Adult Income Data Project

CKME 136 Final Project Shabbir Yousuf Ali #syali@ryerson.ca
#https://github.com/shabbiryousufali/CKME136 Winter 2019

1. Load requied libraries. Install package install.packages("caret") Install package install.packages("corrplot") Install package install.packages('Boruta')

```
library(ggplot2)
library(corrplot)

## Warning: package 'corrplot' was built under R version 3.4.4

## corrplot 0.84 loaded

library(Boruta)

## Warning: package 'Boruta' was built under R version 3.4.4

## Loading required package: ranger

## Warning: package 'ranger' was built under R version 3.4.4

library(randomForest)

## Warning: package 'randomForest' was built under R version 3.4.4

## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ranger':
##
##     importance

## The following object is masked from 'package:ggplot2':
##
##     margin

library(ROCR)

## Warning: package 'ROCR' was built under R version 3.4.4

## Loading required package: gplots

## Warning: package 'gplots' was built under R version 3.4.4

##
## Attaching package: 'gplots'
```

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

library(caret)

## Warning: package 'caret' was built under R version 3.4.4

## Loading required package: lattice

library(rpart)

## Warning: package 'rpart' was built under R version 3.4.4
```

2. Load data.

```
setwd("C:/Ryerson/ckme136/project/rawdata")
loc<-getwd()
censusdata <- read.csv(file="adult.data",header=TRUE,sep=",", na.string =
"?")

#Add header to the columns
names(censusdata) <- c('age',
    'workclass',
    'fnlwgt',
    'education',
    'educationnum',
    'maritalstatus',
    'occupation',
    'relationship',
    'race',
    'sex',
    'capitalgain',
    'capitalloss',
    'hoursperweek',
    'nativecountry',
    'income')
```

2.1. Split the data into train and test data.

```
inTrain <- createDataPartition(y=censusdata$income, p= 0.75, list=FALSE)
training <- censusdata[inTrain,]
testing <- censusdata[-inTrain,]
```

3. Display dimensions, summary of data, names and overall structure of the data.

```
data <- training
dim(data)

## [1] 24421    15

nrow(data)

## [1] 24421
```

```r
ncol(data)

## [1] 15

dim(testing)

## [1] 8139   15

summary(data)

##       age                   workclass         fnlwgt       
##  Min.   :17.0    Private         :17019   Min.   :  12285  
##  1st Qu.:28.0    Self-emp-not-inc: 1906   1st Qu.: 117849  
##  Median :37.0    Local-gov       : 1563   Median : 178272  
##  Mean   :38.6    ?               : 1378   Mean   : 189664  
##  3rd Qu.:48.0    State-gov       :  960   3rd Qu.: 236696  
##  Max.   :90.0    Self-emp-inc    :  859   Max.   :1484705  
##                 (Other)          :  736                    
##          education      educationnum                 maritalstatus  
##   HS-grad     :7844   Min.   : 1.00    Divorced             : 3362  
##   Some-college:5508   1st Qu.: 9.00    Married-AF-spouse    :   17  
##   Bachelors   :4024   Median :10.00    Married-civ-spouse   :11184  
##   Masters     :1287   Mean   :10.09    Married-spouse-absent:  310  
##   Assoc-voc   :1047   3rd Qu.:12.00    Never-married        : 8015  
##   11th        : 891   Max.   :16.00    Separated            :  763  
##  (Other)      :3820                    Widowed              :  770  
##             occupation             relationship  
##   Prof-specialty :3116    Husband        :9876  
##   Craft-repair   :3066    Not-in-family  :6241  
##   Exec-managerial:3042    Other-relative: 748  
##   Adm-clerical   :2853    Own-child      :3818  
##   Sales          :2715    Unmarried      :2585  
##   Other-service  :2479    Wife           :1153  
##  (Other)         :7150                          
##                   race               sex          capitalgain  
##   Amer-Indian-Eskimo:   226    Female: 8143   Min.   :    0  
##   Asian-Pac-Islander:   769    Male  :16278   1st Qu.:    0  
##   Black             : 2348                    Median :    0  
##   Other             :   202                   Mean   : 1090  
##   White             :20876                    3rd Qu.:    0  
##                                               Max.   :99999  
##                                                               
##   capitalloss       hoursperweek        nativecountry      income     
##  Min.   :   0.00   Min.   : 1.0    United-States:21883    <=50K:18540  
##  1st Qu.:   0.00   1st Qu.:40.0    Mexico       :   489    >50K : 5881  
##  Median :   0.00   Median :40.0    ?            :   424                 
##  Mean   :  87.23   Mean   :40.4    Philippines  :   140                 
##  3rd Qu.:   0.00   3rd Qu.:45.0    Germany      :   106                 
##  Max.   :4356.00   Max.   :99.0    Puerto-Rico  :    91                 
##                                   (Other)       : 1288                  
```

```r
names(data)
```

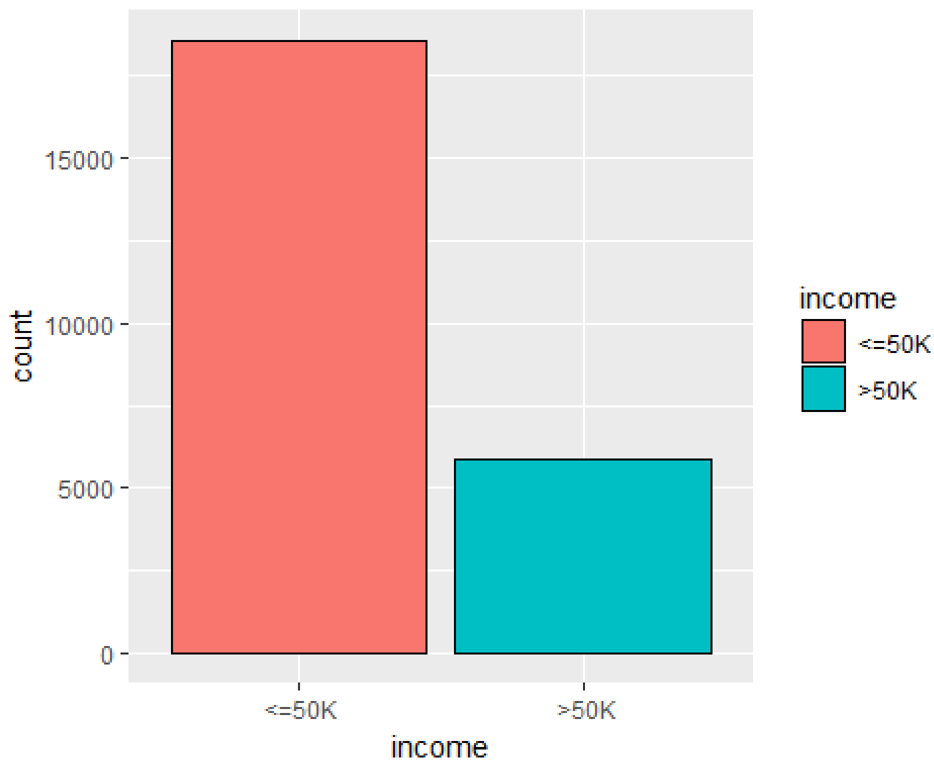
```
## [1] "age"           "workclass"     "fnlwgt"        "education"
## [5] "educationnum"  "maritalstatus" "occupation"    "relationship"
## [9] "race"          "sex"           "capitalgain"   "capitalloss"
## [13] "hoursperweek" "nativecountry" "income"
```

```r
str(data)
```

```
## 'data.frame':    24421 obs. of  15 variables:
##  $ age          : int  50 38 53 31 42 37 30 23 40 25 ...
##  $ workclass    : Factor w/ 9 levels " ?"," Federal-gov",..: 7 5 5 5 5 5 8
5 5 7 ...
##  $ fnlwgt       : int  83311 215646 234721 45781 159449 280464 141297
122272 121772 176756 ...
##  $ education    : Factor w/ 16 levels " 10th"," 11th",..: 10 12 2 13 10 16
10 10 9 12 ...
##  $ educationnum : int  13 9 7 14 13 10 13 13 11 9 ...
##  $ maritalstatus: Factor w/ 7 levels " Divorced"," Married-AF-spouse",..:
3 1 3 5 3 3 3 5 3 5 ...
##  $ occupation   : Factor w/ 15 levels " ?"," Adm-clerical",..: 5 7 7 11 5
5 11 2 4 6 ...
##  $ relationship : Factor w/ 6 levels " Husband"," Not-in-family",..: 1 2 1
2 1 1 1 4 1 4 ...
##  $ race         : Factor w/ 5 levels " Amer-Indian-Eskimo",..: 5 5 3 5 5 3
2 5 2 5 ...
##  $ sex          : Factor w/ 2 levels " Female"," Male": 2 2 2 1 2 2 2 1 2
2 ...
##  $ capitalgain  : int  0 0 0 14084 5178 0 0 0 0 0 ...
##  $ capitalloss  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ hoursperweek : int  13 40 40 50 40 80 40 30 40 35 ...
##  $ nativecountry: Factor w/ 42 levels " ?"," Cambodia",..: 40 40 40 40 40
40 20 40 1 40 ...
##  $ income       : Factor w/ 2 levels " <=50K"," >50K": 1 1 1 2 2 2 2 1 2 1
...
```

4. Display Class Distributions.

