.

This should not be confused with the ks.test function.

```
KS = max(ROCRperf@y.values[[1]]-ROCRperf@x.values[[1]]) # The Maximum the Better
print(KS)

## [1] 0.877551
```

Here,In Training Dataset our Logistic Model done a good job (0.83) in Predicting the Employees who use car as a mode of transport.

Model Performance on Test Data

Confusion Matrix

```
Log_Prediction_Test <- predict(LogTrainModel,test,type = "response")
Log_model.predicted1 <- ifelse(Log_Prediction_Test <0.4,0,1)
Logmodel1 <- table(test$Transport,Log_model.predicted1)
print(Logmodel1)

##    Log_model.predicted1
##      0  1
##   0 61  2
##   1  1 20

# Accuracy
Test_accuracy <- round(sum(diag(Logmodel1))/sum(Logmodel1),2)
print(Test_accuracy)

## [1] 0.96

# Sensitivity
sensitivity <- round(20/(20+4),2)
print(sensitivity)

## [1] 0.83

# Specificity
specificity <-round(59/(59 + 1),2)
print(specificity)

## [1] 0.98
```

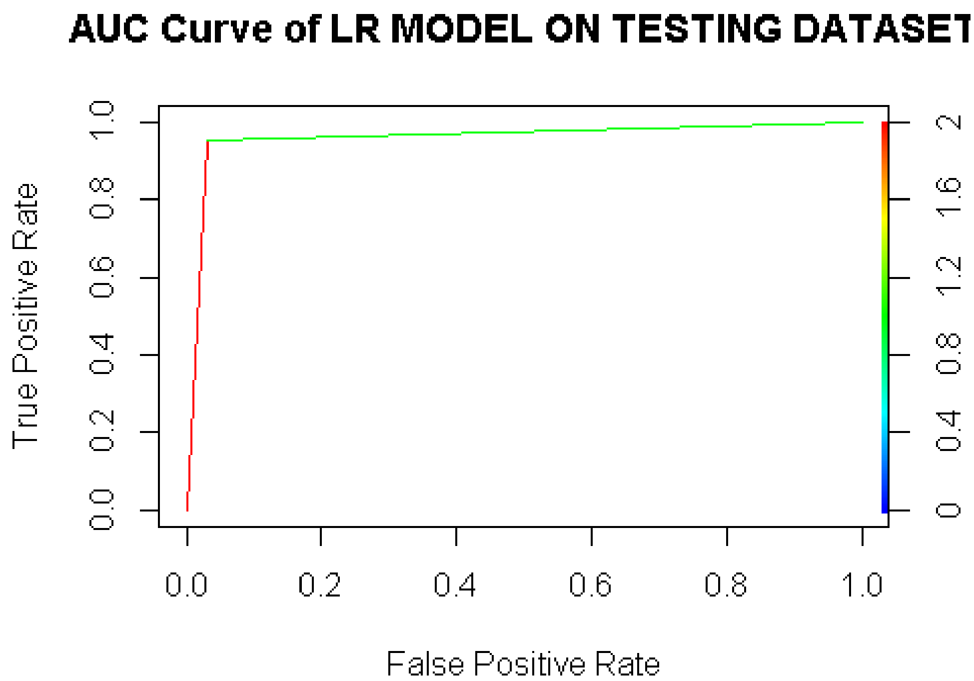
Confusion Matrix Inference on Test Dataset:

Based on Confusion Matrix, with 96% accuracy on the Training Dataset, our model has done well in predicting both the 0 (98%) (Employees who use Public Transport and 2-wheeler) and 1 (83%) (Employees who use car as a mode of transport).

