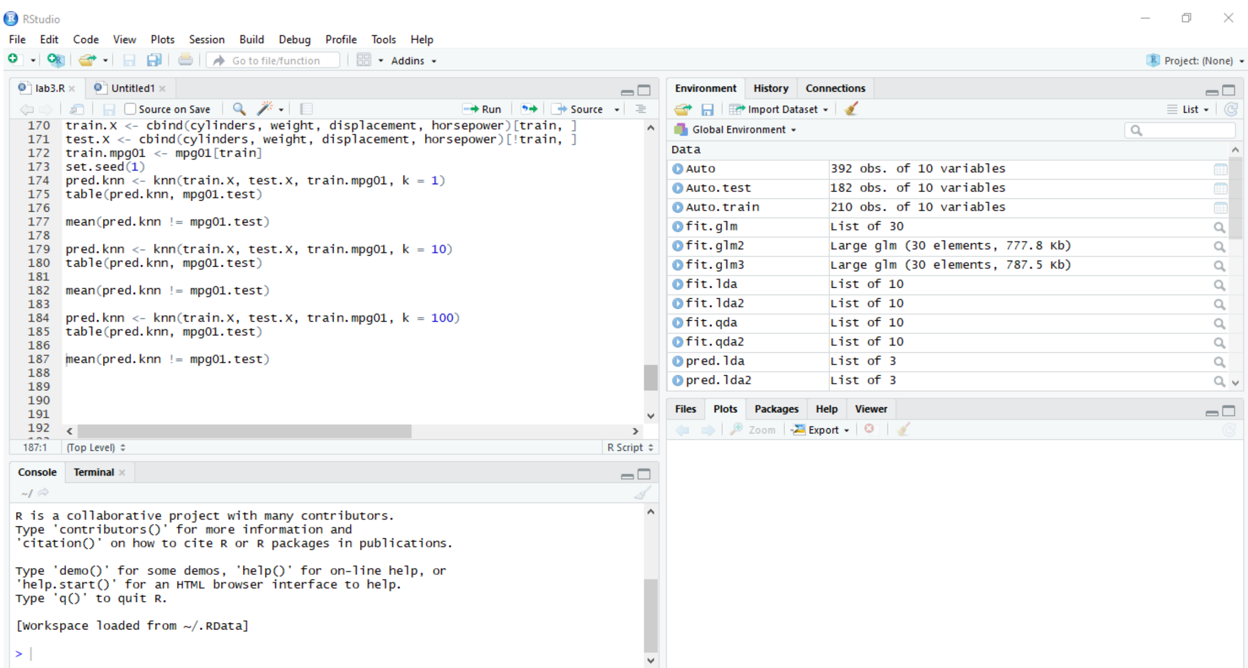
Introduction to Statistical Learning Lab3