```r
# Use the ggplot to find the income distribution <=50K VS >50K based on the
training data
result = summary(data$income)/nrow(data) * 100
ggplot(data=data,aes(income)) + geom_bar(aes(fill = income), color = "black")
```




```
result

##    <=50K     >50K
## 75.91827 24.08173
```

5. Check and remove the missing values.

```
cat("Missing values in training set:", sum(is.na(data)), "\n")

## Missing values in training set: 0

na_count <-sapply(data, function(y) sum(length(which(is.na(y)))))
na_count <- data.frame(na_count)
na_count

##               na_count
## age                  0
## workclass            0
## fnlwgt               0
## education            0
## educationnum         0
## maritalstatus        0
## occupation           0
## relationship         0
## race                 0
## sex                  0
## capitalgain          0
## capitalloss          0
```

```
## hoursperweek         0
## nativecountry        0
## income               0

nrow(data)

## [1] 24421

data <- na.omit(data)
nrow(data)

## [1] 24421

nrow(testing)

## [1] 8139

cat("Missing values in testing set:", sum(is.na(testing)), "\n")

## Missing values in testing set: 0

na_count1 <-sapply(testing, function(y) sum(length(which(is.na(y)))))
na_count1

##           age     workclass        fnlwgt     education  educationnum
##             0             0             0             0             0
## maritalstatus    occupation  relationship          race           sex
##             0             0             0             0             0
##   capitalgain   capitalloss  hoursperweek nativecountry        income
##             0             0             0             0             0

testingdata <- na.omit(testing)
nrow(testingdata)

## [1] 8139
```

5.1 Re-factoring the work class, occupation and native country after removing the NA values (exclude levels not required).

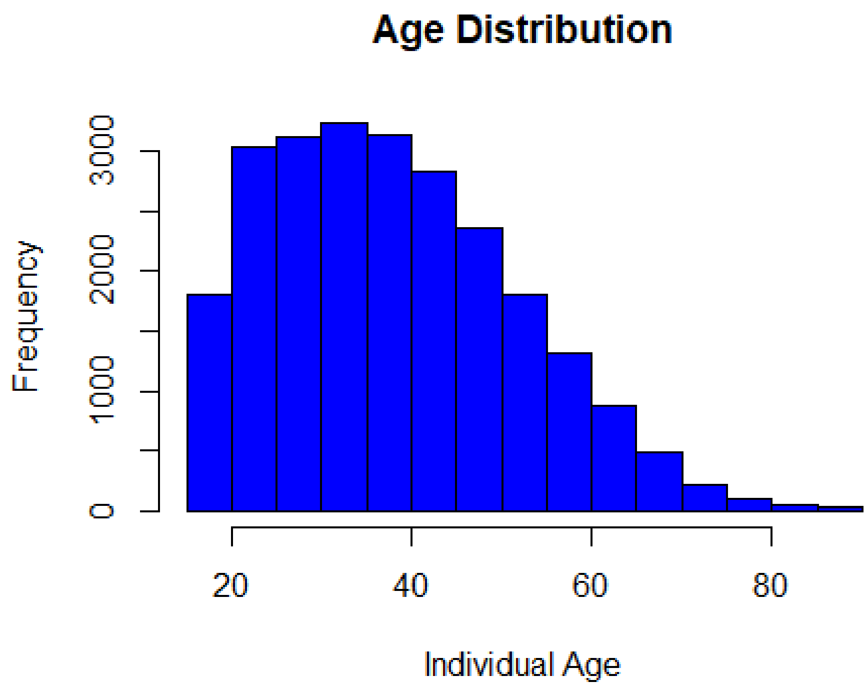
```
data$workclass <- factor(data$workclass)
data$occupation <- factor(data$occupation)
data$native.country <- factor(data$nativecountry)
```

5.1 Re-factoring the work class, occupation and native country after removing the NA values (exclude levels not required) for testing data also.

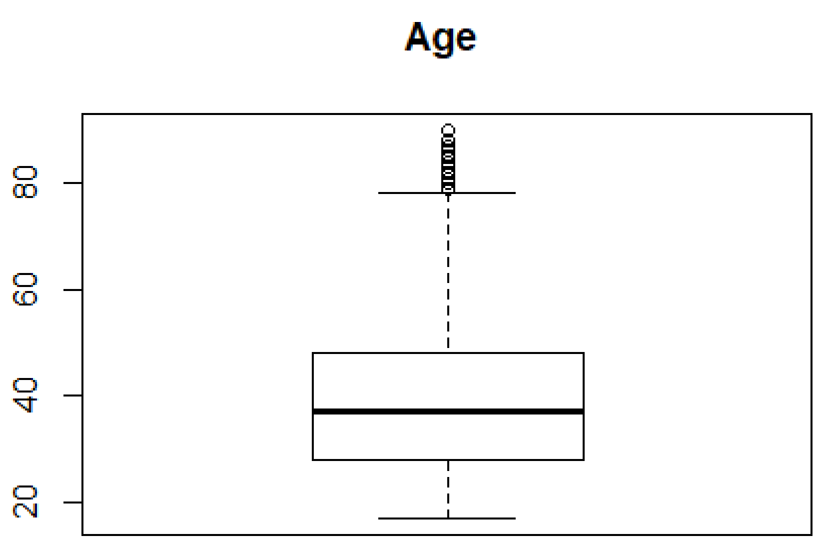
```
testingdata$workclass <- factor(testingdata$workclass)
testingdata$occupation <- factor(testingdata$occupation)
testingdata$native.country <- factor(testingdata$nativecountry)
```

6. Statistics of Numerical attributes

```r
#find the Min, Max, Mean, Median, 1st and 3rd Quarter of the numerical
attributes
summary(data$age)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    17.0    28.0    37.0    38.6    48.0    90.0

summary(data$educationnum)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    9.00   10.00   10.09   12.00   16.00

summary(data$capitalgain)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0       0       0    1090       0   99999

summary(data$capitalloss)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    0.00    0.00   87.23    0.00 4356.00

summary(data$hoursperweek)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     1.0    40.0    40.0    40.4    45.0    99.0

# statistics of numerical attributes
summary(data$age)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    17.0    28.0    37.0    38.6    48.0    90.0

sd(data$age)

## [1] 13.69495

hist(data$age, main = "Age Distribution",xlab = "Individual Age" ,col
="blue")
```




```
boxplot(data$age,main="Age ")
```



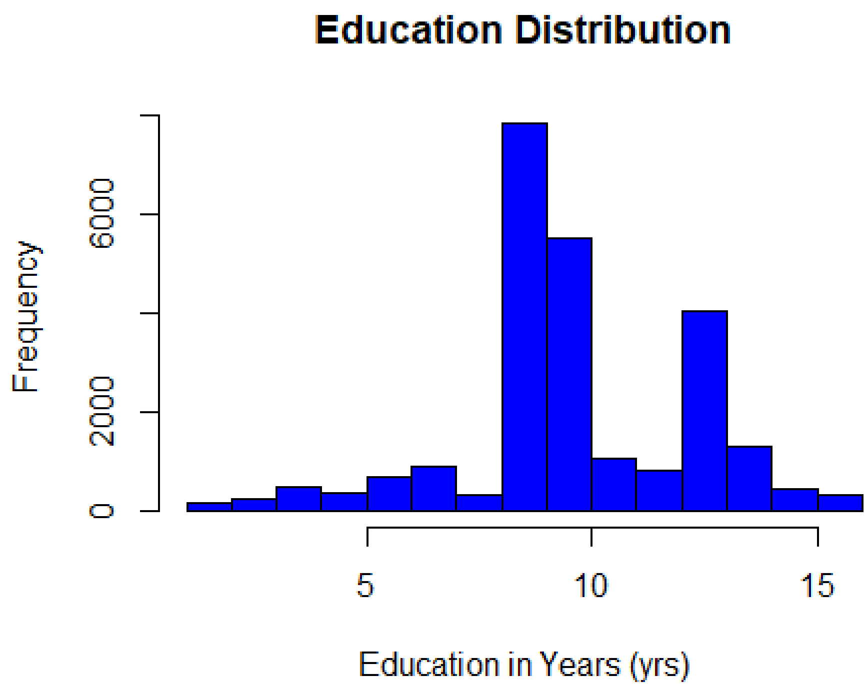