Now Let’s Check Our Logistic Model with other Model Perfomance measures like AUC, Gini,KS

AUC & GINI

```
TestROCRpred <- prediction(Log_model.predicted1, test$Transport)
TestROCRperf <- performance(TestROCRpred, 'tpr','fpr')
plot(TestROCRperf,colorize = TRUE, text.adj = c(-0.2,1.7),main="AUC Curve of LR MODEL O
N TESTING DATASET",xlab="False Positive Rate",ylab="True Positive Rate")
```




```
Testauc = performance(TestROCRpred,"auc");
Testauc = as.numeric(Testauc@y.values)
print(Testauc)

## [1] 0.9603175

# Gini on Test dataset
Testgini = ineq(Log_model.predicted1, type="Gini")
print(Testgini)

## [1] 0.7380952
```

Thumb Rule - Larger the auc and gini coefficient better the model is.

We have an auc of 96% and gini coefficient of 73% which conveys the message that our model has done a good Job in the test datset.

KS

The higher the ks_stat, the more efficient is the model at capturing the Ones.

```
TestKS = max(TestROCRperf@y.values[[1]]-TestROCRperf@x.values[[1]]) # The Maximum the Better
print(TestKS)

## [1] 0.9206349
```

Here, In Test Dataset our Logistic Model done Poorly (0.92) in Predicting the employees who will use car as a mode of transport.

Our Model Has almost performed the Sameway in both the train and Test dataset.

Now, Let's Build a KNN Model and Measure it's Performance

KNN

```
library(class)
knntrain <- train
knntest <- test
knntrain$Gender <- as.numeric(knntrain$Gender)
knntrain$Engineer <- as.numeric(knntrain$Engineer)
knntrain$MBA <- as.numeric(knntrain$MBA)
knntrain$license <- as.numeric(knntrain$license)
knntrain$Transport <- as.numeric(knntrain$Transport)
str(knntrain)

## 'data.frame':    196 obs. of  7 variables:
##  $ Gender   : num  1 1 2 2 1 2 1 2 2 2 ...
##  $ Engineer : num  2 2 2 2 1 2 2 2 2 2 ...
##  $ MBA      : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ Salary   : num  11.5 21.7 14.8 12.7 6.8 22.7 9.6 9.9 13.9 12.9 ...
##  $ Distance : num  5.2 7.3 14.3 8.7 12.2 11.3 8.1 17.2 9.5 13.3 ...
##  $ license  : num  1 1 1 1 1 2 1 1 1 1 ...
##  $ Transport: num  1 1 1 1 1 1 1 1 1 1 ...

knntest$Gender <- as.numeric(knntest$Gender)
knntest$Engineer <- as.numeric(knntest$Engineer)
knntest$MBA <- as.numeric(knntest$MBA)
knntest$license <- as.numeric(knntest$license)
knntest$Transport <- as.numeric(knntest$Transport)
str(knntest)

## 'data.frame':    84 obs. of  7 variables:
##  $ Gender   : num  1 2 2 2 1 2 1 2 1 1 ...
##  $ Engineer : num  2 2 1 1 2 2 1 2 2 2 ...
##  $ MBA      : num  1 1 1 1 1 2 2 2 1 1 ...
##  $ Salary   : num  14.6 8.6 6.9 8.7 12.8 11.7 8.5 13.5 14.7 12.8 ...
##  $ Distance : num  8.1 9.4 13.7 8.4 13.6 11.7 7.9 8.8 8.5 11.8 ...
```

```
##  $ license  : num  1 1 1 1 2 1 1 1 1 1 ...
##  $ Transport: num  1 1 1 1 1 1 1 1 1 1 ...
```

```
knntrain$Transport[knntrain$Transport == 1] <- 0
knntrain$Transport[knntrain$Transport == 2] <- 1
knntrain$Gender[knntrain$Gender == 1] <- 0
knntrain$Gender[knntrain$Gender == 2] <- 1
knntrain$Engineer[knntrain$Engineer == 1] <- 0
knntrain$Engineer[knntrain$Engineer == 2] <- 1
knntrain$MBA[knntrain$MBA == 1] <- 0
knntrain$MBA[knntrain$MBA == 2] <- 1
knntrain$Salary[knntrain$Salary == 1] <- 0
knntrain$Salary[knntrain$Salary == 2] <- 1
knntrain$Distance[knntrain$Distance == 1] <- 0
knntrain$Distance[knntrain$Distance == 2] <- 1
knntrain$license[knntrain$license == 1] <- 0
knntrain$license[knntrain$license == 2] <- 1

knntest$Transport[knntest$Transport == 1] <- 0
knntest$Transport[knntest$Transport == 2] <- 1
knntest$Gender[knntest$Gender == 1] <- 0
knntest$Gender[knntest$Gender == 2] <- 1
knntest$Engineer[knntest$Engineer == 1] <- 0
knntest$Engineer[knntest$Engineer == 2] <- 1
knntest$MBA[knntest$MBA == 1] <- 0
knntest$MBA[knntest$MBA == 2] <- 1
knntest$Salary[knntest$Salary == 1] <- 0
knntest$Salary[knntest$Salary == 2] <- 1
knntest$Distance[knntest$Distance == 1] <- 0
knntest$Distance[knntest$Distance == 2] <- 1
knntest$license[knntest$license == 1] <- 0
knntest$license[knntest$license == 2] <- 1

knnmodel <- knn(scale(knntrain),scale(knntest),knntrain$Transport,k=17)
summary(knnmodel)
```

```
##  0  1
## 63 21
```