Name: Sandeep Reddy Salkuti

Id: 16296868

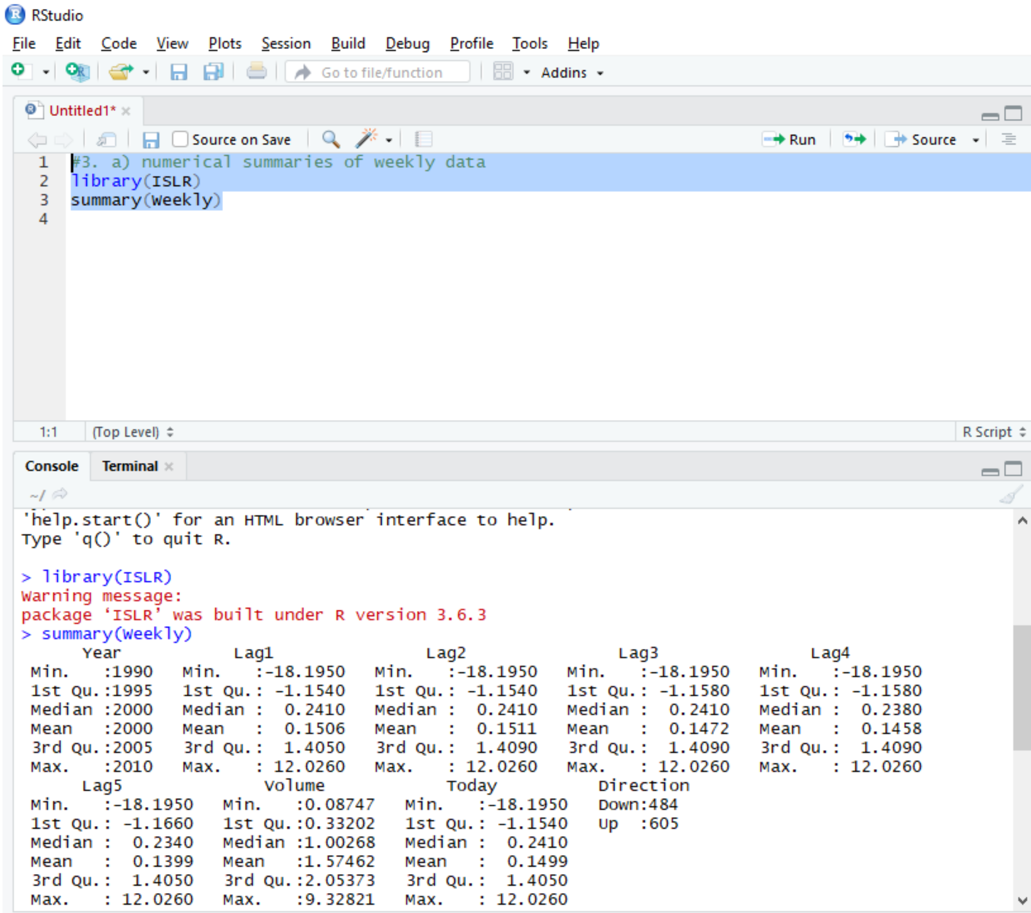
Email: sswf7@umsystem.edu

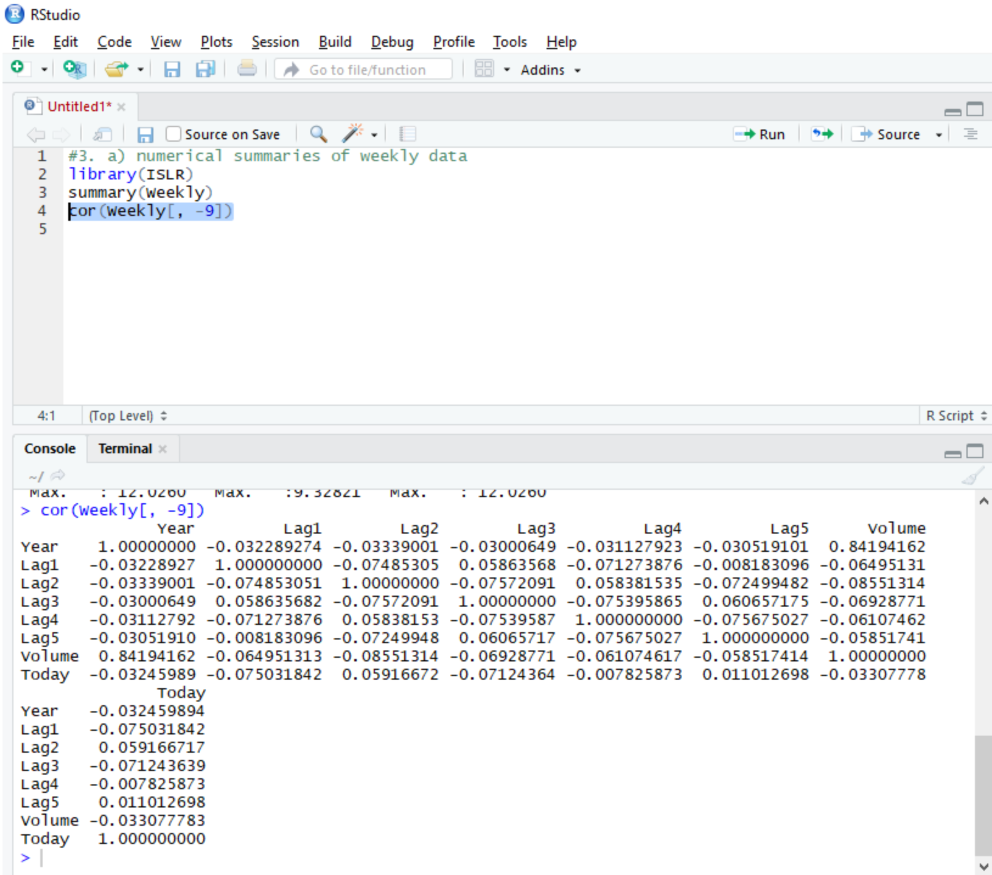
1. **You may download the R Code for Labs and the Data Sets to use from the textbook website.**

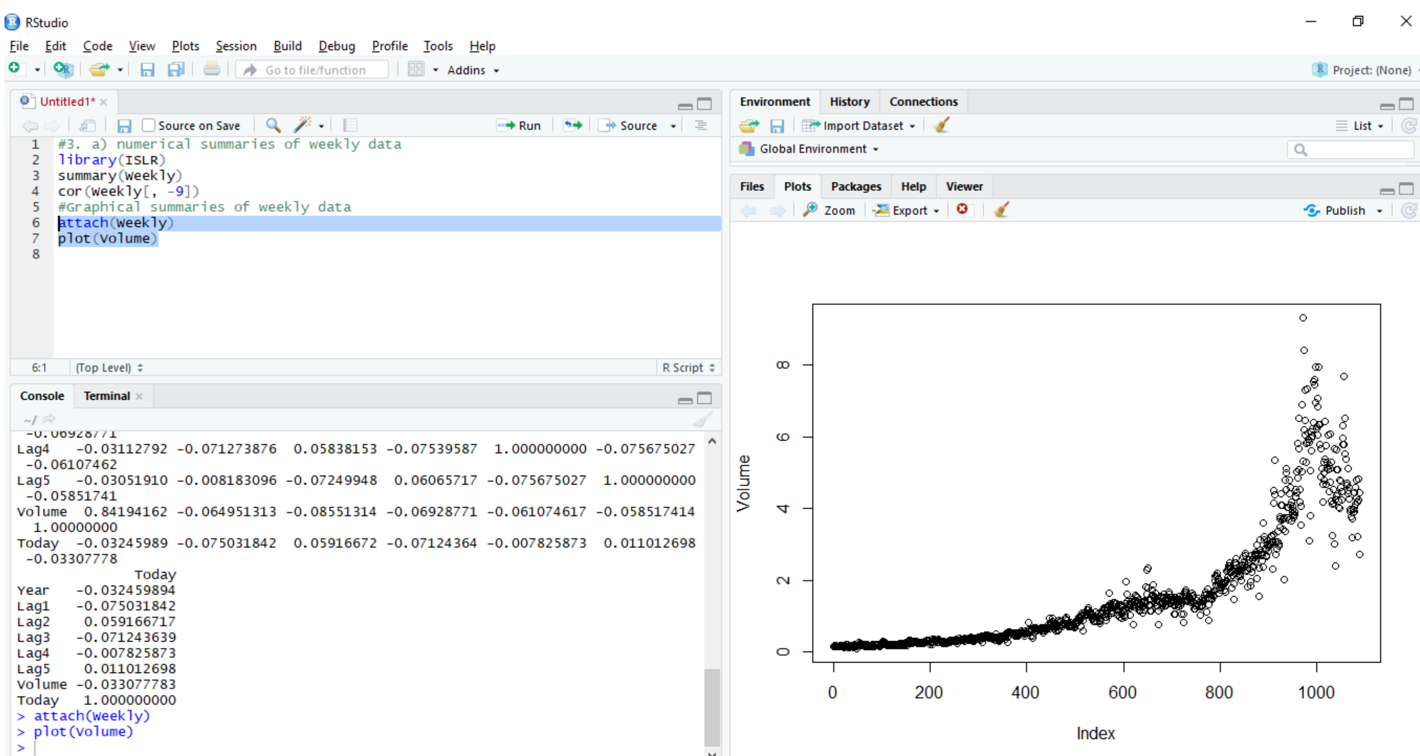


2. This question should be answered using the Weekly data set, which is part of the ISLR package. This data is similar in nature to the Smarket data from this chapters lab, except that it contains 1,089 weekly returns for 21 years, from the beginning of 1990 to the end of 2010.

