Machine Learning – Predict the type of transport

Read the train and test data set

cars = read.csv("cars.csv")
Given sample data set containing 444 rows

carsTest = read.csv("test.csv")
Sample of two tests for which prediction must be done

Data exploration and analysis

```
str(cars)
'data.frame':	444 obs. of  9 variables:
 $ Age      : int  28 23 29 28 27 26 28 26 22 27 ...
 $ Gender   : Factor w/ 2 levels "Female","Male": 2 1 2 1 2 2 2 1 2 2 ...
 $ Engineer : int  0 1 1 1 1 1 1 1 1 1 ...
 $ MBA      : int  0 0 0 1 0 0 0 0 0 0 ...
 $ Work.Exp : int  4 4 7 5 4 4 5 3 1 4 ...
 $ Salary   : num  14.3 8.3 13.4 13.4 13.4 12.3 14.4 10.5 7.5 13.5 ...
 $ Distance : num  3.2 3.3 4.1 4.5 4.6 4.8 5.1 5.1 5.1 5.2 ...
 $ license  : int  0 0 0 0 0 1 0 0 0 0 ...
 $ Transport: Factor w/ 3 levels "2Wheeler","Car",..: 3 3 3 3 3 3 1 3 3 3 ...
```

Variables like Engineer, MBA and license has been read as numeric so should be converted to factors first.

```
cars$Engineer = as.factor(cars$Engineer)
cars$MBA = as.factor(cars$MBA)
cars$license = as.factor(cars$license)
```

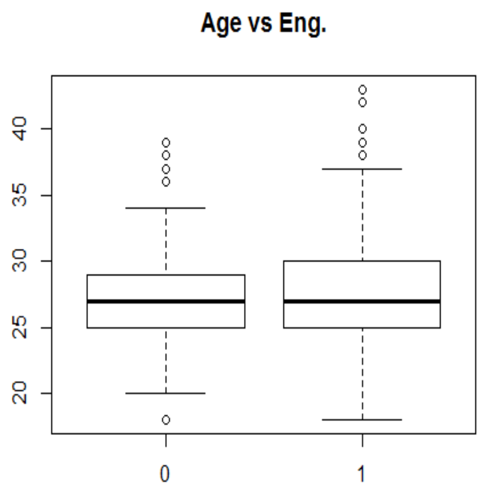
Descriptive Analysis

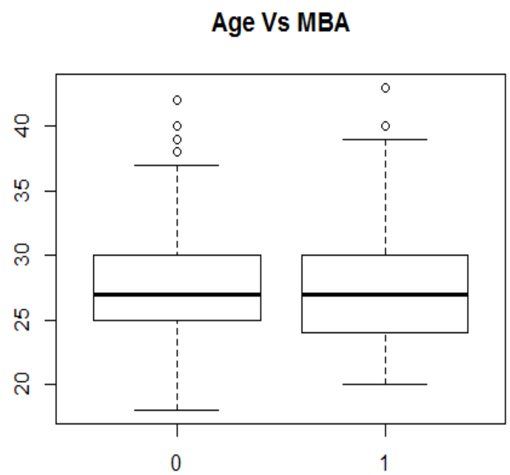
```
summary(cars)
      Age            Gender     Engineer   MBA          Work.Exp          Salary       
Distance
 Min.   :18.00   Female:128   0:109    0   :331   Min.   : 0.0   Min.   : 6.5
0   Min.   : 3.20
 1st Qu.:25.00   Male  :316   1:335    1   :112   1st Qu.: 3.0   1st Qu.: 9.8
0   1st Qu.: 8.80
 Median :27.00                         NA's:  1   Median : 5.0   Median :13.6
0   Median :11.00
 Mean   :27.75                                    Mean   : 6.3   Mean   :16.2
4   Mean   :11.32
 3rd Qu.:30.00                                    3rd Qu.: 8.0   3rd Qu.:15.7
2   3rd Qu.:13.43
 Max.   :43.00                                    Max.   :24.0   Max.   :57.0
0   Max.   :23.40

 license              Transport  
 0:340    2Wheeler        : 83  
 1:104    Car             : 61  
          Public Transport:300  
```