```
summary(data$education.num)
```

```
## Length  Class   Mode
##      0   NULL   NULL
```

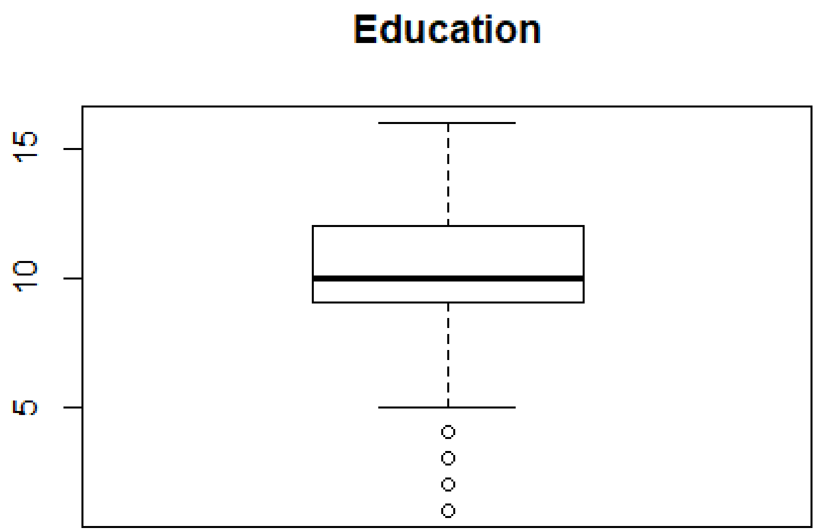
```
sd(data$education.num)
```

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

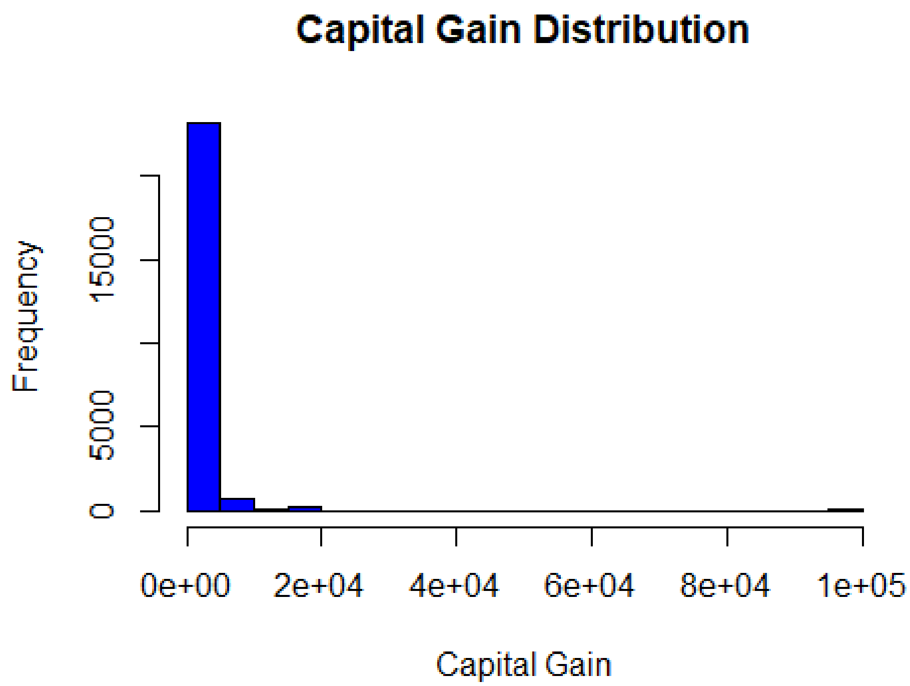
```
hist(data$educationnum,main = "Education Distribution",xlab="Education in
Years (yrs)",col = "blue")
```



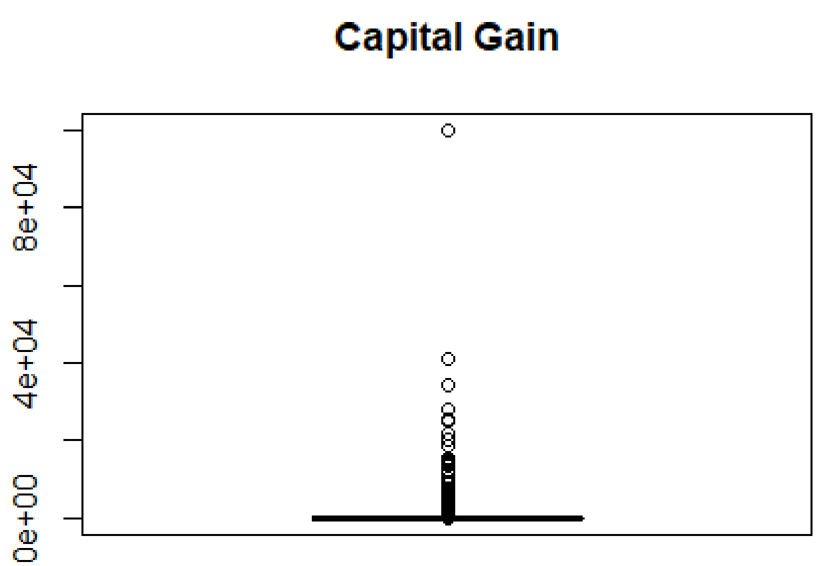

```
boxplot(data$educationnum,main="Education")
```




```
summary(data$capitalgain)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0       0       0    1090       0   99999

sd(data$capitalgain)

## [1] 7440.626

hist(data$capitalgain,main = "Capital Gain Distribution",xlab="Capital
Gain",col = "blue")
```




```r
boxplot(data$capitalgain,main="Capital Gain")
```



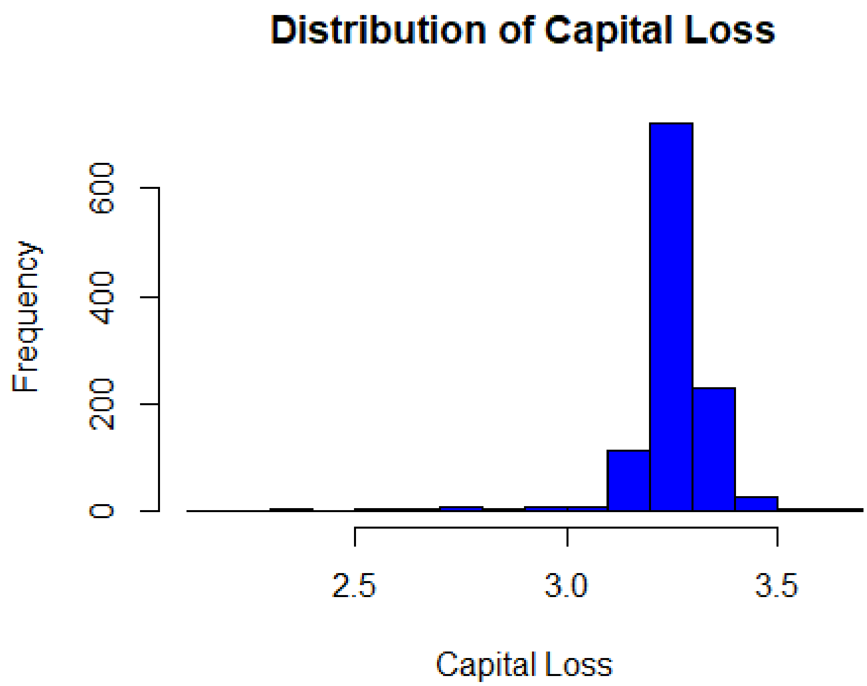

```r
summary(data$capitalloss)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    0.00    0.00   87.23    0.00 4356.00
```

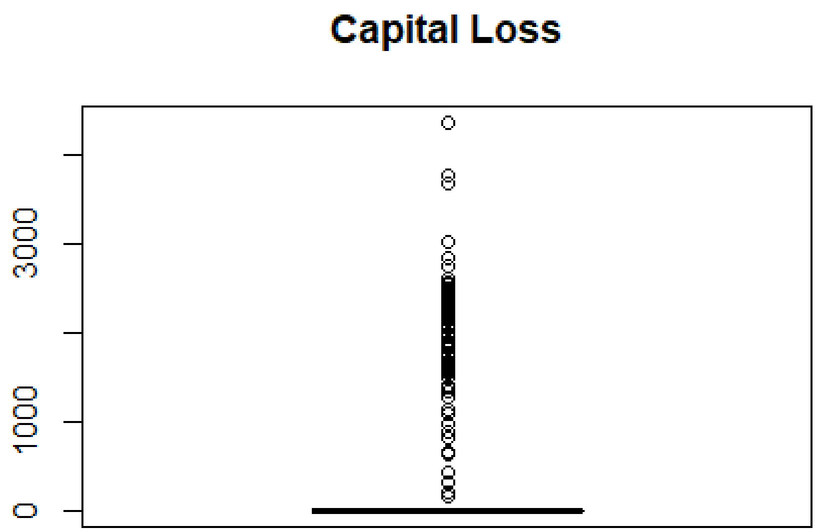
```
sd(data$capitalloss)
```

```
## [1] 403.7928
```

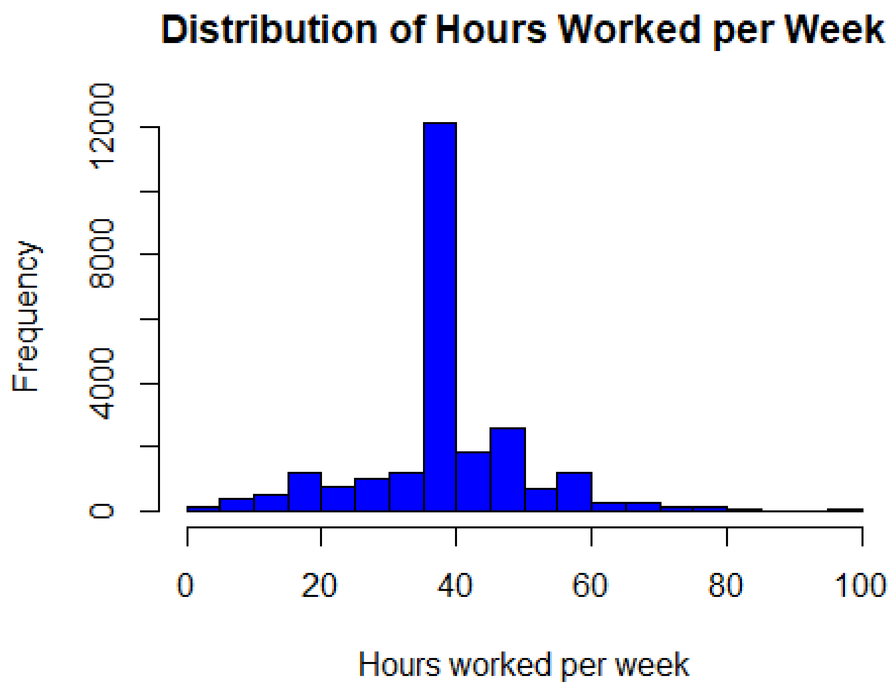
```
hist(log10(data$capitalloss),main = "Distribution of Capital
Loss",xlab="Capital Loss",col = "blue")
```



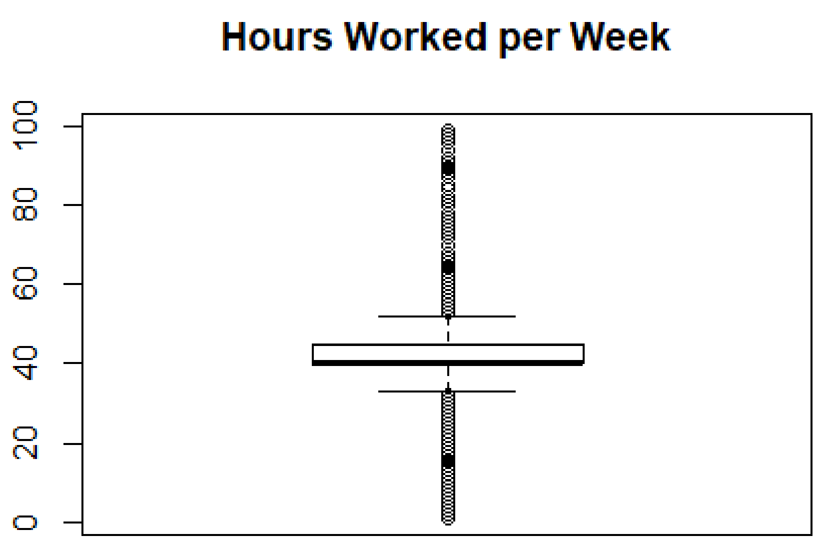