(a) (5 points) Produce some numerical and graphical summaries of the Weekly data. Do there appear to be any patterns?

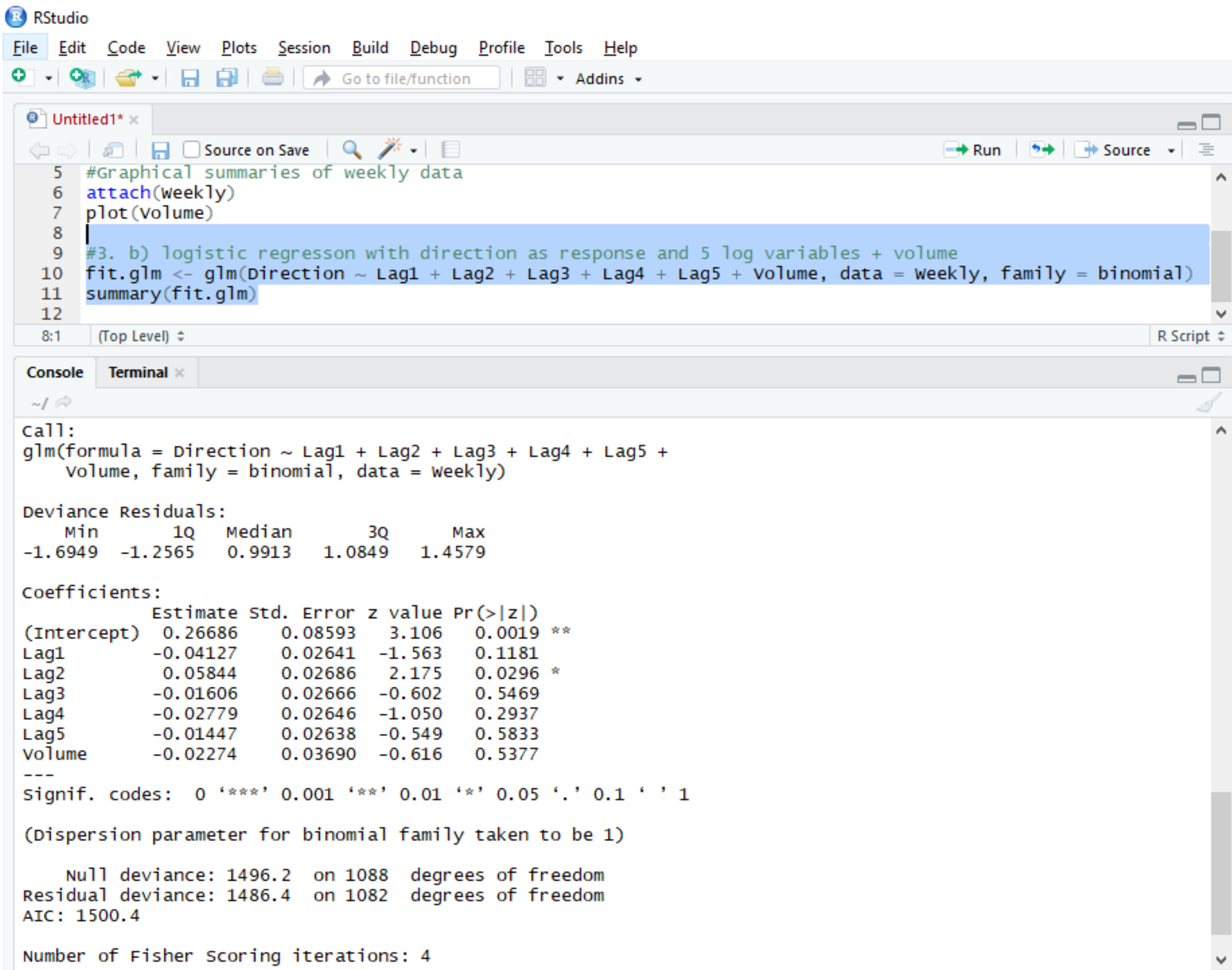

RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
Go to file/function
Addins
Untitled1*
Source on Save
Run
Source
#3. a) numerical summaries of weekly data
library(ISLR)
summary(Weekly)
1:1
(Top Level)
R Script
Console
Terminal
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.
> library(ISLR)
Warning message:
package 'ISLR' was built under R version 3.6.3
> summary(Weekly)
Year Lag1 Lag2 Lag3 Lag4
Min. :1990 Min. :-18.1950 Min. :-18.1950 Min. :-18.1950 Min. :-18.1950
1st Qu.:1995 1st Qu.: -1.1540 1st Qu.: -1.1540 1st Qu.: -1.1580 1st Qu.: -1.1580
Median :2000 Median : 0.2410 Median : 0.2410 Median : 0.2410 Median : 0.2380
Mean :2000 Mean : 0.1506 Mean : 0.1511 Mean : 0.1472 Mean : 0.1458
3rd Qu.:2005 3rd Qu.: 1.4050 3rd Qu.: 1.4090 3rd Qu.: 1.4090 3rd Qu.: 1.4090
Max. :2010 Max. : 12.0260 Max. : 12.0260 Max. : 12.0260 Max. : 12.0260
Lag5 Volume Today Direction
Min. :-18.1950 Min. :0.08747 Min. :-18.1950 Down:484
1st Qu.: -1.1660 1st Qu.:0.33202 1st Qu.: -1.1540 Up :605
Median : 0.2340 Median :1.00268 Median : 0.2410
Mean : 0.1399 Mean :1.57462 Mean : 0.1499
3rd Qu.: 1.4050 3rd Qu.:2.05373 3rd Qu.: 1.4050
Max. : 12.0260 Max. :9.32821 Max. : 12.0260


RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
Go to file/function
Addins
Untitled1*
Source on Save
Run
Source
#3. a) numerical summaries of weekly data
library(ISLR)
summary(Weekly)
cor(Weekly[, -9])
4:1
(Top Level)
R Script
Console
Terminal
Max. : 12.0260 Max. :9.32821 Max. : 12.0260
> cor(Weekly[, -9])
Year Lag1 Lag2 Lag3 Lag4 Lag5 Volume
Year 1.00000000 -0.032289274 -0.03339001 -0.03000649 -0.031127923 -0.030519101 0.84194162
Lag1 -0.03228927 1.000000000 -0.07485305 0.05863568 -0.071273876 -0.008183096 -0.06495131
Lag2 -0.03339001 -0.074853051 1.00000000 -0.07572091 0.058381535 -0.072499482 -0.08551314
Lag3 -0.03000649 0.058635682 -0.07572091 1.00000000 -0.075395865 0.060657175 -0.06928771
Lag4 -0.03112792 -0.071273876 0.05838153 -0.07539587 1.000000000 -0.075675027 -0.06107462
Lag5 -0.03051910 -0.008183096 -0.07249948 0.06065717 -0.075675027 1.000000000 -0.05851741
Volume 0.84194162 -0.064951313 -0.08551314 -0.06928771 -0.061074617 -0.058517414 1.00000000
Today -0.03245989 -0.075031842 0.05916672 -0.07124364 -0.007825873 0.011012698 -0.03307778
Today
Year -0.032459894
Lag1 -0.075031842
Lag2 0.059166717
Lag3 -0.071243639
Lag4 -0.007825873
Lag5 0.011012698
Volume -0.033077783
Today 1.000000000
>


RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
Go to file/function
Addins
Project: (None)
Untitled1*
Source on Save
Run
Source
#3. a) numerical summaries of weekly data
library(ISLR)
summary(Weekly)
cor(Weekly[, -9])
#Graphical summaries of weekly data
attach(Weekly)
plot(Volume)
6:1
(Top Level)
R Script
Console
Terminal
-0.06928771
Lag4 -0.03112792 -0.071273876 0.05838153 -0.07539587 1.000000000 -0.075675027
-0.06107462
Lag5 -0.03051910 -0.008183096 -0.07249948 0.06065717 -0.075675027 1.000000000
-0.05851741
Volume 0.84194162 -0.064951313 -0.08551314 -0.06928771 -0.061074617 -0.058517414
1.00000000
Today -0.03245989 -0.075031842 0.05916672 -0.07124364 -0.007825873 0.011012698
-0.03307778
Today
Year -0.032459894
Lag1 -0.075031842
Lag2 0.059166717
Lag3 -0.071243639
Lag4 -0.007825873
Lag5 0.011012698
Volume -0.033077783
Today 1.000000000
> attach(Weekly)
> plot(Volume)
>
Environment History Connections
Import Dataset
List
Global Environment
Files Plots Packages Help Viewer
Zoom
Export
Publish
Volume
0
2
4
6
8
0
200
400
600
800
1000
Index

From numerical summaries correlations between lag variables and today's returns are close to zero. Their exists substantial correlation between and "year" and "volume". From the above plot it is clear that volume increases for index values and

(b) (5 points)Use the full data set to perform a logistic regression with Direction as the response and the five lag variables plus Volume as predictors. Use the summary function to print the results. Do any of the predictors appear to be statistically significant? If so, which ones?




```r
#Graphical summaries of weekly data
attach(Weekly)
plot(Volume)

#3. b) logistic regresson with direction as response and 5 log variables + volume
fit.glm <- glm(Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 + Volume, data = Weekly, family = binomial)
summary(fit.glm)
```

```
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
```

From the above it is clear that "**Lag2"** appears to be only predictor that is statistically significant. It is because of its p value is less than 0.05 (Pr(>|z|) = 3%.)

(c) (5 points) 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.

```r
#3. c) confusion mtarix and overall fraction of correct predictions
probs <- predict(fit.glm, type = "response")
pred.glm <- rep("Down", length(probs))
pred.glm[probs > 0.5] <- "Up"
table(pred.glm, Direction)
```

```
> probs <- predict(fit.glm, type = "response")
> pred.glm <- rep("Down", length(probs))
> pred.glm[probs > 0.5] <- "Up"
> table(pred.glm, Direction)
        Direction
pred.glm Down  Up
    Down   54  48
    Up    430 557
>
```

From above it is clear that percentage of correct predictions on the training data is (54 + 557)/1089= 0.5610 which is equal to 56.1% In contrast training error rate is 43.89% which is often overly optimistic. We can say that for weeks when the market goes up, the model is 92.0661% of the time (557/(48+557)). For weeks when the market goes down, the model is only 11.15702% of the time (54/(54+430)).

(d) (5 points) 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 and 2010).

RStudio

File Edit Code View Plots Session Build Debug Profile Tools Help

Untitled1*

```r

#3. 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).
train <- (Year < 2009)
Weekly.20092010 <- Weekly[!train, ]
Direction.20092010 <- Direction[!train]
fit.glm2 <- glm(Direction ~ Lag2, data = Weekly, family = binomial, subset = train)
summary(fit.glm2)
```

22:1 (Top Level) R Script

Console Terminal

```
Call:
glm(formula = Direction ~ Lag2, family = binomial, data = Weekly,
    subset = train)

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

probs2 <- predict(fit.glm2, Weekly.20092010, type = "response")
pred.glm2 <- rep("Down", length(probs2))
pred.glm2[probs2 > 0.5] <- "Up"
table(pred.glm2, Direction.20092010)

```

27:1 (Top Level)

Console Terminal

```
> probs2 <- predict(fit.glm2, Weekly.20092010, type = "response")
> pred.glm2 <- rep("Down", length(probs2))
> pred.glm2[probs2 > 0.5] <- "Up"
> table(pred.glm2, Direction.20092010)
         Direction.20092010
pred.glm2 Down Up
     Down    9  5
     Up     34 56
>
```

From the above it is clear that the percentage of correct predictions on the test data is (9+56)/104 which equals to 62.5%. In other words test error rate is 37.5%. Also for weeks when the market goes up, the model is 91.803% of the time (56/(56+5)). For weeks when the market goes down, the model is only 20.930% of the time (9/(9+34)).

