Problem 1:

a) no. of features $P = 1$

$X \rightarrow$ uniformly distributed on $[0, 1]$

10% range is used when predicting a test observation

i.e., for $X = 0.6$ we look at $[0.55, 0.65]$

I $X = 0.5$ we consider $[0.45, 0.55]$

\# but for $X = 0.4$ ($X < 0.5$ scenario)

II we take only $[0, 0.9]$

III Similarly for $(X > 0.95)$ $X = 0.99$

we look at only $[0.94, 1]$

So on an average we consider, the fraction of available observations we consider for prediction is <u>less than 10%</u>

Exact value can be calcutate using area method.

for $[0.05, 0.95] \Rightarrow 10\%$

for $[0, 0.05] \Rightarrow (100x+5)\%$

$[0.95, 1] \Rightarrow (105-100x)\%$

So integral sum of these values give total area (fraction we are interested in)

$$= \int_{0.5}^{0.95} 10\,dx + \int_{0.0}^{0.05} (100x+5)\,dx + \int_{.95}^{1} (105-100x)\,dx$$

$$= 9 + 0.375 + 0.375$$

$$= 9.750$$

$$= \boxed{9.75\%}$$

We expect to look at 9.75% observations on average.

(b) with $p = 2$.

(x_1, x_2) uniformly distributed on $[0,1] \times [0,1]$

$\Rightarrow$ Examples.

I $\quad x_1 = 0.6$; $x_2 = 0.35$.

observation range would be.

$x_1 \rightarrow [0.55, 0.65]$

$x_2 \rightarrow [0.3, 0.4]$

II $\quad x_1 = 0.04$; $x_2 = 0.5$

$x_1 \rightarrow [0, 0.09]$ $\quad x_2 \Rightarrow [0.45, 0.5]$.

it is similar to previous case.

in case $P = 2$

the fraction would be $= (9.75) \times (9.75)$

$= \cancel{.9.5} = \boxed{0.95\%}$

(c) $P = 100$

the fraction aviable observation for making prediction would be

$(0.95)^{100} \simeq 0\%$

(d) as we insremene P (number of featur) we left with fewer fraction of observation for prediction

as $P \to \infty$ this would be zero.

(e) 10% training observations are und for prediction

$P=1 \to$ line $\Rightarrow$ length $= \left(\frac{1}{10}\right)$

$P=2 \to$ Square $=$ length $= \left(\frac{1}{10}\right)^2$

$P=100 \to$ length $= \left(\frac{1}{10}\right)^{100}$

Problem 3

x_1 = hours studied

x_2 = undergrad GPA

y = recieve an A

Coefficient in logistic Regression fit

$\hat{\beta}_0 = -6 \quad \hat{\beta}_1 = 0.05 \; ; \quad \hat{\beta}_2 = 1$

given $x_1 = 40$ & $x_2 = 3.5$

(a) $$\hat{p}(x) = \frac{e^{-6+0.05\times 40+1(3.5)}}{1+e^{-6+0.05\times 40+1(3.5)}}$$

$$\boxed{=0.37754}$$

(b) given $\hat{p}(x) = 50\%$ $\quad x_2 = 3.5$

$$0.5 = e^{-6+0.05x_1+3.5} / 1+e^{-6+0.05x_1+3.5}$$

$$\Rightarrow \boxed{x_1 = 50}$$ 50 hours.

Problem: 2

LDA Vs QDA

a. If the Bayes decision boundary is linear, do we expect LDA or QDA to perform better on the training set? On the test set?
    I. For **Training set**: we expect QDA to perform better as it fits closer to data point in training data set
    II. For **Test set:** We expect LDA to perform better on test set as QDA over fits the training data leading to high variance when applied to test set

b. If the Bayes decision boundary is non-linear, do we expect LDA or QDA to perform better on the training set? On the test set?

   This case we expect QDA to perform better for both training and test data as bias component is too high with LDA model.

c. In general, as the sample size nn increases, do we expect the test prediction accuracy of QDA relative to LDA to improve, decline, or be unchanged? Why?

In general, with higher sample size QDA performs better compared to LDA as variance component is not a big concern when the sample size is large.

d. True or False: Even if the Bayes decision boundary for a given problem is linear, we will probably achieve a superior test error rate using QDA rather than LDA because QDA is flexible enough to model a linear decision boundary. Justify your answer.

False. When the sample size is smaller QDA will over fit the training data, leading to higher error with Test data.

Problem: 4

For KNN with K=1 ➔ we have zero percent training error➔ test error itself 36%

Whereas test error for logistic regression model is 30%, which is better than KNN.