Interpretation:

After Trail and Error Method @ k = 17 the Model performs well in predicting Both 0 (Customer who wil-l not cancel) and 1 (Customer who will cancel) when compared to Logistic Regression model.

Our Model Predicted 64 ‘0’ and 20 ‘1’. Now, Let’s Check how well it have performed by using Confusion Matrix

Confusion Matrix

```
knntable <- table(test$Transport,knnmodel)
print(knntable)
```

```
##    knnmodel
##      0  1
##   0 62  1
##   1  1 20
```

```r
# Accuracy
knnaccuracy <- round(sum(diag(knntable))/sum(knntable),2)
print(knnaccuracy)
```

```
## [1] 0.98
```

```r
# Sensitivity
sensitivity <- round(20/(20+0),2)
print(sensitivity)
```

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

```r
# Specificity
specificity <-round(63/(63 + 1),2)
print(specificity)
```

```
## [1] 0.98
```

With 98% accuracy our KNN-Model has Done well in predicting both the 0 (98%) (employees who use 2wheeler and car as a mode of transport to the office) and 1 (100%) (Employees who are using car as a mode of transport).

Let's Look, How Naive Bayes Model works on this Dataset.

Naive Bayes

1. The Naive Bayes is a classification algorithm that is suitable for binary and multiclass classification.
2. Generally, Naïve Bayes performs well in cases of categorical input variables compared to numerical variables.
3. So therefore, we can use Naive Bayes Algorithm for this use case. Let's Build the model and see its performance on the Train and Test data.

```r
library(e1071)
NBModel <- naiveBayes(Transport~Gender+Engineer+MBA+Distance+license,data = train)
print(NBModel)
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##     0    1
```

```
## 0.75 0.25
##
## Conditional probabilities:
##    Gender
## Y      Female      Male
##   0 0.3401361 0.6598639
##   1 0.2448980 0.7551020
##
##    Engineer
## Y          0         1
##   0 0.2653061 0.7346939
##   1 0.1020408 0.8979592
##
##    MBA
## Y          0         1
##   0 0.8231293 0.1768707
##   1 0.7346939 0.2653061
##
##    Distance
## Y       [,1]     [,2]
##   0 10.61088 3.550982
##   1 17.63776 2.266136
##
##    license
## Y          0         1
##   0 0.8775510 0.1224490
##   1 0.1836735 0.8163265
```

```
NBPredictTrain <- predict(NBModel,newdata = train)
```

The model creates the conditional probability for each feature separately. We also have the a-priori probabilities which indicates the distribution of our data.

Let’s see how the model performs on the Training data.