(e) (5 points) Repeat (d) using LDA.

```
#3. e) Repeat (d) using LDA.
library(MASS)
fit.lda <- lda(Direction ~ Lag2, data = Weekly, subset = train)
fit.lda
```

```
33:1    (Top Level) ÷
```

```
Console   Terminal ×
~/
> library(MASS)
Warning message:
package 'MASS' was built under R version 3.6.3
> fit.lda <- lda(Direction ~ Lag2, data = Weekly, subset = train)
> fit.lda
Call:
lda(Direction ~ Lag2, data = Weekly, subset = train)

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
```

```

pred.lda <- predict(fit.lda, Weekly.20092010)
table(pred.lda$class, Direction.20092010)

```

```
58:1    (Top Level) ÷
```

```
Console   Terminal ×
~/
> pred.lda <- predict(fit.lda, Weekly.20092010)
> table(pred.lda$class, Direction.20092010)
        Direction.20092010
         Down Up
  Down      9  5
  Up       34 56
>
```

From above it is clear that percentage of correct predictions on the test data is 62.5%. In other words test error rate is 37.5%. We can say that for weeks when the market goes up, the model is 91.803% of the time. For weeks when the market goes down, the model is only 20.9302% of the time. These results are very close to those obtained with the logistic regression model which is not surprising.

(f) (5 points) Repeat (d) using QDA.

```r
#3. f) Repeat (d) using QDA.
fit.qda <- qda(Direction ~ Lag2, data = Weekly, subset = train)
fit.qda
```

40:1 (Top Level)

Console Terminal

~/

```
> fit.qda <- qda(Direction ~ Lag2, data = Weekly, subset = train)
> fit.qda
Call:
qda(Direction ~ Lag2, data = Weekly, subset = train)

Prior probabilities of groups:
     Down        Up 
0.4477157 0.5522843 

Group means:
            Lag2
Down -0.03568254
Up    0.26036581
>
```

```r
#3. f) Repeat (d) using QDA.
fit.qda <- qda(Direction ~ Lag2, data = Weekly, subset = train)
fit.qda


pred.qda <- predict(fit.qda, Weekly.20092010)
table(pred.qda$class, Direction.20092010)
```

62:1 (Top Level)

Console Terminal

~/

```
> pred.qda <- predict(fit.qda, Weekly.20092010)
> table(pred.qda$class, Direction.20092010)
      Direction.20092010
       Down Up
  Down    0  0
  Up     43 61
>
```

From above it is clear that the percentage of correct predictions on the test data is 58.6538%. In other words test error rate is 41.3461%. We could also say that for weeks when the market goes up, the model is 100% of the time. For weeks when the market goes down, the model is only 0% of the time. It is clear that QDA achieves a correctness of 58.6538% even though the model chooses "Up" the whole time.

(g) (5 points) Repeat (d) using KNN with K = 1.

```
#3. g) Repeat (d) using KNN with K = 1.
library(class)
train.X <- as.matrix(Lag2[train])
test.X <- as.matrix(Lag2[!train])
train.Direction <- Direction[train]
set.seed(1)
pred.knn <- knn(train.X, test.X, train.Direction, k = 1)
table(pred.knn, Direction.20092010)
```

48:1 (Top Level)

Console Terminal

```
        C:\Users\SandeepReddy\AppData\Local\Temp\RtmpwnA9no\downloaded_packages
> library(class)
Warning message:
package 'class' was built under R version 3.6.3
> train.X <- as.matrix(Lag2[train])
> test.X <- as.matrix(Lag2[!train])
> train.Direction <- Direction[train]
> set.seed(1)
> pred.knn <- knn(train.X, test.X, train.Direction, k = 1)
> table(pred.knn, Direction.20092010)
        Direction.20092010
pred.knn Down Up
    Down   21 30
    Up     22 31
>
```

From above it is clear that the percentage of correct predictions on the test data is 50%. In other words test error rate is 50%. We can also say that for weeks when the market goes up, the model is 50.8196% of the time. For weeks when the market goes down, the model is only 48.8372% of the time.

(h) (5 points) Which of these methods appears to provide the best results on this data?

After comparison of all test error rates, It is clear that logistic regression and LDA have the minimum error rates, followed by QDA and KNN.

(i) (5 points) Experiment with different combinations of predictors, including possible transformations and interactions, for each of the methods. Report the variables, method, and associated confusion matrix that appears to provide the best results on the held out data. Note that you should also experiment with values for K in the KNN classifier.

Logistic regression with Lag2:Lag1

```r
#3. i)Experiment with different combinations of predictors,
#including possible transformations and interactions, for each of the
#methods. Report the variables, method, and associated confusion matrix
#that appears to provide the best results on the held out data. Note that
#you should also experiment with values for K in the KNN classifier.

#logistic regression with Lag2:Lag1
fit.glm3 <- glm(Direction ~ Lag2:Lag1, data = Weekly, family = binomial, subset = train)
probs3 <- predict(fit.glm3, Weekly.20092010, type = "response")
pred.glm3 <- rep("Down", length(probs3))
pred.glm3[probs3 > 0.5] = "Up"
table(pred.glm3, Direction.20092010)
```

63:1 (Top Level)