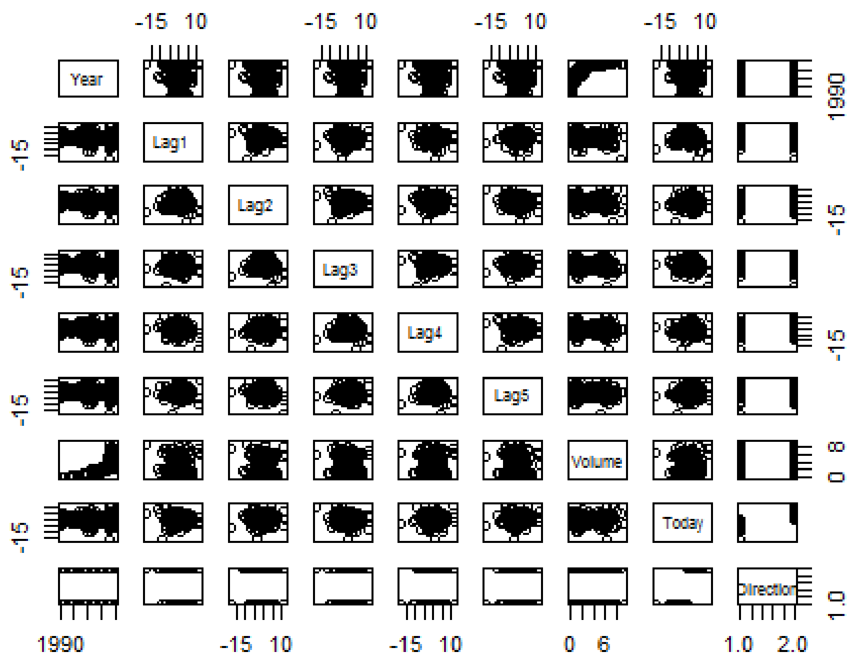
So we choose Logistic regression over KNN with k=1 model

Problem: 5

(a) Produce some numerical and graphical summaries of the Weekly data. Do there appear to be any patterns?

```
library(ISLR)

## Warning: package 'ISLR' was built under R version 3.2.5

summary(Weekly)

##       Year           Lag1               Lag2               Lag3
##  Min.   :1990   Min.   :-18.1950   Min.   :-18.1950   Min.   :-18.1950
##  1st Qu.:1995   1st Qu.: -1.1540   1st Qu.: -1.1540   1st Qu.: -1.1580
##  Median :2000   Median :  0.2410   Median :  0.2410   Median :  0.2410
##  Mean   :2000   Mean   :  0.1506   Mean   :  0.1511   Mean   :  0.1472
##  3rd Qu.:2005   3rd Qu.:  1.4050   3rd Qu.:  1.4090   3rd Qu.:  1.4090
##  Max.   :2010   Max.   : 12.0260   Max.   : 12.0260   Max.   : 12.0260
##       Lag4               Lag5              Volume
##  Min.   :-18.1950   Min.   :-18.1950   Min.   :0.08747
##  1st Qu.: -1.1580   1st Qu.: -1.1660   1st Qu.:0.33202
##  Median :  0.2380   Median :  0.2340   Median :1.00268
##  Mean   :  0.1458   Mean   :  0.1399   Mean   :1.57462
##  3rd Qu.:  1.4090   3rd Qu.:  1.4050   3rd Qu.:2.05373
##  Max.   : 12.0260   Max.   : 12.0260   Max.   :9.32821
##      Today          Direction
##  Min.   :-18.1950   Down:484
##  1st Qu.: -1.1540   Up  :605
##  Median :  0.2410
##  Mean   :  0.1499
##  3rd Qu.:  1.4050
##  Max.   : 12.0260
```

```r
pairs(Weekly)
```

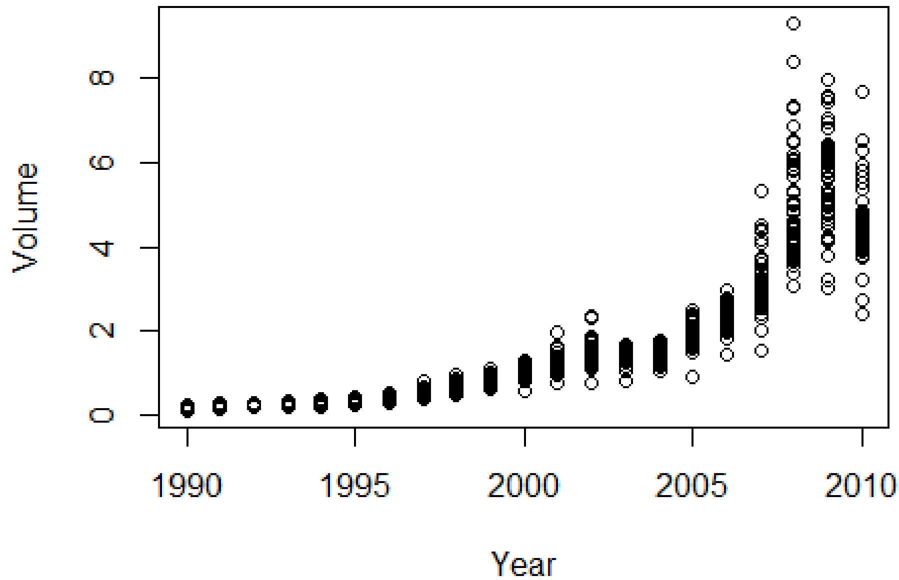



```r
cor(Weekly[,-9])
```

```
##              Year         Lag1        Lag2        Lag3         Lag4
## Year    1.00000000 -0.032289274 -0.03339001 -0.03000649 -0.031127923
## Lag1   -0.03228927  1.000000000 -0.07485305  0.05863568 -0.071273876
## Lag2   -0.03339001 -0.074853051  1.00000000 -0.07572091  0.058381535
## Lag3   -0.03000649  0.058635682 -0.07572091  1.00000000 -0.075395865
## Lag4   -0.03112792 -0.071273876  0.05838153 -0.07539587  1.000000000
## Lag5   -0.03051910 -0.008183096 -0.07249948  0.06065717 -0.075675027
## Volume  0.84194162 -0.064951313 -0.08551314 -0.06928771 -0.061074617
## Today  -0.03245989 -0.075031842  0.05916672 -0.07124364 -0.007825873
##                Lag5      Volume        Today
## Year   -0.030519101  0.84194162 -0.032459894
## Lag1   -0.008183096 -0.06495131 -0.075031842
## Lag2   -0.072499482 -0.08551314  0.059166717
## Lag3    0.060657175 -0.06928771 -0.071243639
## Lag4   -0.075675027 -0.06107462 -0.007825873
## Lag5    1.000000000 -0.05851741  0.011012698
## Volume -0.058517414  1.00000000 -0.033077783
## Today   0.011012698 -0.03307778  1.000000000
```