- We can conclude that we have majority of Males approx.. 75%
- Similarly Engineers outnumber MBA's
- Total number of engineers and MBA's is greater then 444, hence possibly some of candidates have dual degree
- One of data point for MBA is missing
- Salary might have skewed distribution
- Again, public transport is most common mode of transportation

Visual Analysis

```
boxplot(cars$Age ~cars$Engineer, main = "Age vs Eng.")
boxplot(cars$Age ~cars$MBA, main ="Age Vs MBA")
```

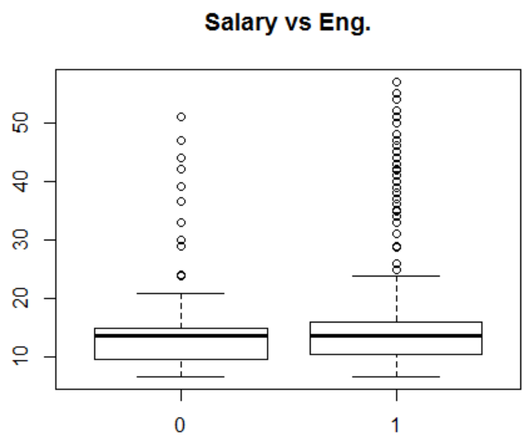




As expected not much of difference here, people for all qulaifications and all work exp would be employ ed in firm

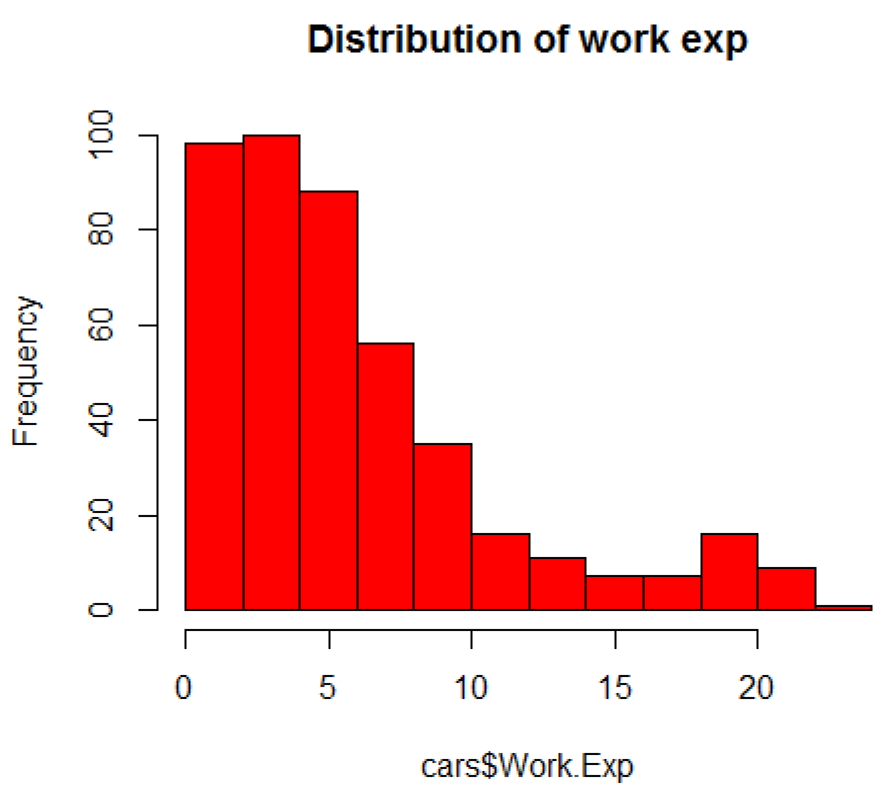
Let us see the avg difference in salary for two profession

```
boxplot(cars$Salary ~cars$Engineer, main = "Salary vs Eng.")
boxplot(cars$Salary ~cars$MBA, main = "Salary vs MBA.")
```



We do not see any appreciable difference in salary of Engs Vs Non-Engs or Mba vs Non-MBA's
Also, mean salary for both MBA's and Eng is around 16

```
hist(cars$Work.Exp, col = "red", main = "Distribution of work exp")
```