```
boxplot(data$capitalloss,main="Capital Loss")
```




```
summary(data$hoursperweek)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     1.0    40.0    40.0    40.4    45.0    99.0

sd(data$`hours.per.week`)

## [1] NA

hist(data$hoursperweek,main = "Distribution of Hours Worked per
Week",xlab="Hours worked per week",col = "blue")
```

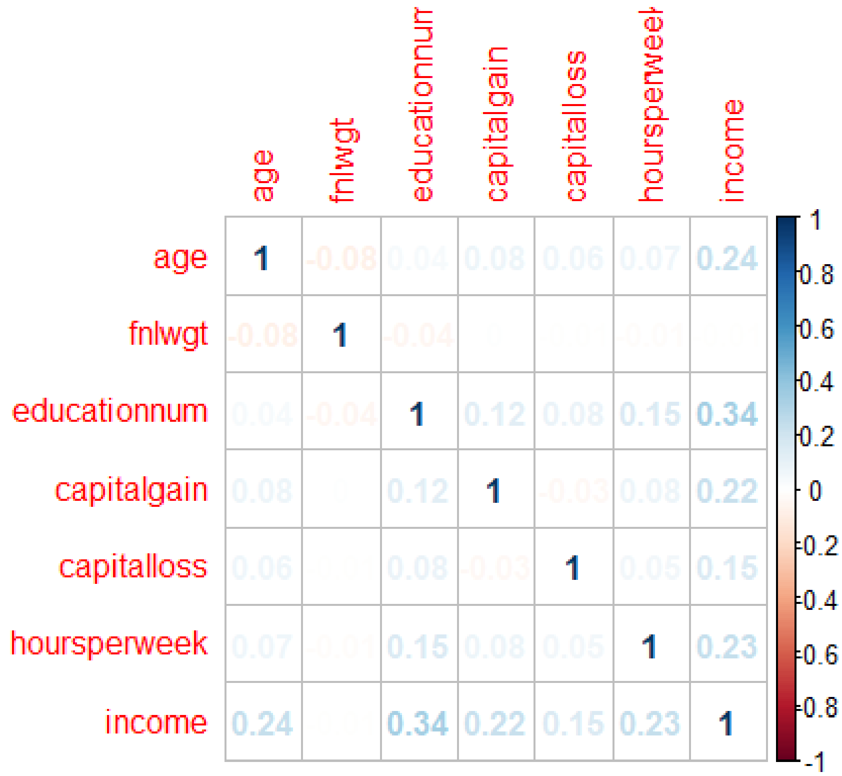



```
boxplot(data$hoursperweek,main="Hours Worked per Week")
```



7a. Find the Correlation between numerical attributes.

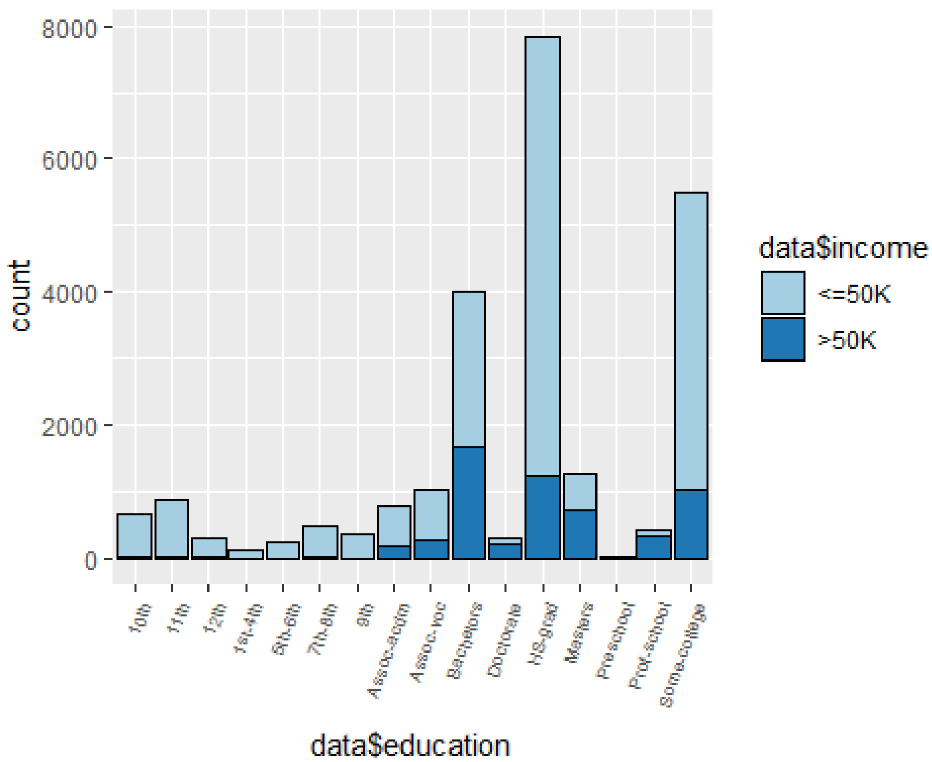
```r
#Changing income to 0 <= 50k, 1 > 50k

data1 <- data
data1$income <- as.numeric(data1$income)-1
#Correlation plot
M <- c(1, 3, 5, 11:13, 15)
corrplot(cor(data1[,M]),method = "number")
```



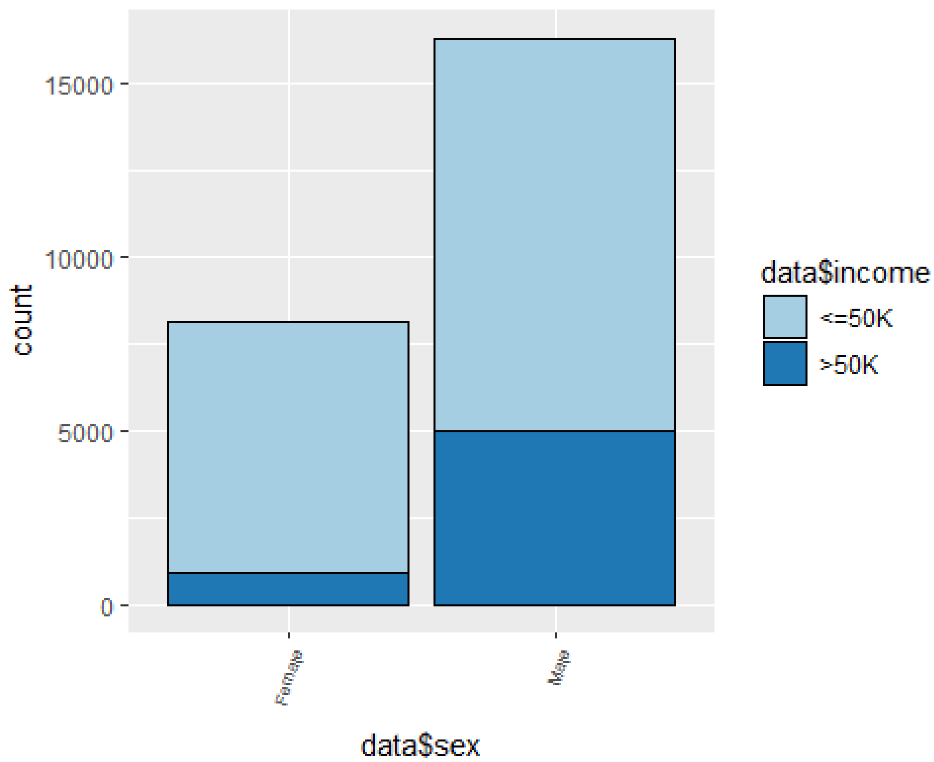