Thera is high correlation between Year and Volume, lets plot bivariate plot for these variables

```r
attach(Weekly)
plot(Year,Volume)
```



Median volume is increasing each year

(b) Use the full data set to perform a logistic regression with Direction as the response and the five lag variables plus Volume as predictors.

```r
glm_model <- glm(Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 + Volume, data
= Weekly, family = binomial)
summary(glm_model)

##
## Call:
## glm(formula = Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 +
##     Volume, family = binomial, data = Weekly)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6949  -1.2565   0.9913   1.0849   1.4579
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.26686    0.08593   3.106   0.0019 **
## Lag1        -0.04127    0.02641  -1.563   0.1181
```

```
## Lag2         0.05844    0.02686   2.175   0.0296 *
## Lag3        -0.01606    0.02666  -0.602   0.5469
## Lag4        -0.02779    0.02646  -1.050   0.2937
## Lag5        -0.01447    0.02638  -0.549   0.5833
## Volume      -0.02274    0.03690  -0.616   0.5377
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1496.2  on 1088  degrees of freedom
## Residual deviance: 1486.4  on 1082  degrees of freedom
## AIC: 1500.4
##
## Number of Fisher Scoring iterations: 4
```

Only Lag2 is statistically significant variable among all other X variables

(c) Compute the confusion matrix and overall fraction of correct predictions. Explain what the confusion matrix is telling you about the types of mistakes made by logistic regression.

```
ods <- predict(glm_model, type = "response")
glm_pred <- rep("Down", length(ods))
glm_pred[ods > 0.5] <- "Up"
table(glm_pred, Direction)
```

```
##         Direction
## glm_pred Down  Up
##     Down   54  48
##     Up    430 557
```

- By looking at the above confusion matrix, we can calculate training error rate: (430+48)/1089 = 43.89348 %
- Also training error is really high when Direction is Down: 430/ (54+430): 88.84298 %
- When the Direction is Up, the training error is better: 48/ (48+557): 7.93388%

(d) Now fit the logistic regression model using a training data period from 1990 to 2008, with "Lag2" as the only predictor. Compute the confusion matrix and the overall fraction of correct predictions for the held out data (that is, the data from 2009 to 2010).

```
Weekly_Pre2009 <- Weekly[Year<2009, ]
Weekly_Post2009 <- Weekly[Year>2008, ]
glm_model <- glm(Direction ~ Lag2, data = Weekly_Pre2009, family = binomial)
summary(glm_model)
```

```
##
## Call:
## glm(formula = Direction ~ Lag2, family = binomial, data = Weekly_Pre2009)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.536  -1.264   1.021   1.091   1.368
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.20326    0.06428   3.162  0.00157 **
## Lag2         0.05810    0.02870   2.024  0.04298 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1354.7  on 984  degrees of freedom
## Residual deviance: 1350.5  on 983  degrees of freedom
## AIC: 1354.5
##
## Number of Fisher Scoring iterations: 4
```

```r
ods <- predict(glm_model, Weekly_Post2009, type = "response")
glm_pred <- rep("Down", length(ods))
glm_pred[ods > 0.5] <- "Up"
table(glm_pred, Weekly_Post2009$Direction)
```

```
##
## glm_pred Down Up
##     Down    9  5
##     Up     34 56
```

- By looking at the above confusion matrix, we can calculate test error rate: 39/104= **37.5%**
- Also test error is really high when Direction is Down: 34/43: **79.0697 %**
- When the Direction is Up: 5/61: **8.19672%**

(e) Repeat (d) using LDA.

```r
library(MASS)
lda_model <- lda(Direction ~ Lag2, data = Weekly_Pre2009)
lda_model
```

```
## Call:
## lda(Direction ~ Lag2, data = Weekly_Pre2009)
##
```

```
## Prior probabilities of groups:
##      Down        Up 
## 0.4477157 0.5522843 
## 
## Group means:
##             Lag2
## Down -0.03568254
## Up    0.26036581
## 
## Coefficients of linear discriminants:
##            LD1
## Lag2 0.4414162
```

```
lda_pred <- predict(lda_model, Weekly_Post2009)
table(lda_pred$class, Weekly_Post2009$Direction)
```

```
## 
##        Down Up
##   Down    9  5
##   Up     34 56
```

- By looking at the above confusion matrix, we can calculate test error rate: 39/104= **37.5%**
- Also test error is really high when Direction is Down: 34/43: **79.0697 %**
- When the Direction is Up: 5/61: **8.19672%**
- This results are similar to what wo got from Logistic Regression Model