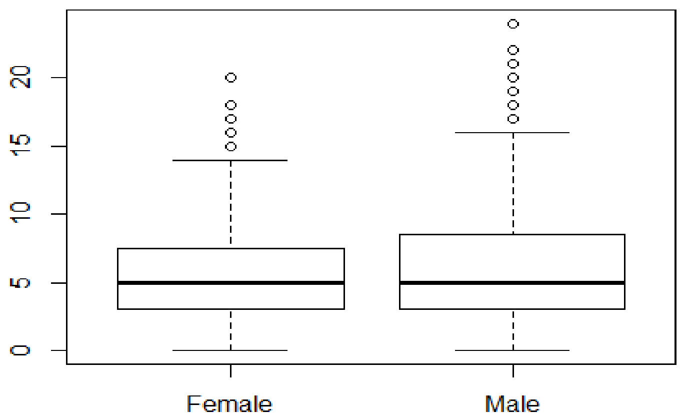


This is skewed towards right, again this would be on expected lines as there would be more juniors then seniors in any firm

```
table(cars$license,cars$Transport)
```

```
    2Wheeler Car Public Transport
  0       60  13              267
  1       23  48               33
```

```
boxplot(cars$Work.Exp ~ cars$Gender)
```

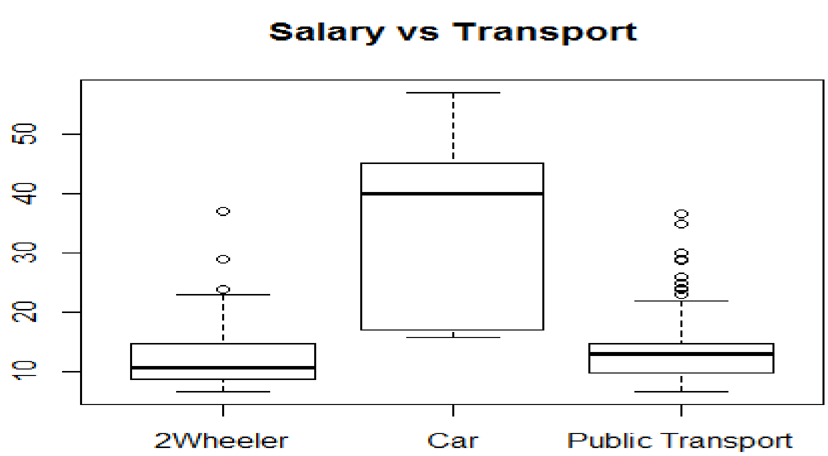


Not much of difference between mean work experience in two genders, so popula tion is equally distributed for both male and females.

Hypothesis Testing

1. Higher the salary more the chances of using car for commute.

```
boxplot(cars$Salary~cars$Transport, main="Salary vs Transport")
```

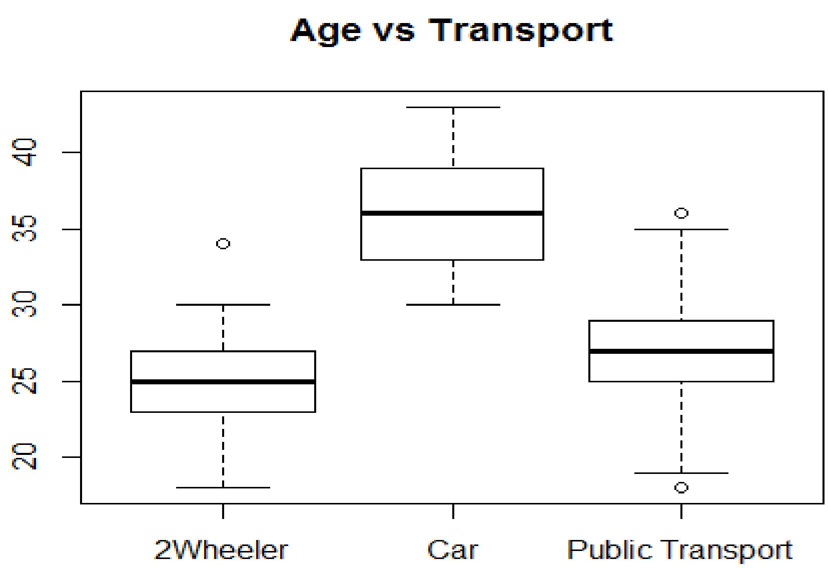


Plot clearly shows as salary increase, inclination of commuting by car is higher.