Confusion Matrix on Train Dataset

```
NBTrainTable <- table(train$Transport,NBPredictTrain)
print(NBTrainTable)
```

```
##    NBPredictTrain
##       0   1
##   0 138   9
##   1   8  41
```

```
# Accuracy
NBTrainaccuracy <- round(sum(diag(NBTrainTable))/sum(NBTrainTable),2)
print(NBTrainaccuracy)
```

```
## [1] 0.91
```

```r
# Sensitivity
NBTrainsensitivity <- round(42/(42+4),2)
print(NBTrainsensitivity)

## [1] 0.91

# Specificity
NBTrainspecificity <-round(143/(143 + 7),2)
print(NBTrainspecificity)

## [1] 0.95
```

Based on Confusion Matrix, with 91% accuracy on the Training Dataset Our Naive Bayes Model Done well in predicting both the 0 (95%) and 1 (91%)

Let's Look, how the Naive Bayes Model performs on the Test Data set

```r
NBTestPredict <- predict(NBModel,newdata = test)
```

Confusion Matrix on Test Dataset

```r
NBTestTable <- table(test$Transport,NBTestPredict)
print(NBTestTable)

##    NBTestPredict
##      0  1
##   0 61  2
##   1  1 20

# Accuracy
NBTestaccuracy <- round(sum(diag(NBTestTable))/sum(NBTestTable),2)
print(NBTestaccuracy)

## [1] 0.96

# Sensitivity
NBTestsensitivity <- round(20/(20+1),2)
print(NBTestsensitivity)

## [1] 0.95

# Specificity
NBTestspecificity <-round(62/(62 + 1),2)
print(NBTestspecificity)

## [1] 0.98
```

Based on Confusion Matrix, with 96% accuracy on the Test Dataset Our Naive Bayes Model Done well in predicting both the 0 (98%) and 1 (95%)

LOGISTIC REGRESSION vs NAÏVE BAYES vs KNN

PERFORMANCE MEASURES		Model Evaluation				
		Logistic Regression		Naïve Bayes		KNN
		TRAIN	TEST	TRAIN	TEST	TEST
CONFUSION MATRIX	Accuracy	95	96	91	96	98
	Sensitivity (1)	83	83	91	95	100
	Specificity (0)	97	98	95	98	98
AUC		94	96	-	-	-
KS		87	92	-	-	-
GINI		73	73	-	-	-

- The above table clearly shows that the Logistic Model Ranks the Lowest when Compared to Naïve Bayes and KNN.
- Though Logistic Regression did a Great Job in predicting the employees who travel to office via public transport and two-wheeler. It did a Pretty ok Job in Predicting the employees who travel to office via Car.
- On the Other Hand, Naïve Bayes was performed Good in predicting both 0 (employees who travel to office via public transport and two-wheeler) and 1 (Employees who travel to office via Car)
- In the End, the one model which performed exceedingly well in predicting both 0 (employees who travel to office via public transport and two-wheeler) and 1 (Employees who travel to office via Car) is **KNN**
- Let's check out how bagging and boosting models perform in this dataset

Bagging

Bagging is a way to decrease the variance in the prediction by generating additional data for training from dataset using combinations with repetitions to produce multi-sets of the original data

```
library(gbm)        # basic implementation using AdaBoost

## Warning: package 'gbm' was built under R version 3.6.2

## Loaded gbm 2.1.5

library(xgboost)      # a faster implementation of a gbm

## Warning: package 'xgboost' was built under R version 3.6.2

library(caret)       # an aggregator package for performing many machine learning models
library(ipred)
library(rpart)

bagging = bagging(Transport~ Gender+Engineer+MBA+Distance+license,data=train,control=rpart.control(maxdepth = 5,minsplit =15 ))

Bagging_Prediction = predict(bagging,test)

Bagging_CM=table(test$Transport,Bagging_Prediction)
Bagging_CM

##    Bagging_Prediction
##      0  1
##   0 62  1
##   1  1 20
```