(f) Repeat (d) using QDA.

```
qda_model <- qda(Direction ~ Lag2, data = Weekly_Pre2009)
qda_model
```

```
## Call:
## qda(Direction ~ Lag2, data = Weekly_Pre2009)
## 
## Prior probabilities of groups:
##      Down        Up 
## 0.4477157 0.5522843 
## 
## Group means:
##             Lag2
```

```
## Down -0.03568254
## Up    0.26036581

qda_pred <- predict(qda_model, Weekly_Post2009)
table(qda_pred$class, Weekly_Post2009$Direction)

##
##         Down Up
##   Down     0  0
##   Up      43 61
```

- By looking at the above confusion matrix, we can calculate test error rate: 61/104= **58.6538%**
- Also test error is really high when Direction is Down being **100 %**
- **Even with moderate overall test error, we don't want to consider this model as it always predict when Direction is UP**

(g) Repeat (d) using KNN with K=1

```
set.seed(12)
library(class)

## Warning: package 'class' was built under R version 3.2.5

## with K =5
knn_pred <- knn(as.matrix(Weekly_Pre2009[,c("Lag2")]), as.matrix(Weekly_Post2
009[,c("Lag2")]), Weekly_Pre2009$Direction, k = 1)
table(knn_pred, Weekly_Post2009$Direction)

##
## knn_pred Down Up
##     Down   21 29
##     Up     22 32
```

- Test error rate: 22+29/(104) : **41.34615%**
- Also test error is really high when Direction is Down: **51.162790%**
- When the Direction is Up: 29/61: **47.54098%**

(h) Which of these methods appears to provide the best results on this data?

If we compare the test error rates, we see that logistic regression and LDA have the minimum error rates, followed by KNN and QDA.

(i) examine whether it is worth to include interactions via a forward selection scheme for LDA, which greedily minimizes the test error as it adds variables to the model one at a time.

```
library(MASS)
## step 1
lda_model <- lda(Direction ~ Lag2, data = Weekly_Pre2009)
lda_model
```

```
## Call:
## lda(Direction ~ Lag2, data = Weekly_Pre2009)
##
## Prior probabilities of groups:
##      Down        Up
## 0.4477157 0.5522843
##
## Group means:
##             Lag2
## Down -0.03568254
## Up    0.26036581
##
## Coefficients of linear discriminants:
##            LD1
## Lag2 0.4414162
```

```
lda_pred <- predict(lda_model, Weekly_Post2009)
table(lda_pred$class, Weekly_Post2009$Direction)
```

```
##
##         Down Up
##   Down     9  5
##   Up      34 56
```

```
mean(lda_pred$class !=Weekly_Post2009$Direction)
```

```
## [1] 0.375
```

```
library(MASS)
## step 2
lda_model <- lda(Direction ~ Lag2:Lag3, data = Weekly_Pre2009)
lda_model
```

```
## Call:
## lda(Direction ~ Lag2:Lag3, data = Weekly_Pre2009)
##
## Prior probabilities of groups:
```

```
##      Down        Up
## 0.4477157 0.5522843
##
## Group means:
##       Lag2:Lag3
## Down -0.1937158
## Up   -0.6405132
##
## Coefficients of linear discriminants:
##                 LD1
## Lag2:Lag3 0.1012928
```

```
lda_pred <- predict(lda_model, Weekly_Post2009)
table(lda_pred$class, Weekly_Post2009$Direction)
```

```
##
##        Down Up
##   Down    0  0
##   Up     43 61
```

```
mean(lda_pred$class !=Weekly_Post2009$Direction)
```

```
## [1] 0.4134615
```

```
library(MASS)
## step 3
lda_model <- lda(Direction ~ Lag2:Lag4, data = Weekly_Pre2009)
lda_model
```

```
## Call:
## lda(Direction ~ Lag2:Lag4, data = Weekly_Pre2009)
##
## Prior probabilities of groups:
##      Down        Up
## 0.4477157 0.5522843
##
## Group means:
##       Lag2:Lag4
## Down 0.78824608
## Up   0.04407141
##
## Coefficients of linear discriminants:
##                 LD1
## Lag2:Lag4 0.1287072
```

```
lda_pred <- predict(lda_model, Weekly_Post2009)
table(lda_pred$class, Weekly_Post2009$Direction)
```

```
##
##        Down Up
##   Down    1  4
##   Up     42 57
```

```r
mean(lda_pred$class !=Weekly_Post2009$Direction)

## [1] 0.4423077

library(MASS)
## step 4
lda_model <- lda(Direction ~ Lag2:Lag5, data = Weekly_Pre2009)
lda_model

## Call:
## lda(Direction ~ Lag2:Lag5, data = Weekly_Pre2009)
##
## Prior probabilities of groups:
##      Down        Up
## 0.4477157 0.5522843
##
## Group means:
##       Lag2:Lag5
## Down -0.3132494
## Up   -0.3497535
##
## Coefficients of linear discriminants:
##                 LD1
## Lag2:Lag5 0.1105356

lda_pred <- predict(lda_model, Weekly_Post2009)
table(lda_pred$class, Weekly_Post2009$Direction)

##
##        Down Up
##   Down    0  0
##   Up     43 61

mean(lda_pred$class !=Weekly_Post2009$Direction)

## [1] 0.4134615
```

With forward selection after Step 1, as we add more variable using forward selection the test errors are increasing, so there is no point adding variables other Lag2 in the model.