```r
##########################################################
# Correlations shows that numeric attributes are related but are not strongly correlated.
# Education has the highest correlation 0.33 with income followed by
# Capital gain 0.22, age 0.24 and hours worked 0.23.
# The variables are positively correlted with each other.
##########################################################
```

7b. Find the Correlation between categorical attributes with numerical attribute (income)

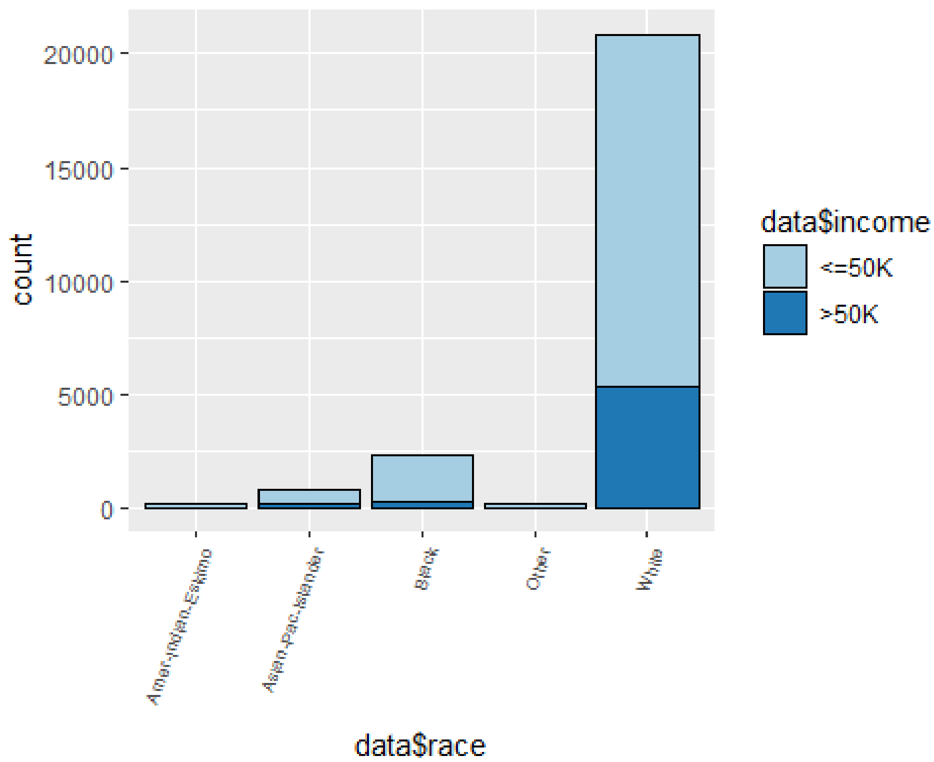
```r
#based on the Education level
ggplot(data, aes(x=data$education,fill=data$income)) + geom_bar(position = "stack", color = "black") + theme(axis.text.x=element_text(angle = 70 , hjust= 1, size=7)) + scale_fill_brewer(palette="Paired")
```



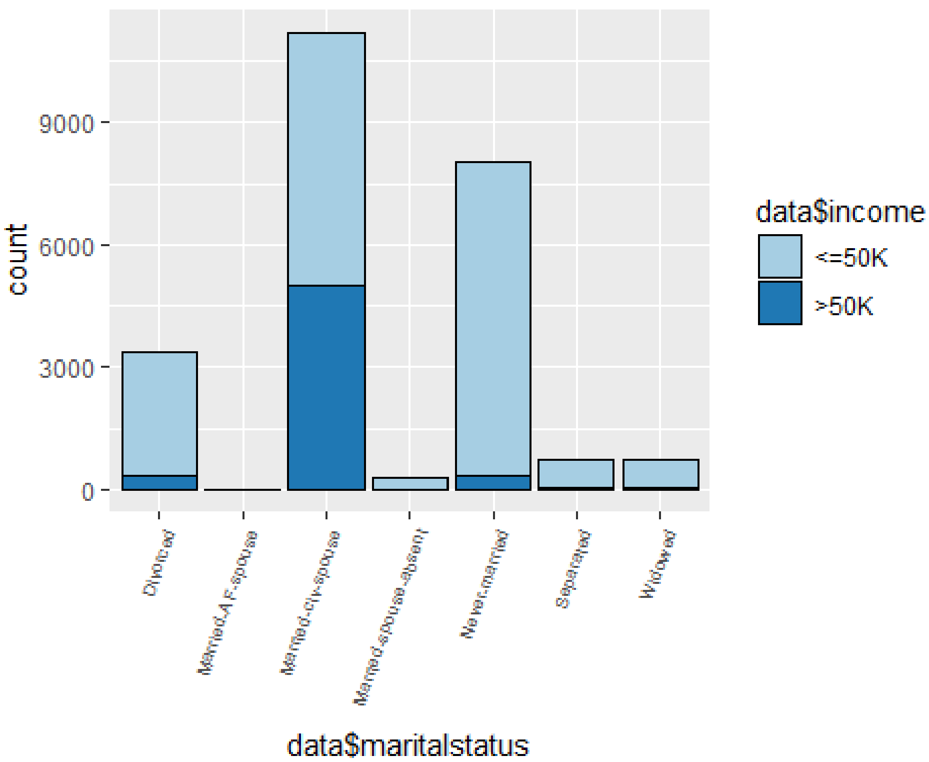

```
# Result shows adults with higher education has earning > 50K
# Adults with Bachelors degree have maximum number of earnings > 50K,
followed by doctorate and masters
# Adults with Lower education level have maximum portion of income <= 50K

#based on the sex
ggplot(data, aes(x=data$sex,fill=data$income)) + geom_bar(position = "stack",
color = "black") + theme(axis.text.x=element_text(angle = 70 , hjust= 1,
size=7)) + scale_fill_brewer(palette="Paired")
```



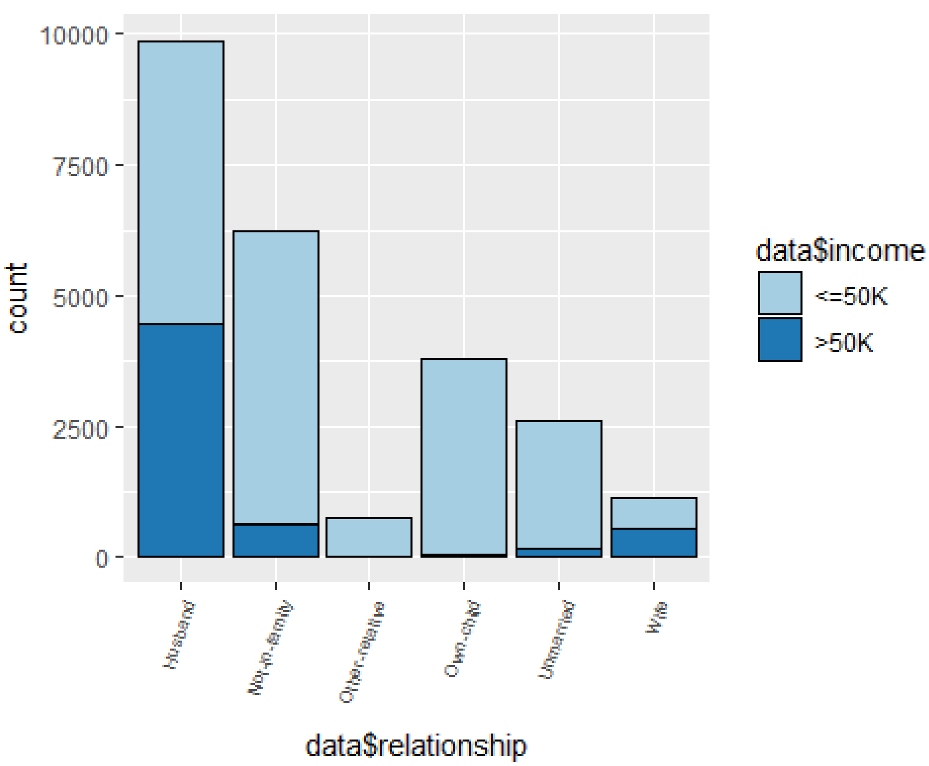

```
#Result shows the ratio of male earning income > 50K is more than female

#based on the race
ggplot(data, aes(x=data$race,fill=data$income)) + geom_bar(position =
"stack", color = "black") + theme(axis.text.x=element_text(angle = 70 ,
hjust= 1, size=7)) + scale_fill_brewer(palette="Paired")
```



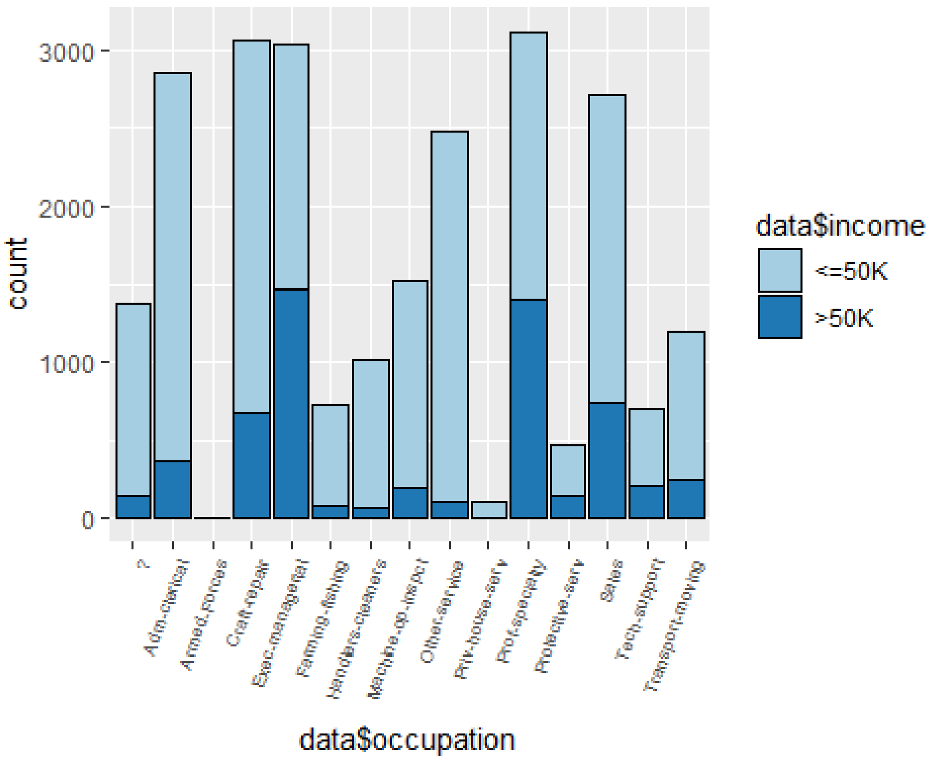

```
#Result shows the highest earning adults are white followed by Black and Asia pacific