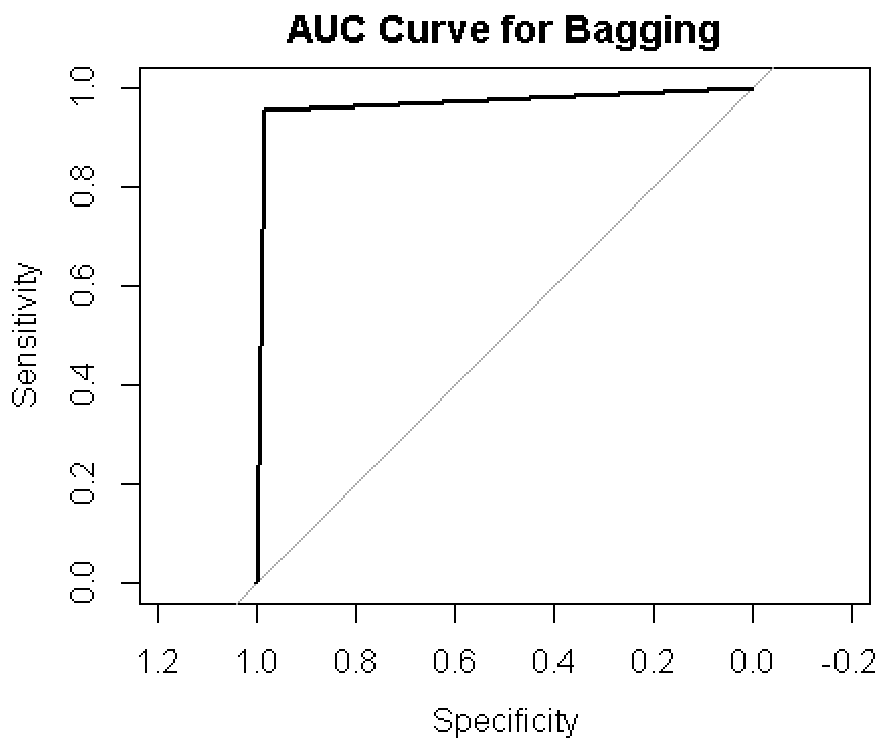
Model performance for bagging

```
#specificity
bag_Specificity = round(61/(61 + 2),2)
bag_Specificity

## [1] 0.97

#sensitivity

bag_Sensitiviity=round(19/(19 + 2),2)
bag_Sensitiviity

## [1] 0.9

#accuracy
bag_Accuracy=round(sum(diag(Bagging_CM))/sum(Bagging_CM),2)
bag_Accuracy
```

```
## [1] 0.98
```

Based on Confusion Matrix, with 98% accuracy on the Test Dataset Our Bagging Model has done well in predicting both the 0 (97%) and 1 (90%)

```
#ROC Curve
library(pROC)

## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var

test$Transport =as.numeric(test$Transport)
Bagging_Prediction=as.numeric(Bagging_Prediction)
roc(test$Transport,Bagging_Prediction)

## Setting levels: control = 1, case = 2

## Setting direction: controls < cases

##
## Call:
## roc.default(response = test$Transport, predictor = Bagging_Prediction)
##
## Data: Bagging_Prediction in 63 controls (test$Transport 1) < 21 cases (test$Transport 2).
## Area under the curve: 0.9683

plot.roc(test$Transport,Bagging_Prediction, main="AUC Curve for Bagging")

## Setting levels: control = 1, case = 2
## Setting direction: controls < cases
```