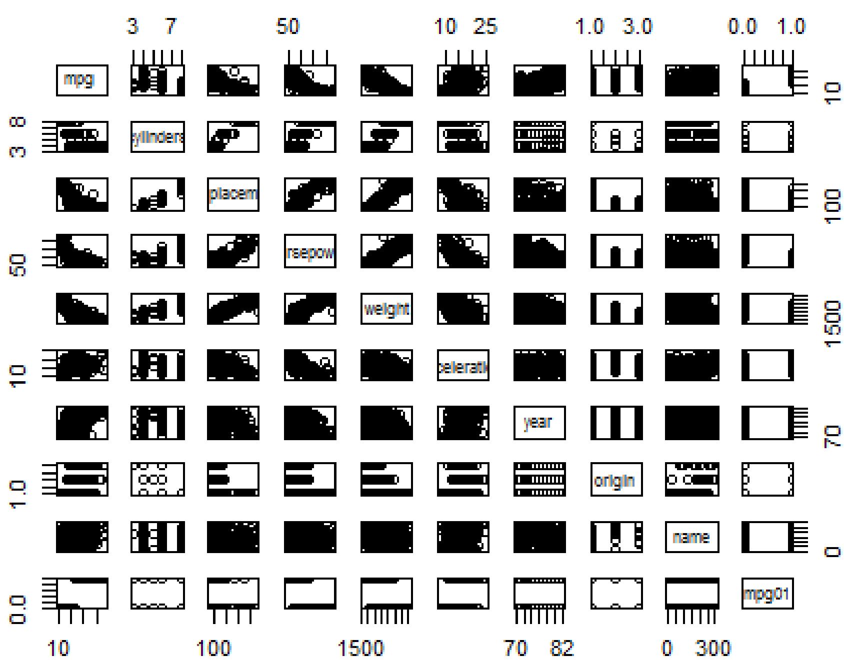
Problem 6

(j) Create a binary variable, mpg01, that contains a 1 if mpg contains a value above its median, and a 0 if mpg contains a value below its median.

```
library(ISLR)

## Warning: package 'ISLR' was built under R version 3.2.5

attach(Auto)
Auto$mpg01 <- 0
Auto[mpg > median(mpg),]$mpg01 <- 1
```

(b)Explore the data graphically in order to investigate the association between mpg01 and the other features. Which of the other features seem most likely to be useful in predicting mpg01?