2. Again with age or work. Exp (Age and work exp would be collinear), propensity of using car Increases

```
cor(cars$Age, cars$Work.Exp)
[1] 0.8408335
```

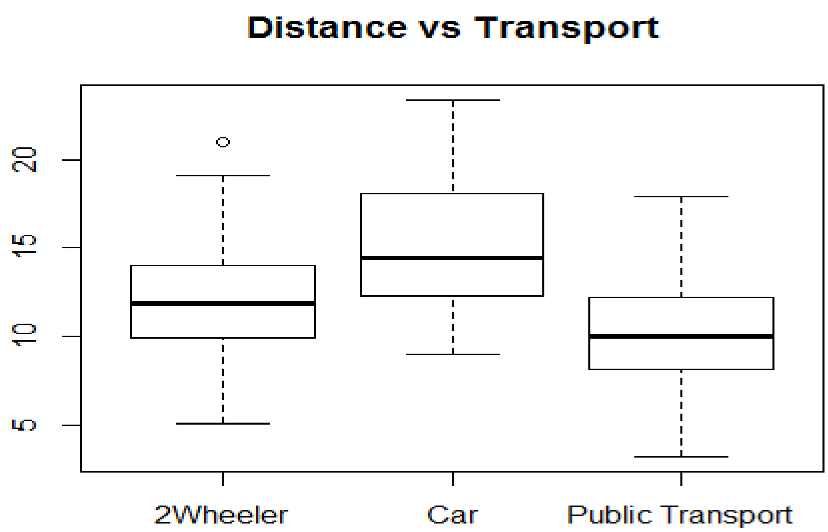
```
boxplot(cars$Age~cars$Transport, main="Age vs Transport")
```



As was the case with salary, we could see clear demarcation in usage of transport. With lower age group 2-wheeler is preferable and with higher work exp car is preferred.

3. As distance increase employee, would prefer car for comfort and ease.

```
boxplot(cars$Distance~cars$Transport, main="Distance vs Transport")
```



There is a slight pattern that could be observed here. For greater distance car is preferred followed by 2-wheeler and then public transport.

4. Females would prefer more of private transfer then public transport

```
table(cars$Gender,cars$Transport)

         2Wheeler Car Public Transport
  Female       38  13               77
  Male         45  48              223
```

We could see that around 40 % of females use private transport and 10% use car compared to males wh ere 15% prefers car and total of 30% uses private transport.Thus, even though percentage of car usage is high but they are also high on public transport.

Data cleaning

Missing values

```
anyNA(cars)
[1] TRUE
```

Finding out where the missing value is

```
cars[!complete.cases(cars), ]
    Age Gender Engineer  MBA Work.Exp Salary Distance license        Transpor
t
145  28 Female        0 <NA>        6   13.7      9.4       0 PublicTransport
```

Use KNN means method to impute the missing value
library(DMwR)

```
cars = knnImputation(cars, 5)
```

Normalize continuous variables

```
cars$Salary = log(cars$Salary)
```

Perform similar transformation on test data

```
carsTest$Salary = log(carsTest$Salary)
carsTest$Engineer = as.factor(carsTest$Engineer)
carsTest$MBA = as.factor(carsTest$MBA)
carsTest$license = as.factor(carsTest$license)
```

Create test and train data from sample data

```
library(caret)
random <- createDataPartition(cars$Transport, p=0.70, list=FALSE)
cars_train<- cars[ random,]
cars_test<- cars[-random,]
```

This sample has all the three categories representation above 10% so we can go ahead without any over sampling