Console Terminal

```
~/
> fit.glm3 <- glm(Direction ~ Lag2:Lag1, data = Weekly, family = binomial, subset = train)
> probs3 <- predict(fit.glm3, Weekly.20092010, type = "response")
> pred.glm3 <- rep("Down", length(probs3))
> pred.glm3[probs3 > 0.5] = "Up"
> table(pred.glm3, Direction.20092010)
         Direction.20092010
pred.glm3 Down Up
     Down    1  1
     Up     42 60
>
```

```
> mean(pred.glm3 == Direction.20092010)
[1] 0.5865385
>
```

LDA with Lag2 interaction with Lag1

```
> # LDA with Lag2 interaction with Lag1
> fit.lda2 <- lda(Direction ~ Lag2:Lag1, data = Weekly, subset = train)
> pred.lda2 <- predict(fit.lda2, Weekly.20092010)
> mean(pred.lda2$class == Direction.20092010)
[1] 0.5769231
>
```

QDA with sqrt(abs(Lag2))

```
> # QDA with sqrt(abs(Lag2))
> fit.qda2 <- qda(Direction ~ Lag2 + sqrt(abs(Lag2)), data = Weekly, subset = train)
> pred.qda2 <- predict(fit.qda2, Weekly.20092010)
> table(pred.qda2$class, Direction.20092010)
       Direction.20092010
        Down Up
  Down    12 13
  Up      31 48
> 
```

```
> mean(pred.qda2$class == Direction.20092010)
[1] 0.5769231
> 
```

KNN with K=10

```
> # KNN k =10
> pred.knn2 <- knn(train.X, test.X, train.Direction, k = 10)
> table(pred.knn2, Direction.20092010)
          Direction.20092010
pred.knn2 Down Up
     Down   17 18
     Up     26 43
> 
```

```
> mean(pred.knn2 == Direction.20092010)
[1] 0.5769231
> 
```

KNN with K=100

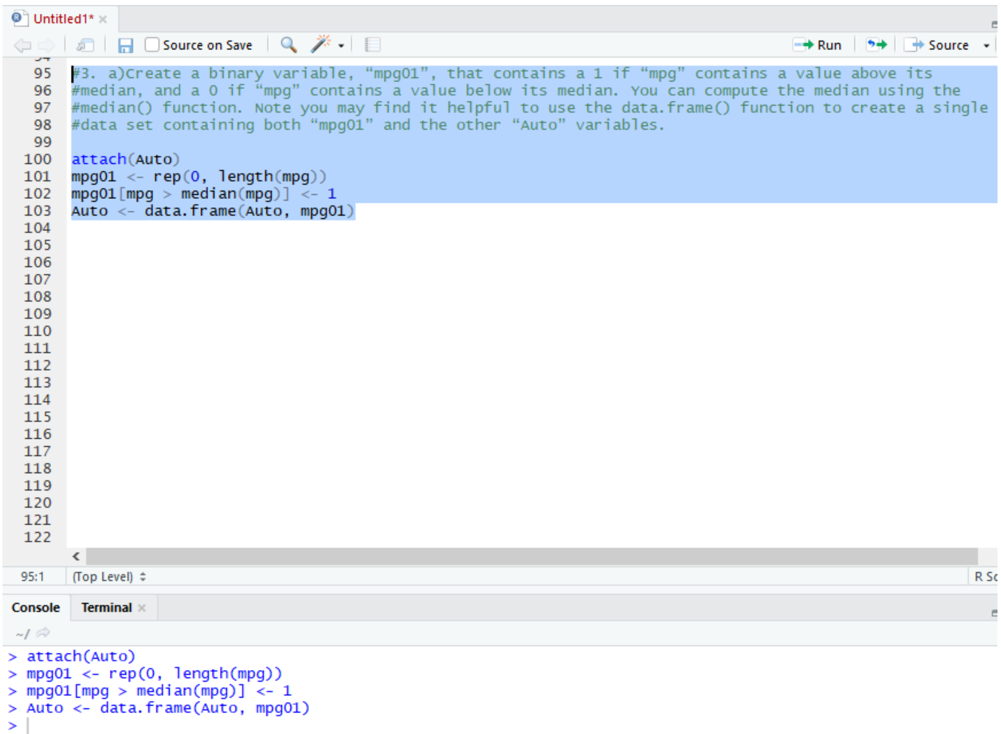
```
> # KNN k = 100
> pred.knn3 <- knn(train.X, test.X, train.Direction, k = 100)
> table(pred.knn3, Direction.20092010)
          Direction.20092010
pred.knn3 Down Up
     Down    9 12
     Up     34 49
> 
```

```
> mean(pred.knn3 == Direction.20092010)
[1] 0.5576923
> 
```

Out of all of these combinations, the original logistic regression and LDA have the best performance in terms of test error rates.

3. In this problem, you will develop a model to predict whether a given car gets high or low gas mileage based on the Auto data set.

(a) (5 points) 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. You can 2 compute the median using the median() function. Note you may find it helpful to use the data.frame() function to create a single data set containing both mpg01 and the other Auto variables.



(b) (5 points) 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? Scatterplots and boxplots may be useful tools to answer this question. Describe your findings.