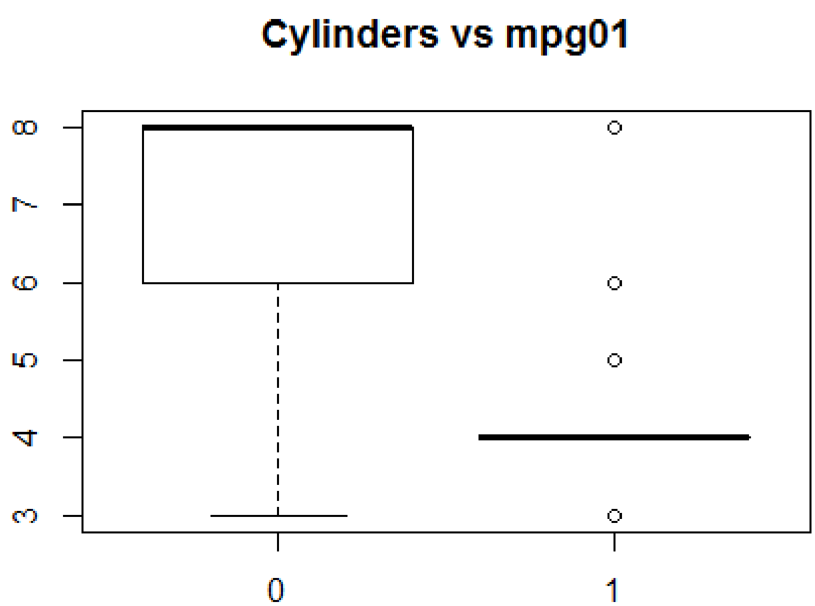
```
pairs(Auto)
```



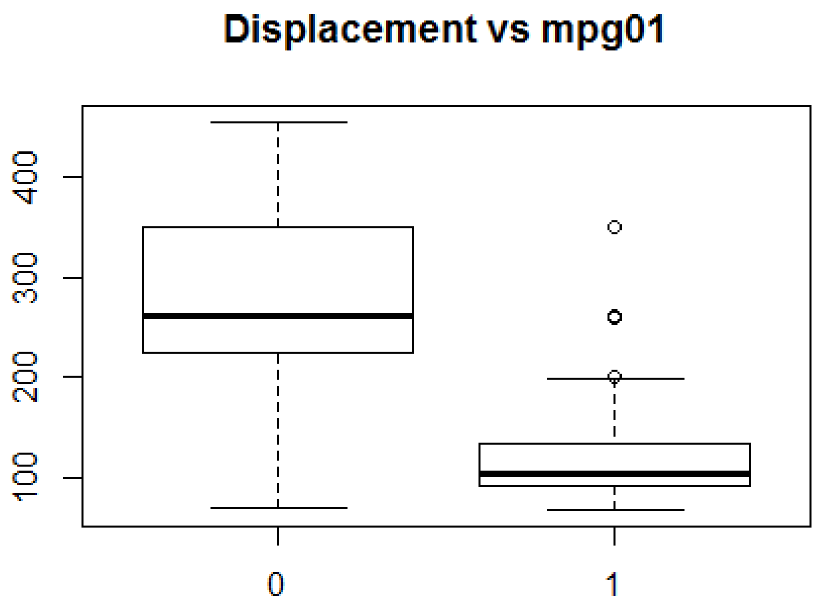

```
cor(Auto[,-9])

##                     mpg  cylinders displacement horsepower     weight
## mpg           1.0000000 -0.7776175   -0.8051269 -0.7784268 -0.8322442
## cylinders    -0.7776175  1.0000000    0.9508233  0.8429834  0.8975273
```

```
## displacement -0.8051269  0.9508233    1.0000000  0.8972570  0.9329944
## horsepower   -0.7784268  0.8429834    0.8972570  1.0000000  0.8645377
## weight       -0.8322442  0.8975273    0.9329944  0.8645377  1.0000000
## acceleration  0.4233285 -0.5046834   -0.5438005 -0.6891955 -0.4168392
## year          0.5805410 -0.3456474   -0.3698552 -0.4163615 -0.3091199
## origin        0.5652088 -0.5689316   -0.6145351 -0.4551715 -0.5850054
## mpg01         0.8369392 -0.7591939   -0.7534766 -0.6670526 -0.7577566
##              acceleration       year     origin      mpg01
## mpg             0.4233285  0.5805410  0.5652088  0.8369392
## cylinders      -0.5046834 -0.3456474 -0.5689316 -0.7591939
## displacement   -0.5438005 -0.3698552 -0.6145351 -0.7534766
## horsepower     -0.6891955 -0.4163615 -0.4551715 -0.6670526
## weight         -0.4168392 -0.3091199 -0.5850054 -0.7577566
## acceleration    1.0000000  0.2903161  0.2127458  0.3468215
## year            0.2903161  1.0000000  0.1815277  0.4299042
## origin          0.2127458  0.1815277  1.0000000  0.5136984
## mpg01           0.3468215  0.4299042  0.5136984  1.0000000
```

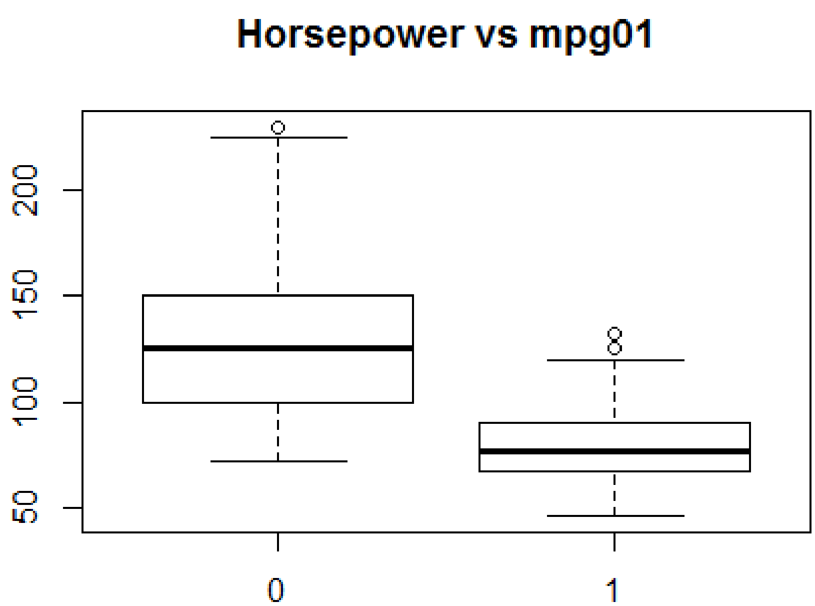
```
boxplot(cylinders ~ mpg01, data = Auto, main = "Cylinders vs mpg01")
```



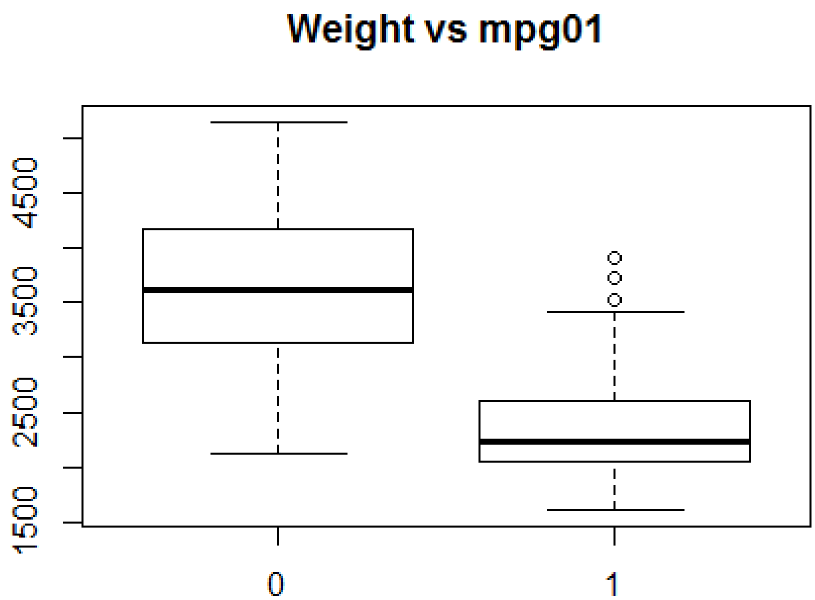

```
boxplot(displacement ~ mpg01, data = Auto, main = "Displacement vs mpg01")
```