__Model Building and Predictions__

__Naïve Bayes__

```
library(e1071)
Naive_Bayes_Model=naiveBayes(cars_train$Transport ~., data=cars_train)
Naive_Bayes_Model

Naive Bayes Classifier for Discrete Predictors

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

A-priori probabilities:
Y
        2Wheeler              Car  Public Transport
       0.1891026        0.1378205         0.6730769

Conditional probabilities:
                  Age
Y                       [,1]     [,2]
  2Wheeler          25.42373 2.620893
  Car               35.72093 3.340413
  Public Transport  26.73333 2.924134

                  Gender
Y                     Female      Male
  2Wheeler         0.4915254 0.5084746
  Car              0.2558140 0.7441860
  Public Transport 0.2761905 0.7238095

                  Engineer
Y                          0         1
  2Wheeler         0.2542373 0.7457627
```

```
  Car                0.1395349 0.8604651
  Public Transport 0.2714286 0.7285714

                  MBA
Y                           0         1
  2Wheeler         0.7966102 0.2033898
  Car              0.7674419 0.2325581
  Public Transport 0.7333333 0.2666667

Work.Exp
Y                       [,1]     [,2]
  2Wheeler          4.084746 3.114417
  Car              15.674419 4.921870
  Public Transport  4.866667 3.062559

                  Salary
Y                      [,1]      [,2]
  2Wheeler         2.452621 0.3659353
  Car              3.514029 0.4321709
  Public Transport 2.508357 0.3066213

                  Distance
Y                      [,1]     [,2]
  2Wheeler         11.92881 3.524009
  Car              15.85581 3.864263
  Public Transport 10.27286 3.090404

                  license
Y                           0         1
  2Wheeler         0.7288136 0.2711864
  Car              0.2558140 0.7441860
  Public Transport 0.8857143 0.1142857
```

This gives us the rule or factors which can help us employees decision to use car or not.
(These are summarized at the end)

General way to interpret this output is that for any factor variable say license we can say that 72% of people without license use 2-wheeler and 27% with license.
For continuous variables for example distance we can say 2-wheeler is used by people for whom commute distance is 11.9 with sd of 3.5

```
#Prediction on the test dataset
NB_Predictions=predict(Naive_Bayes_Model,cars_test)
table(NB_Predictions,cars_test$Transport)

NB_Predictions     2Wheeler Car Public Transport
  2Wheeler                8   0                6
  Car                     3  14                3
  Public Transport       13   4               81

# prediction for test sample
NB_Predictions=predict(Naive_Bayes_Model,carsTest)
NB_Predictions
[1] Public Transport Public Transport
Levels: 2Wheeler Car Public Transport
```

LDA

We would once again import the two files and do data cleaning as required by LDA. LDA works best with continuous variables hence convert factors as 1 and 0.

```
cars = read.csv("cars.csv")
carsTest = read.csv("test.csv")
cars[145,4] = 0
```

Normalize continuous variables

```
cars$Salary = log(cars$Salary)
carsTest$Salary = log(carsTest$Salary)
cars$Gender<-ifelse(cars$Gender=="Male",1,0)
carsTest$Gender<-ifelse(carsTest$Gender=="Male",1,0)

random <- createDataPartition(cars$Transport, p=0.70, list=FALSE)
cars_train<- cars[ random,]
cars_test<- cars[-random,]

library(MASS)
fit.ld=lda(Transport~., data=cars_train, cv=TRUE)
fit.ld
```

```
Call:
lda(Transport ~ ., data = cars_train, cv = TRUE)

Prior probabilities of groups:
        2Wheeler              Car Public Transport
       0.1891026        0.1378205        0.6730769

Group means:
                      Age    Gender  Engineer       MBA  Work.Exp   Salary Di
stance   license
2Wheeler         25.42373 0.5593220 0.7288136 0.1694915  4.186441 2.450022 11
.56102 0.2372881
Car              35.67442 0.7441860 0.8139535 0.1860465 15.790698 3.536208 15
.50000 0.7906977
Public Transport 26.76190 0.7666667 0.7285714 0.2857143  4.980952 2.515765 10
.35238 0.1190476

Coefficients of linear discriminants:
                 LD1        LD2
Age      -0.11042612 -0.3860466
Gender    0.25706348 -1.3517327
Engineer -0.14185048  0.2586975
MBA       0.18988407 -0.7316381
Work.Exp -0.07413621  0.2145325
Salary   -0.58477768 -0.5036353
Distance -0.10677304  0.1340226
license  -1.11223223  1.5268154

Proportion of trace:
   LD1    LD2
0.9029 0.0971
```