Untitled1* ×

Source on Save Run Source

```
#3. 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 predictiong "mpg01" ?
#Scatterplots and boxplots may be useful tools to answer this question. Describe your findings.

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

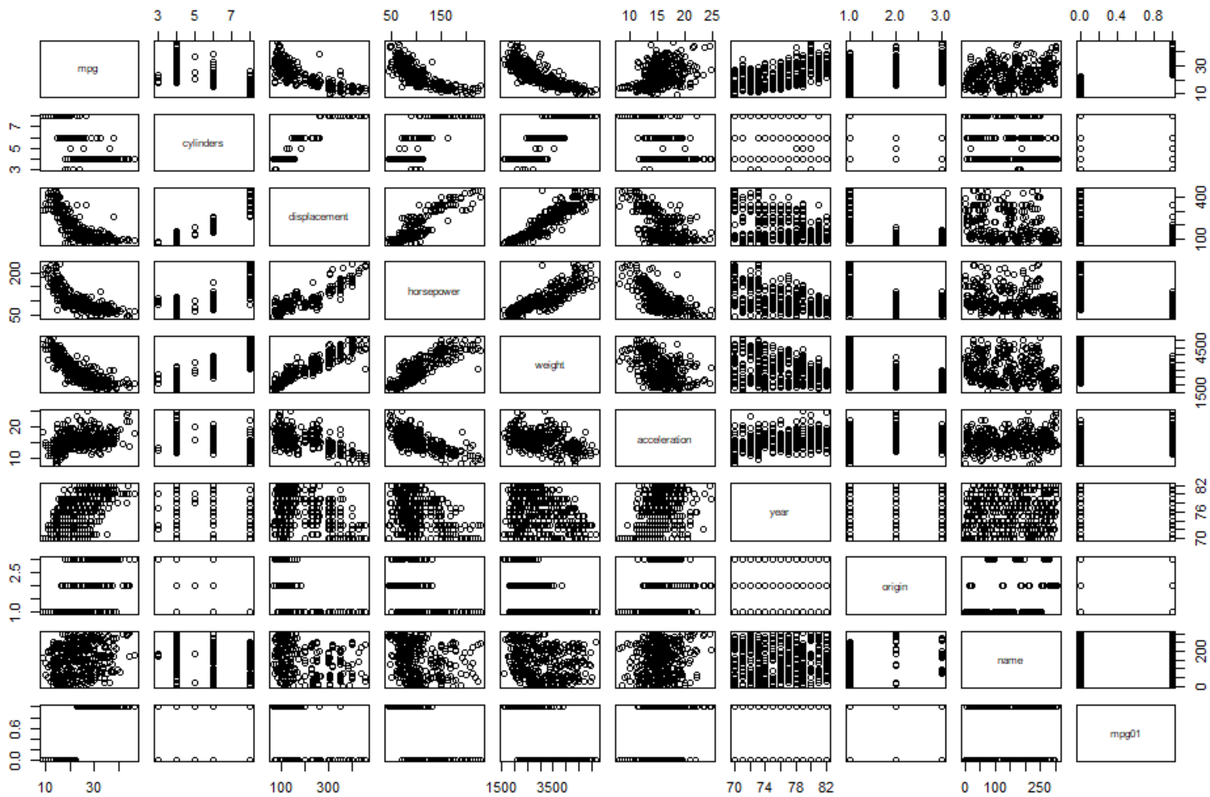
105:1 (Top Level) R

Console Terminal ×

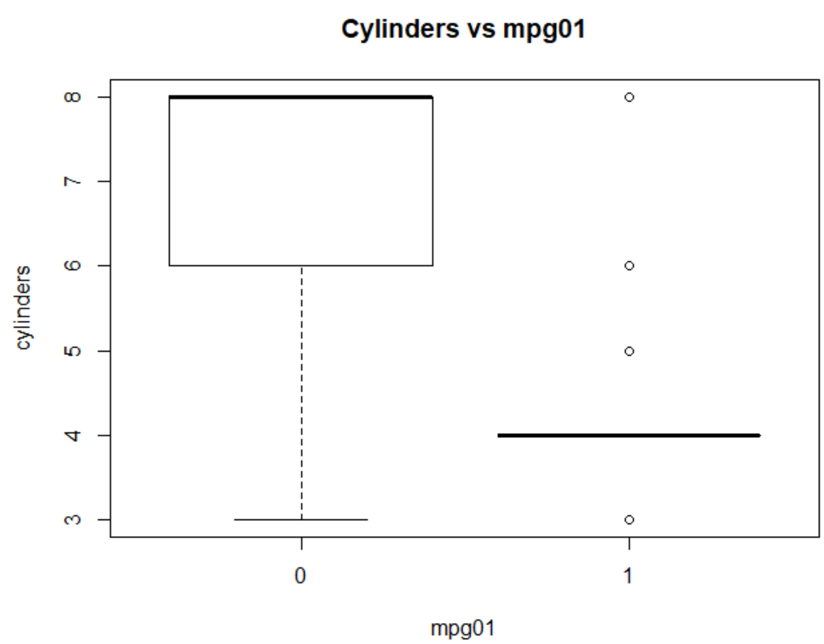
~/