Boosting

Now let’s try some general boosting techniques.

```
str(train)

## 'data.frame':    196 obs. of  7 variables:
##  $ Gender   : Factor w/ 2 levels "Female","Male": 1 1 2 2 1 2 1 2 2 2 ...
##  $ Engineer : Factor w/ 2 levels "0","1": 2 2 2 2 1 2 2 2 2 2 ...
##  $ MBA      : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Salary   : num  11.5 21.7 14.8 12.7 6.8 22.7 9.6 9.9 13.9 12.9 ...
##  $ Distance : num  5.2 7.3 14.3 8.7 12.2 11.3 8.1 17.2 9.5 13.3 ...
##  $ license  : Factor w/ 2 levels "0","1": 1 1 1 1 1 2 1 1 1 1 ...
##  $ Transport: Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...

boosttrain <- train
boosttest <- test
boosttrain$Gender <- as.numeric(boosttrain$Gender)
boosttrain$Engineer <- as.numeric(boosttrain$Engineer)
boosttrain$MBA <- as.numeric(boosttrain$MBA)
boosttrain$license <- as.numeric(boosttrain$license)
boosttrain$Transport <- as.numeric(boosttrain$Transport)
str(boosttrain)

## 'data.frame':    196 obs. of  7 variables:
##  $ Gender   : num  1 1 2 2 1 2 1 2 2 2 ...
```

```
##  $ Engineer : num  2 2 2 2 1 2 2 2 2 2 ...
##  $ MBA      : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ Salary   : num  11.5 21.7 14.8 12.7 6.8 22.7 9.6 9.9 13.9 12.9 ...
##  $ Distance : num  5.2 7.3 14.3 8.7 12.2 11.3 8.1 17.2 9.5 13.3 ...
##  $ license  : num  1 1 1 1 1 2 1 1 1 1 ...
##  $ Transport: num  1 1 1 1 1 1 1 1 1 1 ...
```

```
boosttest$Gender <- as.numeric(boosttest$Gender)
boosttest$Engineer <- as.numeric(boosttest$Engineer)
boosttest$MBA <- as.numeric(boosttest$MBA)
boosttest$license <- as.numeric(boosttest$license)
boosttest$Transport <- as.numeric(boosttest$Transport)
str(boosttest)
```

```
## 'data.frame':    84 obs. of  7 variables:
##  $ Gender   : num  1 2 2 2 1 2 1 2 1 1 ...
##  $ Engineer : num  2 2 1 1 2 2 1 2 2 2 ...
##  $ MBA      : num  1 1 1 1 1 2 2 2 1 1 ...
##  $ Salary   : num  14.6 8.6 6.9 8.7 12.8 11.7 8.5 13.5 14.7 12.8 ...
##  $ Distance : num  8.1 9.4 13.7 8.4 13.6 11.7 7.9 8.8 8.5 11.8 ...
##  $ license  : num  1 1 1 1 2 1 1 1 1 1 ...
##  $ Transport: num  1 1 1 1 1 1 1 1 1 1 ...
```

```
boosttrain$Transport[boosttrain$Transport == 1] <- 0
boosttrain$Transport[boosttrain$Transport == 2] <- 1
boosttrain$Gender[boosttrain$Gender == 1] <- 0
boosttrain$Gender[boosttrain$Gender == 2] <- 1
boosttrain$Engineer[boosttrain$Engineer == 1] <- 0
boosttrain$Engineer[boosttrain$Engineer == 2] <- 1
boosttrain$MBA[boosttrain$MBA == 1] <- 0
boosttrain$MBA[boosttrain$MBA == 2] <- 1
boosttrain$Salary[boosttrain$Salary == 1] <- 0
boosttrain$Salary[boosttrain$Salary == 2] <- 1
boosttrain$Distance[boosttrain$Distance == 1] <- 0
boosttrain$Distance[boosttrain$Distance == 2] <- 1
boosttrain$license[boosttrain$license == 1] <- 0
boosttrain$license[boosttrain$license == 2] <- 1


boosttest$Transport[boosttest$Transport == 1] <- 0
boosttest$Transport[boosttest$Transport == 2] <- 1
boosttest$Gender[boosttest$Gender == 1] <- 0
boosttest$Gender[boosttest$Gender == 2] <- 1
boosttest$Engineer[boosttest$Engineer == 1] <- 0
boosttest$Engineer[boosttest$Engineer == 2] <- 1
boosttest$MBA[boosttest$MBA == 1] <- 0
boosttest$MBA[boosttest$MBA == 2] <- 1
boosttest$Salary[boosttest$Salary == 1] <- 0
boosttest$Salary[boosttest$Salary == 2] <- 1
boosttest$Distance[boosttest$Distance == 1] <- 0
boosttest$Distance[boosttest$Distance == 2] <- 1
boosttest$license[boosttest$license == 1] <- 0
```

```
boosttest$license[boosttest$license == 2] <- 1

boost_model=gbm(Transport ~ Gender+Engineer+MBA+Distance+license,distribution = "berno
ulli",data=boosttrain,n.trees = 100,interaction.depth =1,shrinkage = 0.001,cv.folds = 5,n.cores=N
ULL,verbose=FALSE)

boost_prediction <- predict(boost_model,boosttest,type="response")

## Using 100 trees...

boost_prediction <-ifelse(boost_prediction>0.27,"1","0")
print(boost_prediction)

##  [1] "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0"
## [18] "0" "0" "0" "0" "0" "0" "1" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0"
## [35] "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0"
## [52] "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "0" "1"
## [69] "1" "1" "1" "1" "1" "1" "1" "0" "0" "0" "1" "1" "1" "0" "1" "1"

boost_CM= table(boosttest$Transport,boost_prediction)
print(boost_CM)

##    boost_prediction
##      0  1
##   0 62  1
##   1  8 13
```