#based on the marital status and relationship

ggplot(data, aes(x=data$maritalstatus,fill=data$income)) + geom_bar(position
= "stack", color = "black") + theme(axis.text.x=element_text(angle = 70 ,
hjust= 1, size=7)) + scale_fill_brewer(palette="Paired")
```



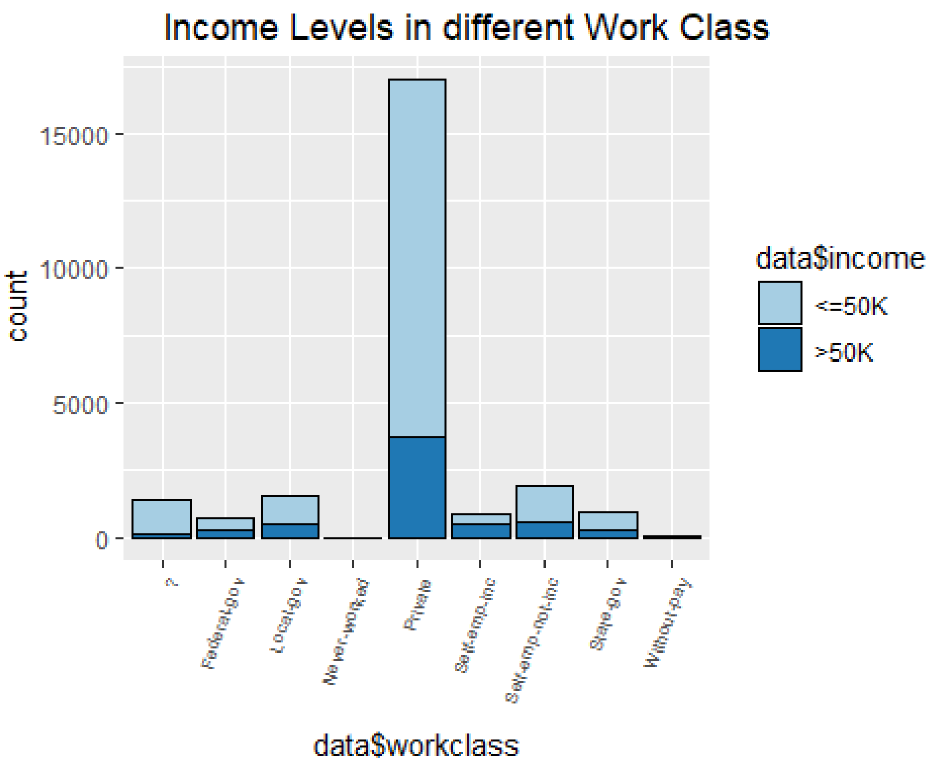

```
ggplot(data, aes(x=data$relationship,fill=data$income)) + geom_bar(position =
"stack", color = "black") + theme(axis.text.x=element_text(angle = 70 ,
hjust= 1, size=7)) + scale_fill_brewer(palette="Paired")
```



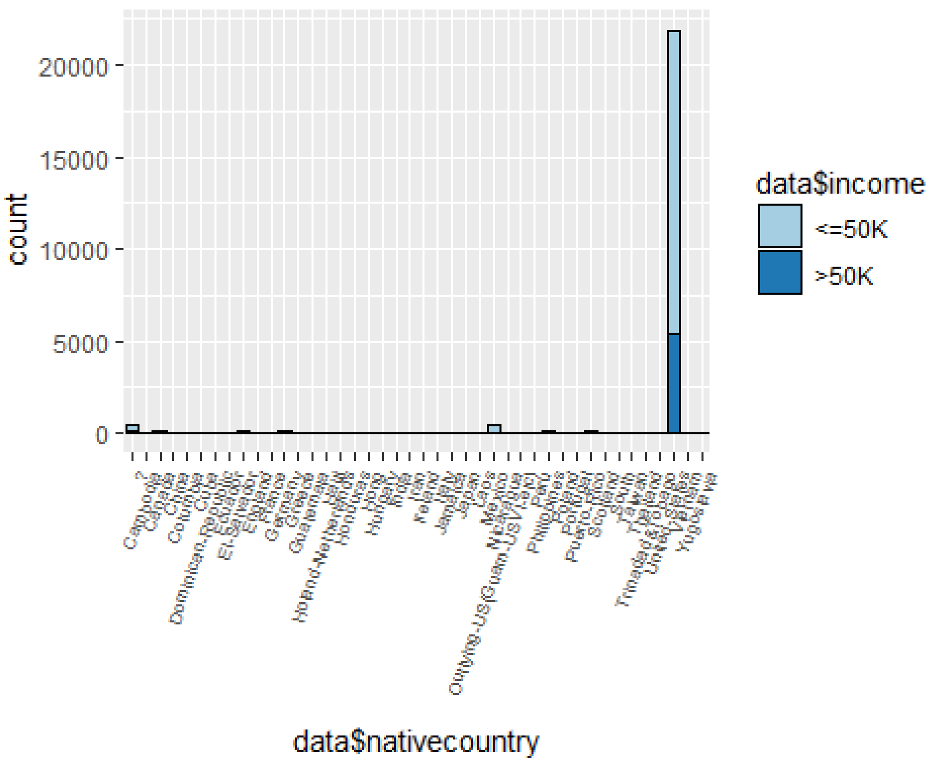
```
#Results in both the graphs show that Male and married people are earning more than 50K, as compared to female and unmarried people

#based on the occupation
ggplot(data, aes(x=data$occupation,fill=data$income)) + geom_bar(position = "stack", color = "black") + theme(axis.text.x=element_text(angle = 70 , hjust= 1, size=7)) + scale_fill_brewer(palette="Paired")
```




```
#Result shows adults with higher position like Manager, Professor are earning > 50K

#based on the work class
ggplot(data, aes(x=data$workclass,fill=data$income)) + geom_bar(position = "stack", color = "black") + ggtitle('    Income Levels in different Work Class')+ theme(axis.text.x=element_text(angle = 70 , hjust= 1, size=7))  + scale_fill_brewer(palette="Paired")
```




```
#Result shows adults in private sector have maximum number of earning of >
50K

ggplot(data, aes(x=data$nativecountry,fill=data$income)) + geom_bar(position
= "stack", color = "black") + theme(axis.text.x=element_text(angle = 70 ,
hjust= 1, size=7)) + scale_fill_brewer(palette="Paired")
```




```
#Result shows marjority of the adults belongs to the United States
```

Save the clean test and train data testdata.csv and traindata.csv files respectively.

```
traindata <- data
testdata  <- testingdata

write.csv(traindata, "traindata.csv", row.names = FALSE)
write.csv(testdata, "testdata.csv", row.names = FALSE)
```

Now we predict the data based on the traindata

```
model <- glm(income ~ age+ workclass+ education+maritalstatus+ occupation+
sex +hoursperweek, data = traindata, family = binomial('logit'))
summary(model)

## 
## Call:
## glm(formula = income ~ age + workclass + education + maritalstatus + 
##     occupation + sex + hoursperweek, family = binomial("logit"), 
##     data = traindata)
## 
## Deviance Residuals: 
##     Min       1Q   Median       3Q      Max  
## -2.8154  -0.5518  -0.2372  -0.0526   3.3876  
## 
## Coefficients: (1 not defined because of singularities)
##                                       Estimate Std. Error z value Pr(>|z|)
```

```
## (Intercept)                         -6.971653   0.242925 -28.699  < 2e-16
## age                                  0.029373   0.001760  16.693  < 2e-16
## workclass Federal-gov                0.966112   0.166737   5.794 6.86e-09
## workclass Local-gov                  0.362486   0.151204   2.397   0.0165
## workclass Never-worked             -10.740772 333.392623  -0.032   0.9743
## workclass Private                    0.554583   0.134859   4.112 3.92e-05
## workclass Self-emp-inc               0.825242   0.161448   5.112 3.20e-07
## workclass Self-emp-not-inc           0.106586   0.148343   0.719   0.4724
## workclass State-gov                  0.156498   0.165129   0.948   0.3433
## workclass Without-pay              -12.229956 218.138278  -0.056   0.9553
## education 11th                      -0.056833   0.233697  -0.243   0.8079
## education 12th                       0.607009   0.277971   2.184   0.0290
## education 1st-4th                   -0.725741   0.464978  -1.561   0.1186
## education 5th-6th                   -0.460474   0.348199  -1.322   0.1860
## education 7th-8th                   -0.591074   0.254284  -2.324   0.0201
## education 9th                       -0.555298   0.296418  -1.873   0.0610
## education Assoc-acdm                 1.276529   0.193340   6.602 4.04e-11
## education Assoc-voc                  1.313741   0.185128   7.096 1.28e-12
## education Bachelors                  1.971646   0.172237  11.447  < 2e-16
## education Doctorate                  2.955892   0.232274  12.726  < 2e-16
## education HS-grad                    0.738202   0.168210   4.389 1.14e-05
## education Masters                    2.353122   0.183330  12.835  < 2e-16
## education Preschool                -11.633386 129.576912  -0.090   0.9285
## education Prof-school                3.043054   0.217199  14.010  < 2e-16
## education Some-college               1.074970   0.170528   6.304 2.90e-10
## maritalstatus Married-AF-spouse      2.419811   0.575338   4.206 2.60e-05
## maritalstatus Married-civ-spouse     2.093609   0.070977  29.497  < 2e-16
## maritalstatus Married-spouse-absent  0.019944   0.233382   0.085   0.9319
## maritalstatus Never-married         -0.466253   0.086986  -5.360 8.32e-08
## maritalstatus Separated             -0.245498   0.174889  -1.404   0.1604
## maritalstatus Widowed               -0.042687   0.154873  -0.276   0.7828
## occupation Adm-clerical              0.104270   0.107293   0.972   0.3311
## occupation Armed-Forces             -0.519519   1.396471  -0.372   0.7099
## occupation Craft-repair              0.141664   0.092960   1.524   0.1275
## occupation Exec-managerial           0.904007   0.094987   9.517  < 2e-16
## occupation Farming-fishing          -0.922612   0.154606  -5.968 2.41e-09
## occupation Handlers-cleaners        -0.671411   0.162294  -4.137 3.52e-05
## occupation Machine-op-inspct        -0.173751   0.115034  -1.510   0.1309
## occupation Other-service            -0.793418   0.135386  -5.860 4.62e-09
## occupation Priv-house-serv          -2.547249   1.217294  -2.093   0.0364
## occupation Prof-specialty            0.628490   0.101722   6.178 6.47e-10
## occupation Protective-serv           0.596874   0.145475   4.103 4.08e-05
## occupation Sales                     0.406006   0.098008   4.143 3.43e-05
## occupation Tech-support              0.753259   0.129899   5.799 6.68e-09
## occupation Transport-moving                NA         NA      NA       NA
## sex Male                             0.113354   0.056383   2.010   0.0444
## hoursperweek                         0.031028   0.001761  17.615  < 2e-16
##
## (Intercept)                        ***
## age                                ***
```