Almost similar output as in Naïve Bayes

Predictions and accuracy

```
LDA_predictions = predict(fit.ld,cars_train)
table(LDA_predictions$class, cars_train$Transport)
```

```
                   2Wheeler Car Public Transport
  2Wheeler               18   0               11
  Car                     3  36                3
  Public Transport       38   7              196
```

```
LDA_predictions = predict(fit.ld,cars_test)
table(LDA_predictions$class, cars_test$Transport)
```

```
                   2Wheeler Car Public Transport
  2Wheeler               11   0                6
  Car                     1  14                1
  Public Transport       12   4               83
```

```
predict(fit.ld,carsTest)
```

```
$class
[1] Public Transport Public Transport
Levels: 2Wheeler Car Public Transport

$posterior
   2Wheeler          Car Public Transport
1 0.2036210 7.228535e-05        0.7963068
2 0.2078997 5.165238e-06        0.7920952

$x
        LD1       LD2
1 0.7702525 0.2470294
2 1.4835708 0.3306443
```

KNN

```
cars = read.csv("cars.csv")
carsTest = read.csv("test.csv")

cars[145,4] = 0
```

Normalize continuous variables

```
cars$Salary = log(cars$Salary)
carsTest$Salary = log(carsTest$Salary)

cars$Gender<-ifelse(cars$Gender=="Male",1,0)
carsTest$Gender<-ifelse(carsTest$Gender=="Male",1,0)


random <- createDataPartition(cars$Transport, p=0.70, list=FALSE)
cars_train<- cars[ random,]
cars_test<- cars[-random,]
```

```
library(class)

trControl<- trainControl(method  = "cv", number  = 10)
fit.knn<- train(Transport ~ .,
+                  method     = "knn",
+ tuneGrid   = expand.grid(k = 2:20),
+ trControl  = trControl,
+                  metric     = "Accuracy",
+ preProcess = c("center","scale"),
+                  data       = cars_train)
fit.knn
k-Nearest Neighbors

312 samples
  8 predictor
  3 classes: '2Wheeler', 'Car', 'Public Transport'

Pre-processing: centered (8), scaled (8)
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 281, 281, 280, 281, 280, 282, ...
Resampling results across tuning parameters:

  k   Accuracy   Kappa
   2  0.7365457  0.4543489
   3  0.7855712  0.5248631
   4  0.7629839  0.4800127
   5  0.7828562  0.5081854
   6  0.7734812  0.4905393
   7  0.7634005  0.4624704
   8  0.7408065  0.4118105
   9  0.7534005  0.4199273
  10  0.7536022  0.4116860
  11  0.7598454  0.4168749
  12  0.7662970  0.4266860
  13  0.7662970  0.4213708
  14  0.7566129  0.3930122
  15  0.7661895  0.4135919
  16  0.7660887  0.4090611
  17  0.7566129  0.3862387
  18  0.7629637  0.3926229
  19  0.7661895  0.4026549
  20  0.7661895  0.3942178

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was k = 3.

KNN_predictions = predict(fit.knn,cars_train)
table(KNN_predictions, cars_train$Transport)

KNN_predictions    2Wheeler Car Public Transport
  2Wheeler               37   0                8
  Car                     0  35                2
  Public Transport       22   8              200

KNN_predictions = predict(fit.knn,cars_test)
table(KNN_predictions, cars_test$Transport)
```

```
KNN_predictions    2Wheeler Car Public Transport
  2Wheeler                9   0               11
  Car                     1  15                3
  Public Transport       14   3               76
```

```
predict(fit.knn,carsTest)
[1] Public Transport Public Transport
Levels: 2Wheeler Car Public Transport
```

We see that all three models predict **Public Transport** for the two test samples

Let us summarize the conclusions from analysis and models for employee's decision whether to use car Or not:

- Important variables are Age, Work.Exp, Distance and License
- Age and Work.Exp are correlated hence we could use any one (prefer Work.Exp) here
- Hence employees with work exp of 10 and above are likely to use car
- Employees who must commute for distance greater than 12 are more likely to prefer car
- With license, we do see that 74% who commute through car have license and 89% who commut e through bus don't have. But surprisingly 72% without license use 2-wheeler.
- Again, people with higher salaries (>20) are likely to use cars