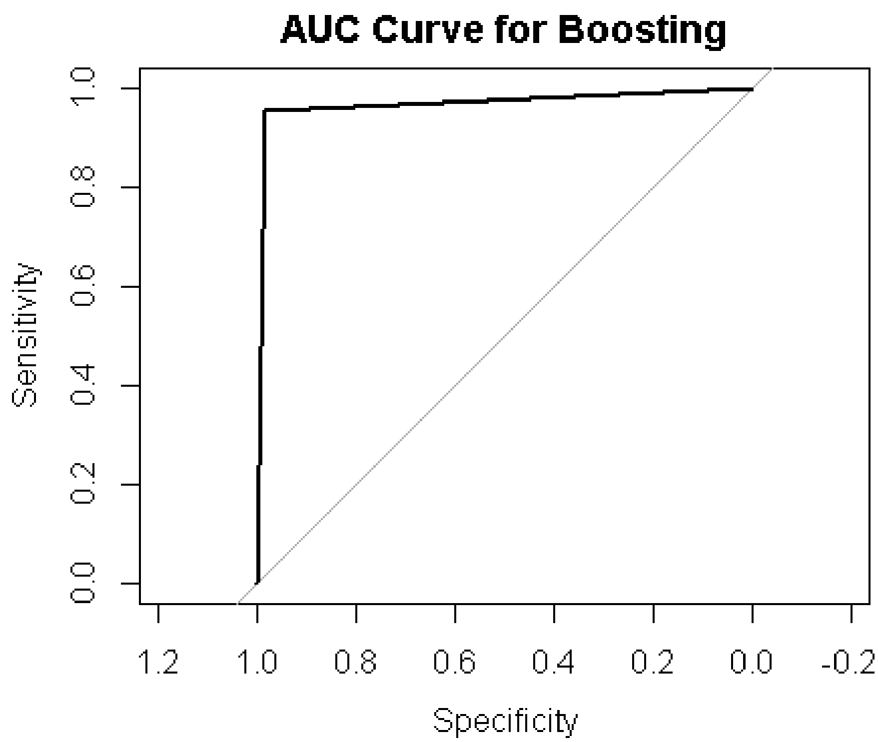
Confusion Matrix

```
#specificity
boost_Specificity = round(55/(55 + 3),2)
print(boost_Specificity)

## [1] 0.95

#sensitivity


bag_Sensitiviity=round(18/(18 + 8),2)
print(bag_Sensitiviity)

## [1] 0.69

#accuracy
boost_Accuracy=round(sum(diag(boost_CM))/sum(boost_CM),2)
print(boost_Accuracy)

## [1] 0.89
```