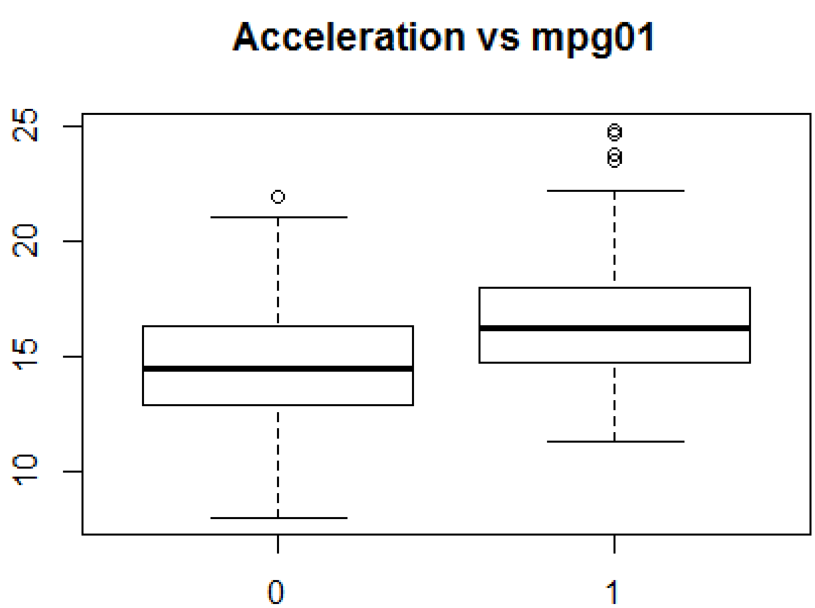

```r
boxplot(horsepower ~ mpg01, data = Auto, main = "Horsepower vs mpg01")
```



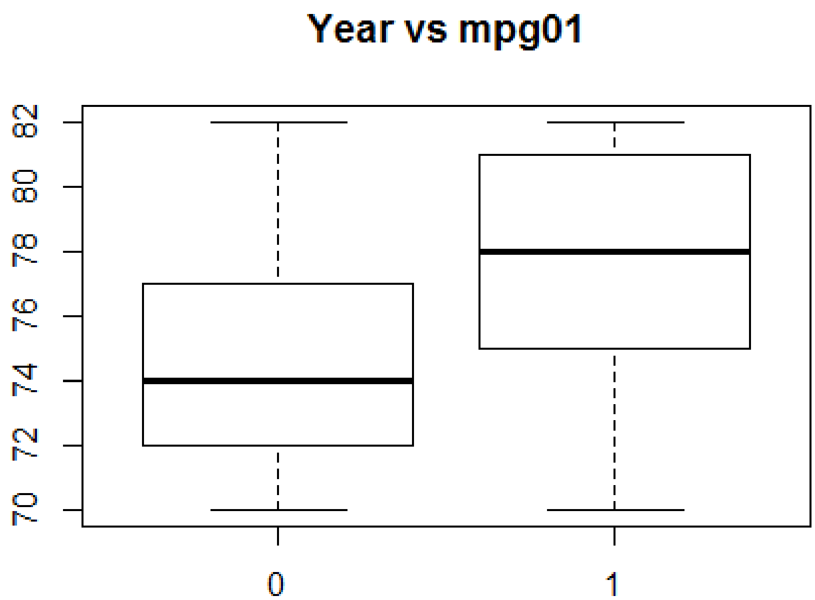

```r
boxplot(weight ~ mpg01, data = Auto, main = "Weight vs mpg01")
```




```r
boxplot(acceleration ~ mpg01, data = Auto, main = "Acceleration vs mpg01")
```




```r
boxplot(year ~ mpg01, data = Auto, main = "Year vs mpg01")
```



By looking at correlation matrix, scatterplot and boxplots we can say there is some relationship between mpg01 and cylinders, weight, displacement and horsepower.

(c) Split the data into a training set and a test set.

```
## add rnum coloumn
Auto$rnum<-seq(1,nrow(Auto),1)
## split data
Auto_train <- Auto[Auto$rnum %% 2 ==0, ]
Auto_test<- Auto[Auto$rnum %% 2 !=0, ]
##drop runm coloumn
Auto_train<-Auto_train[,!(names(Auto_train)  %in% c("rnum"))]
Auto_test<-Auto_test[,!(names(Auto_test) %in% c("rnum"))]
Auto<-Auto[,!(names(Auto)  %in% c("rnum"))]
```