```
## workclass Federal-gov              ***
## workclass Local-gov                *
## workclass Never-worked
## workclass Private                  ***
## workclass Self-emp-inc             ***
## workclass Self-emp-not-inc
## workclass State-gov
## workclass Without-pay
## education 11th
## education 12th                     *
## education 1st-4th
## education 5th-6th
## education 7th-8th                  *
## education 9th                      .
## education Assoc-acdm               ***
## education Assoc-voc                ***
## education Bachelors                ***
## education Doctorate                ***
## education HS-grad                  ***
## education Masters                  ***
## education Preschool
## education Prof-school              ***
## education Some-college             ***
## maritalstatus Married-AF-spouse    ***
## maritalstatus Married-civ-spouse   ***
## maritalstatus Married-spouse-absent
## maritalstatus Never-married        ***
## maritalstatus Separated
## maritalstatus Widowed
## occupation Adm-clerical
## occupation Armed-Forces
## occupation Craft-repair
## occupation Exec-managerial         ***
## occupation Farming-fishing         ***
## occupation Handlers-cleaners       ***
## occupation Machine-op-inspct
## occupation Other-service           ***
## occupation Priv-house-serv         *
## occupation Prof-specialty          ***
## occupation Protective-serv         ***
## occupation Sales                   ***
## occupation Tech-support            ***
## occupation Transport-moving
## sex Male                           *
## hoursperweek                       ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
```

```
##     Null deviance: 26962  on 24420  degrees of freedom
## Residual deviance: 17240  on 24375  degrees of freedom
## AIC: 17332
##
## Number of Fisher Scoring iterations: 13
```

```
predicttrain <- predict(model,traindata,type='response')
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```
pred1 <- rep('<=50K', length(predicttrain))
pred1[predicttrain>=.5] <- '>50K'
tb1 <- table(pred1, traindata$income)
tb1
```

```
##
## pred1    <=50K  >50K
##   <=50K  17168  2644
##   >50K    1372  3237
```

Apply different algorithm to predict the results using train and test data

1) DECISION TREE

```
Dectree<- rpart(income~ age+ workclass+ education+maritalstatus+ occupation+
sex +hoursperweek, data = traindata, method='class',cp =1e-3)

#Result using traindata
Dectree.Ptrain <- predict(Dectree,newdata= traindata, type = 'class')
confusionMatrix(traindata$income,Dectree.Ptrain)
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction  <=50K  >50K
##      <=50K  17269  1271
##      >50K    2508  3373
##
##                Accuracy : 0.8453
##                  95% CI : (0.8407, 0.8498)
##     No Information Rate : 0.8098
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5441
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.8732
##             Specificity : 0.7263
##          Pos Pred Value : 0.9314
##          Neg Pred Value : 0.5735
##              Prevalence : 0.8098
```

```
##          Detection Rate : 0.7071
##    Detection Prevalence : 0.7592
##       Balanced Accuracy : 0.7997
##
##        'Positive' Class :  <=50K
##
```

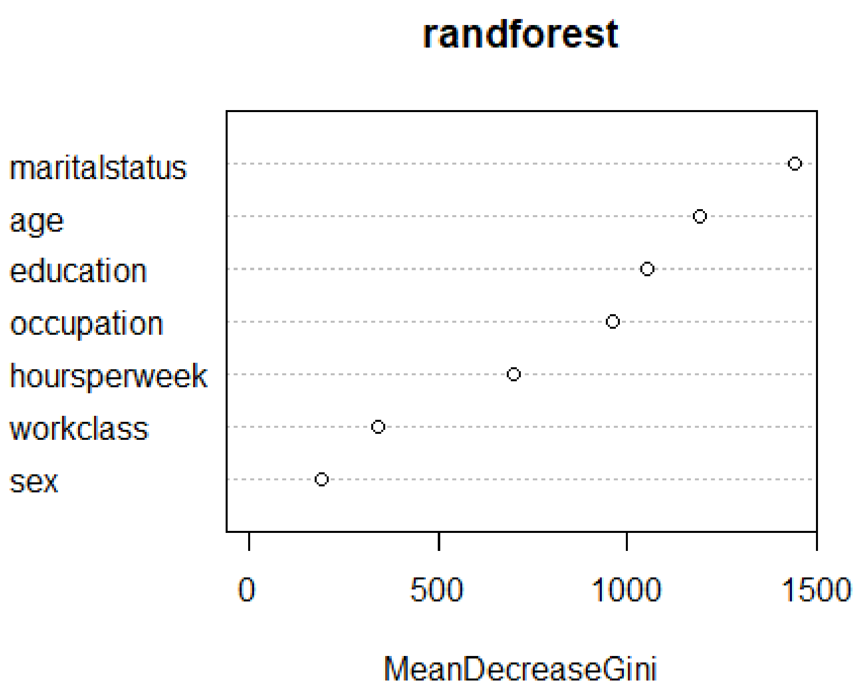
```r
#Result using testdata
Dectree.pred.prob <- predict(Dectree, newdata = testdata, type = 'prob')
Dectree.pred <- predict(Dectree, newdata = testdata, type = 'class')
confusionMatrix(testdata$income,Dectree.pred)
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction  <=50K  >50K
##      <=50K   5700   479
##      >50K     888  1072
##
##                Accuracy : 0.832
##                  95% CI : (0.8237, 0.8401)
##     No Information Rate : 0.8094
##     P-Value [Acc > NIR] : 7.256e-08
##
##                   Kappa : 0.5054
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.8652
##             Specificity : 0.6912
##          Pos Pred Value : 0.9225
##          Neg Pred Value : 0.5469
##              Prevalence : 0.8094
##          Detection Rate : 0.7003
##    Detection Prevalence : 0.7592
##       Balanced Accuracy : 0.7782
##
##        'Positive' Class :  <=50K
##
```

2) RANDOM FOREST

```r
library(randomForest)
levels(testdata$workclass) <- levels(traindata$workclass)
randforest <- randomForest(income ~ age+ workclass+
education+maritalstatus+occupation+ sex+hoursperweek, data = traindata, ntree
= 500)
randforest.pred.prob <- predict(randforest, newdata = testdata, type =
'prob')
randforest.pred <- predict(randforest, newdata = testdata, type = 'class')

# confusion matrix
```

```
tb3 <- table(randforest.pred, testdata$income)
tb3

##
## randforest.pred  <=50K  >50K
##           <=50K   5654   820
##           >50K     525  1140

confusionMatrix(testdata$income,randforest.pred)

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  <=50K  >50K
##      <=50K   5654   525
##      >50K     820  1140
##
##                Accuracy : 0.8347
##                  95% CI : (0.8265, 0.8428)
##     No Information Rate : 0.7954
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5236
##  Mcnemar's Test P-Value : 1.088e-15
##
##             Sensitivity : 0.8733
##             Specificity : 0.6847
##          Pos Pred Value : 0.9150
##          Neg Pred Value : 0.5816
##              Prevalence : 0.7954
##          Detection Rate : 0.6947
##    Detection Prevalence : 0.7592
##       Balanced Accuracy : 0.7790
##
##        'Positive' Class :  <=50K
##

varImpPlot (randforest)
```



3) LINEAR REGRESION

```
linReg <- glm(income ~ age+ workclass+ education+maritalstatus+ occupation+
sex +hoursperweek, data = traindata, family = binomial('logit'))
summary(linReg)

##
## Call:
## glm(formula = income ~ age + workclass + education + maritalstatus +
##     occupation + sex + hoursperweek, family = binomial("logit"),
##     data = traindata)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.8154  -0.5518  -0.2372  -0.0526   3.3876
##
## Coefficients: (1 not defined because of singularities)
##                                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)                           -6.971653   0.242925 -28.699  < 2e-16
## age                                    0.029373   0.001760  16.693  < 2e-16
## workclass Federal-gov                  0.966112   0.166737   5.794 6.86e-09
## workclass Local-gov                    0.362486   0.151204   2.397   0.0165
## workclass Never-worked               -10.740772 333.392623  -0.032   0.9743
## workclass Private                      0.554583   0.134859   4.112 3.92e-05
## workclass Self-emp-inc                 0.825242   0.161448   5.112 3.20e-07
## workclass Self-emp-not-inc             0.106586   0.148343   0.719   0.4724
## workclass State-gov                    0.156498   0.165129   0.948   0.3433
## workclass Without-pay                -12.229956 218.138278  -0.056   0.9553
```