Based on Confusion Matrix, with 89% accuracy on the Test Dataset Our Boosting Model has done well in predicting the 0 (95%) than in predicting 1 (69%)

ROC Curve

```
boosttest$Transport <- as.numeric(boosttest$Transport)
boost_prediction <- as.numeric(boost_prediction)
roc(test$Transport,boost_prediction)

## Setting levels: control = 1, case = 2

## Setting direction: controls < cases

##
## Call:
## roc.default(response = test$Transport, predictor = boost_prediction)
##
## Data: boost_prediction in 63 controls (test$Transport 1) < 21 cases (test$Transport 2).
## Area under the curve: 0.8016

plot.roc(test$Transport,Bagging_Prediction, main="AUC Curve for Boosting")

## Setting levels: control = 1, case = 2
## Setting direction: controls < cases
```




```
library(fastAdaboost)

## Warning: package 'fastAdaboost' was built under R version 3.6.2

library(xgboost)

features_train = as.matrix(boosttrain[,-7])
```

```
label_train = as.matrix(boosttrain[,-c(1:6)])
features_test = as.matrix(boosttest[,-7])
tp_xbg=vector()
lr=c(0.001,0.01,0.1,0.3,0.5,0.7,1)
md=c(1,3,5,7,9,15)
nr=c(2,50,100,1000,1000)
for (i in lr) {
  xgb.fit=xgboost(
    data = features_train,
    label= label_train,
    eta = 0.001,
    max_depth = 5,
    nrounds = 10,
    nfold=5,
    objective = "binary:logistic",
    verbose = 0,
    early_stopping_rounds = 10
  )
  XGBpredTest=boosttest$xgb.pred = predict(xgb.fit, features_test)
  sum(boosttest$Transport==1&boosttest$xgb.pred>=0.5)
  tabXGB=table(boosttest$Transport, XGBpredTest>0.5)
}
xgboost_CM <- table(boosttest$Transport,boosttest$xgb.pred>=0.5)
```

XG Boost Confusion Matrix

```
#specificity
xgboost_Specificity = round(63/(63 + 3),2)
print(xgboost_Specificity)

## [1] 0.95

#sensitivity


xgboost_Sensitiviity=round(18/(18 + 0),2)
print(xgboost_Sensitiviity)

## [1] 1

#accuracy
xgboost_Accuracy=round(sum(diag(xgboost_CM))/sum(xgboost_CM),2)
print(boost_Accuracy)

## [1] 0.89
```

Based on Confusion Matrix, with 89% accuracy on the Test Dataset Our Boosting Model has done well in predicting the 0 (95%) than in predicting 1 (100%)

KNN vs Bagging vs Boosting

PERFORMANCE MEASURES		Model Evaluation			
		Bagging	ADA-Boosting	XG-Boosting	KNN
CONFUSION MATRIX	Accuracy	98	89	89	98
	Sensitivity (1)	90	69	100	100
	Specificity (0)	97	95	95	98

CONCLUSION

In this project, we had analyzed what mode of transport employees prefers to commute to their office.

We did analysis based on the professional details like age, salary, work exp, Distance. Then we found out the existence of multi-collinearity and we have an unbalanced classification Dataset. We dealt it with SMOTE Technique.

After Data Preparation is done. We build a Multiple Classification models which can predict whether an employee will use car as mode of transport to office.

In the end based on the Performance Measures, we decided that **KNN** algorithm did well in predicting whether a n employee will use car as mode of transport to office.

Then, we did Bagging and Boosting model and compared its performance with KNN algorithm and found out that to our surprise, KNN did Better than XGBoost model.

In the end, I would Recommend using KNN Model to Predict whether an employee will use car as mode of transport to office.