(d) Perform LDA on the training data in order to predict "mpg01" using the variables that seemed most associated with "mpg01" in (b). What is the test error of the model obtained?

```
library(MASS)
lda_model <- lda(mpg01 ~ cylinders + weight + displacement + horsepower, data
= Auto_train)
lda_model

## Call:
## lda(mpg01 ~ cylinders + weight + displacement + horsepower, data = Auto_tr
ain)
##
```

```
## Prior probabilities of groups:
##         0         1 
## 0.4897959 0.5102041 
## 
## Group means:
##   cylinders   weight displacement horsepower
## 0  6.760417 3653.583      273.500   132.4271
## 1  4.170000 2305.070      114.045    78.8700
## 
## Coefficients of linear discriminants:
##                        LD1
## cylinders    -0.4297440160
## weight       -0.0011996694
## displacement  0.0003516146
## horsepower    0.0021885992
```

```
lda_pred <- predict(lda_model, Auto_test)
table(lda_pred$class, Auto_test$mpg01)
```

```
## 
##      0  1
##   0 83  6
##   1 17 90
```

```
mean(lda_pred$class !=Auto_test$mpg01)
```

```
## [1] 0.1173469
```

Hence the error rate is 11.73%

(e) Perform QDA on the training data in order to predict "mpg01"

```
qda_model <- qda(mpg01 ~ cylinders + weight + displacement + horsepower, data
= Auto_train)
qda_model
```

```
## Call:
## qda(mpg01 ~ cylinders + weight + displacement + horsepower, data = Auto_tr
ain)
## 
## Prior probabilities of groups:
##         0         1 
## 0.4897959 0.5102041 
## 
## Group means:
##   cylinders   weight displacement horsepower
## 0  6.760417 3653.583      273.500   132.4271
## 1  4.170000 2305.070      114.045    78.8700
```

```
qda_pred <- predict(qda_model, Auto_test)
table(qda_pred$class, Auto_test$mpg01)
```

```
##
##      0  1
##   0 89  9
##   1 11 87
```

```
mean(qda_pred$class != Auto_test$mpg01)
```

```
## [1] 0.1020408
```

Hence the error rate with QDA model is **10.20%** which is lower compared to LDA

(f) Perform logistic regression on the training data in order to predict "mpg01"

```
glm_model <- glm(mpg01 ~ cylinders + weight + displacement + horsepower, data
= Auto_train, family = binomial)
summary(glm_model)
```

```
##
## Call:
## glm(formula = mpg01 ~ cylinders + weight + displacement + horsepower,
##     family = binomial, data = Auto_train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.2416  -0.1088   0.1038   0.3176   2.9731
##
## Coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)  13.1401211  2.5218930   5.210 1.88e-07 ***
## cylinders    -0.0665897  0.4846865  -0.137   0.8907
## weight       -0.0025557  0.0009355  -2.732   0.0063 **
## displacement -0.0084554  0.0109024  -0.776   0.4380
## horsepower   -0.0431963  0.0197508  -2.187   0.0287 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 271.632  on 195  degrees of freedom
## Residual deviance:  97.301  on 191  degrees of freedom
## AIC: 107.3
##
## Number of Fisher Scoring iterations: 7
```

```
ods <- predict(glm_model, Auto_test, type = "response")
glm_pred <- rep(0, length(ods))
glm_pred[ods > 0.5] <- 1
table(glm_pred, Auto_test$mpg01)
```

```
##
## glm_pred  0  1
```

```
##        0 88  8
##        1 12 88
```

```
mean(glm_pred != Auto_test$mpg01)
```

```
## [1] 0.1020408
```

Test Error rate here is:10.20 %

(g) Perform KNN on the training data, with several values of K, in order to predict "mpg01"

```
set.seed(12)
library(class)
```

```
## Warning: package 'class' was built under R version 3.2.5
```

```
## with K =5
knn_pred <- knn(Auto_train[,c("cylinders", "weight", "displacement", "horsepo
wer")], Auto_test[,c("cylinders", "weight", "displacement", "horsepower")], A
uto_train$mpg01, k = 5)
table(knn_pred, Auto_test$mpg01)
```

```
##
## knn_pred  0  1
##        0 86 17
##        1 14 79
```

```
mean(knn_pred != Auto_test$mpg01)
```

```
## [1] 0.1581633
```

```
## with K =10
knn_pred <- knn(Auto_train[,c("cylinders", "weight", "displacement", "horsepo
wer")], Auto_test[,c("cylinders", "weight", "displacement", "horsepower")], A
uto_train$mpg01, k = 10)
table(knn_pred, Auto_test$mpg01)
```

```
##
## knn_pred  0  1
##        0 85 18
##        1 15 78
```

```
mean(knn_pred != Auto_test$mpg01)
```

```
## [1] 0.1683673
```

```
## with K =100
knn_pred <- knn(Auto_train[,c("cylinders", "weight", "displacement", "horsepo
wer")], Auto_test[,c("cylinders", "weight", "displacement", "horsepower")], A
uto_train$mpg01, k = 100)
table(knn_pred, Auto_test$mpg01)
```

```
##
## knn_pred  0  1
```

```
##        0 82  7
##        1 18 89

mean(knn_pred != Auto_test$mpg01)

## [1] 0.127551

## with K =125
knn_pred <- knn(Auto_train[,c("cylinders", "weight", "displacement", "horsepo
wer")], Auto_test[,c("cylinders", "weight", "displacement", "horsepower")], A
uto_train$mpg01, k =125)
table(knn_pred, Auto_test$mpg01)

##
## knn_pred  0  1
##        0 78  4
##        1 22 92

mean(knn_pred != Auto_test$mpg01)

## [1] 0.1326531
```

For KNN with K=125, the error rate is lower, hence better performance model among other KNN models