```
## education 11th                        -0.056833   0.233697  -0.243   0.8079
## education 12th                         0.607009   0.277971   2.184   0.0290
## education 1st-4th                     -0.725741   0.464978  -1.561   0.1186
## education 5th-6th                     -0.460474   0.348199  -1.322   0.1860
## education 7th-8th                     -0.591074   0.254284  -2.324   0.0201
## education 9th                         -0.555298   0.296418  -1.873   0.0610
## education Assoc-acdm                   1.276529   0.193340   6.602 4.04e-11
## education Assoc-voc                    1.313741   0.185128   7.096 1.28e-12
## education Bachelors                    1.971646   0.172237  11.447  < 2e-16
## education Doctorate                    2.955892   0.232274  12.726  < 2e-16
## education HS-grad                      0.738202   0.168210   4.389 1.14e-05
## education Masters                      2.353122   0.183330  12.835  < 2e-16
## education Preschool                  -11.633386 129.576912  -0.090   0.9285
## education Prof-school                  3.043054   0.217199  14.010  < 2e-16
## education Some-college                 1.074970   0.170528   6.304 2.90e-10
## maritalstatus Married-AF-spouse        2.419811   0.575338   4.206 2.60e-05
## maritalstatus Married-civ-spouse       2.093609   0.070977  29.497  < 2e-16
## maritalstatus Married-spouse-absent    0.019944   0.233382   0.085   0.9319
## maritalstatus Never-married           -0.466253   0.086986  -5.360 8.32e-08
## maritalstatus Separated               -0.245498   0.174889  -1.404   0.1604
## maritalstatus Widowed                 -0.042687   0.154873  -0.276   0.7828
## occupation Adm-clerical                0.104270   0.107293   0.972   0.3311
## occupation Armed-Forces               -0.519519   1.396471  -0.372   0.7099
## occupation Craft-repair                0.141664   0.092960   1.524   0.1275
## occupation Exec-managerial             0.904007   0.094987   9.517  < 2e-16
## occupation Farming-fishing            -0.922612   0.154606  -5.968 2.41e-09
## occupation Handlers-cleaners          -0.671411   0.162294  -4.137 3.52e-05
## occupation Machine-op-inspct          -0.173751   0.115034  -1.510   0.1309
## occupation Other-service              -0.793418   0.135386  -5.860 4.62e-09
## occupation Priv-house-serv            -2.547249   1.217294  -2.093   0.0364
## occupation Prof-specialty              0.628490   0.101722   6.178 6.47e-10
## occupation Protective-serv             0.596874   0.145475   4.103 4.08e-05
## occupation Sales                       0.406006   0.098008   4.143 3.43e-05
## occupation Tech-support                0.753259   0.129899   5.799 6.68e-09
## occupation Transport-moving                  NA         NA      NA       NA
## sex Male                               0.113354   0.056383   2.010   0.0444
## hoursperweek                           0.031028   0.001761  17.615  < 2e-16
##
## (Intercept)                          ***
## age                                  ***
## workclass Federal-gov                ***
## workclass Local-gov                  *
## workclass Never-worked
## workclass Private                    ***
## workclass Self-emp-inc               ***
## workclass Self-emp-not-inc
## workclass State-gov
## workclass Without-pay
## education 11th
## education 12th                       *
```

```
## education 1st-4th
## education 5th-6th
## education 7th-8th                *
## education 9th                    .
## education Assoc-acdm             ***
## education Assoc-voc              ***
## education Bachelors              ***
## education Doctorate              ***
## education HS-grad                ***
## education Masters                ***
## education Preschool
## education Prof-school            ***
## education Some-college           ***
## maritalstatus Married-AF-spouse     ***
## maritalstatus Married-civ-spouse    ***
## maritalstatus Married-spouse-absent
## maritalstatus Never-married         ***
## maritalstatus Separated
## maritalstatus Widowed
## occupation Adm-clerical
## occupation Armed-Forces
## occupation Craft-repair
## occupation Exec-managerial          ***
## occupation Farming-fishing          ***
## occupation Handlers-cleaners        ***
## occupation Machine-op-inspct
## occupation Other-service            ***
## occupation Priv-house-serv          *
## occupation Prof-specialty           ***
## occupation Protective-serv          ***
## occupation Sales                    ***
## occupation Tech-support             ***
## occupation Transport-moving
## sex Male                            *
## hoursperweek                        ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 26962  on 24420  degrees of freedom
## Residual deviance: 17240  on 24375  degrees of freedom
## AIC: 17332
##
## Number of Fisher Scoring iterations: 13
```

```
predictiontrain <- predict(linReg,traindata,type='response')
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```
pred1 <- rep('<=50K', length(predictiontrain))
pred1[predictiontrain>=.5] <- '>50K'
tb1 <- table(pred1, traindata$income)
tb1

##
## pred1    <=50K  >50K
##   <=50K  17168  2644
##   >50K    1372  3237

prob <- predict(linReg, testdata, type = 'response')

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading

prediction <- predict(linReg,testdata,type='response')

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading

########################################################################
# P values shows that Age ,workclass, education, marital status, occupation,
# race, sex, hours per week  are the significant attributes.
########################################################################
pred <- rep('<=50K', length(prob))
pred[prob>=.5] <- '>50K'
tb <- table(pred, testdata$income)
tb

##
## pred     <=50K  >50K
##   <=50K   5684   904
##   >50K     495  1056

# Confusion matrix shows that it has an Accuracy of 83.01%
# misclasification 17%.
```

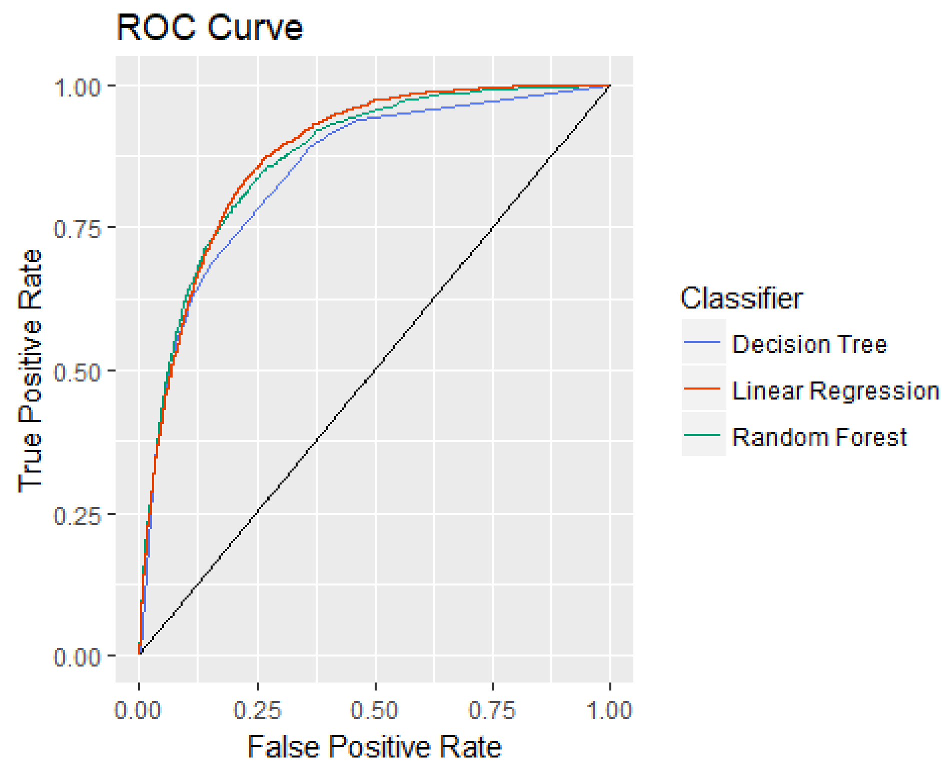
Finally we have to compare the the Algorithm

```
###DECISION TREE
prtree <- prediction(Dectree.pred.prob[,2],testdata$income)
perftree  <- performance(prtree,measure="tpr",x.measure="fpr")
DTFrametree <-
data.frame(FP=perftree@x.values[[1]],TP=perftree@y.values[[1]])
auctree <- performance(prtree, measure='auc')@y.values[[1]]
auctree

## [1] 0.8500693

###RANDOM FOREST
prRForest <- prediction(randforest.pred.prob[,2],testdata$income)
perfRForest  <- performance(prRForest,measure="tpr",x.measure="fpr")
```

```r
DTFrameRForest <-
data.frame(FP=perfRForest@x.values[[1]],TP=perfRForest@y.values[[1]])
aucFtree <- performance(prRForest, measure='auc')@y.values[[1]]
aucFtree

## [1] 0.8733921

## LINEAR REGRESION
pr  <- prediction(prob,testdata$income)
perf <- performance(pr,measure="tpr", x.measure="fpr")
DtFrameReg <- data.frame(FP=perf@x.values[[1]],TP=perf@y.values[[1]])
aucRegresion <- performance(pr,measure='auc')@y.values[[1]]
aucRegresion

## [1] 0.879603
```

Use of ROC curve

```r
g <- ggplot() +
  geom_line(data = DTFrametree, aes(x = FP, y = TP, color = 'Decision Tree'))
+
  geom_line(data = DTFrameRForest, aes(x = FP, y = TP, color = 'Random
Forest')) +
  geom_line(data = DtFrameReg, aes(x = FP, y = TP, color = 'Linear
Regression')) +
  geom_segment(aes(x = 0, xend = 1, y = 0, yend = 1)) +
  ggtitle('ROC Curve') +
  labs(x = 'False Positive Rate', y = 'True Positive Rate')

g +  scale_colour_manual(name = 'Classifier', values = c('Decision
Tree'='#5674E9', 'Random Forest'='#009E73', 'Linear Regression'='#E63F00'))
```




```
auc <- rbind(aucRegresion,auctree,aucFtree)
rownames(auc) <- (c('Decision Tree', 'Random Forest', 'Linear Regression'))
colnames(auc) <- 'ROC Curve Area'
round(auc, 6)

##                     ROC Curve Area
## Decision Tree             0.879603
## Random Forest             0.850069
## Linear Regression         0.873392
```