```
> cor(Auto[, -9])
                    mpg  cylinders displacement horsepower     weight acceleration       year     origin
mpg           1.0000000 -0.7776175   -0.8051269 -0.7784268 -0.8322442    0.4233285  0.5805410  0.5652088
cylinders    -0.7776175  1.0000000    0.9508233  0.8429834  0.8975273   -0.5046834 -0.3456474 -0.5689316
displacement -0.8051269  0.9508233    1.0000000  0.8972570  0.9329944   -0.5438005 -0.3698552 -0.6145351
horsepower   -0.7784268  0.8429834    0.8972570  1.0000000  0.8645377   -0.6891955 -0.4163615 -0.4551715
weight       -0.8322442  0.8975273    0.9329944  0.8645377  1.0000000   -0.4168392 -0.3091199 -0.5850054
acceleration  0.4233285 -0.5046834   -0.5438005 -0.6891955 -0.4168392    1.0000000  0.2903161  0.2127458
year          0.5805410 -0.3456474   -0.3698552 -0.4163615 -0.3091199    0.2903161  1.0000000  0.1815277
origin        0.5652088 -0.5689316   -0.6145351 -0.4551715 -0.5850054    0.2127458  0.1815277  1.0000000
mpg01         0.8369392 -0.7591939   -0.7534766 -0.6670526 -0.7577566    0.3468215  0.4299042  0.5136984
                  mpg01
mpg           0.8369392
cylinders    -0.7591939
displacement -0.7534766
horsepower   -0.6670526
weight       -0.7577566
acceleration  0.3468215
year          0.4299042
origin        0.5136984
mpg01         1.0000000
>
```

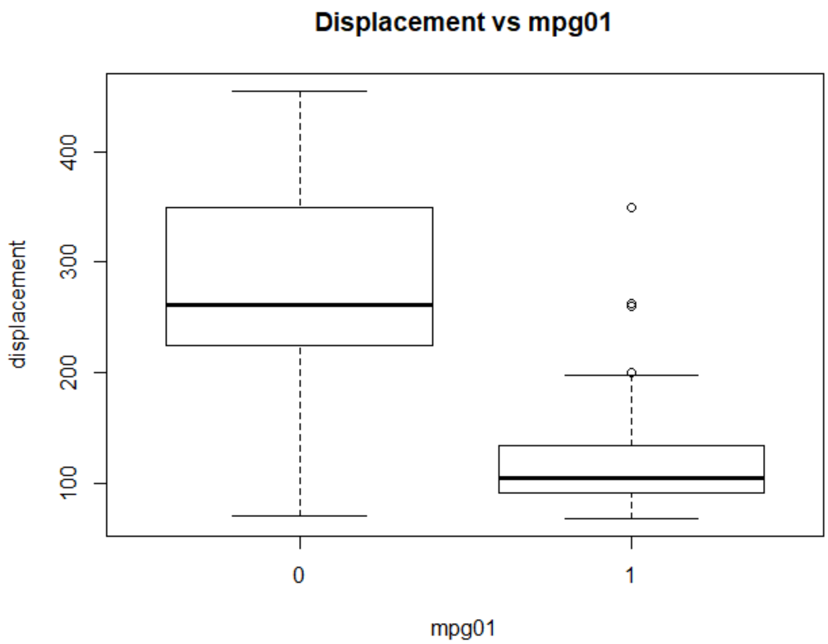
```
> pairs(Auto)
>
```



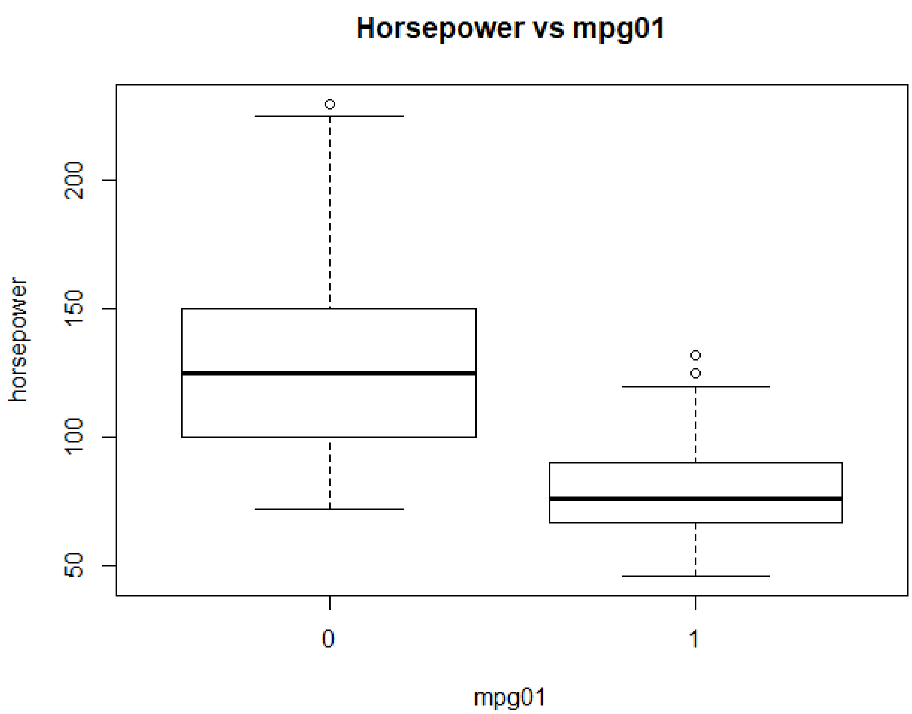

```
> boxplot(cylinders ~ mpg01, data = Auto, main = "Cylinders vs mpg01")
>
```



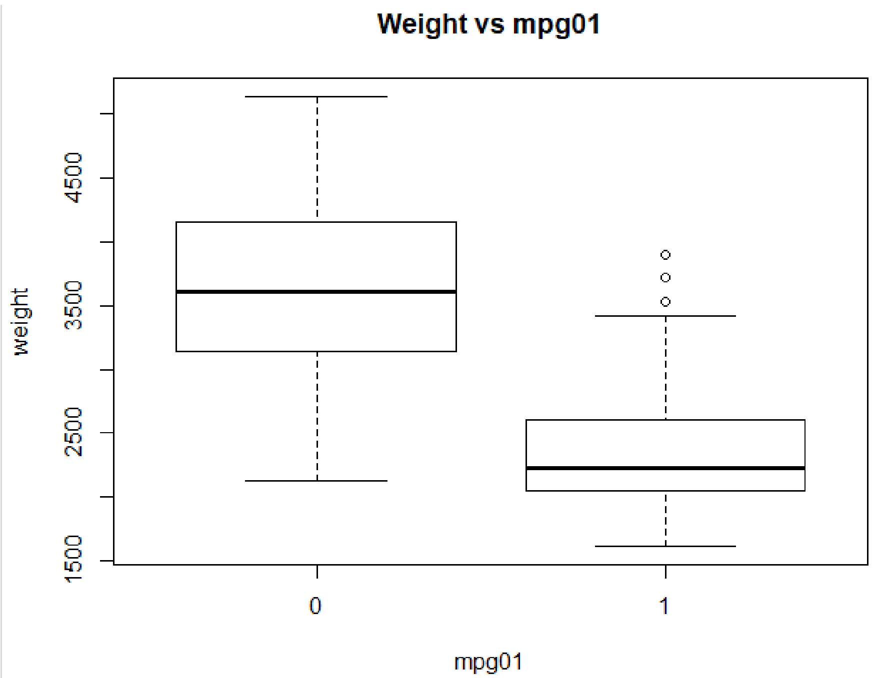

```
> boxplot(displacement ~ mpg01, data = Auto, main = "Displacement vs mpg01")
>
```



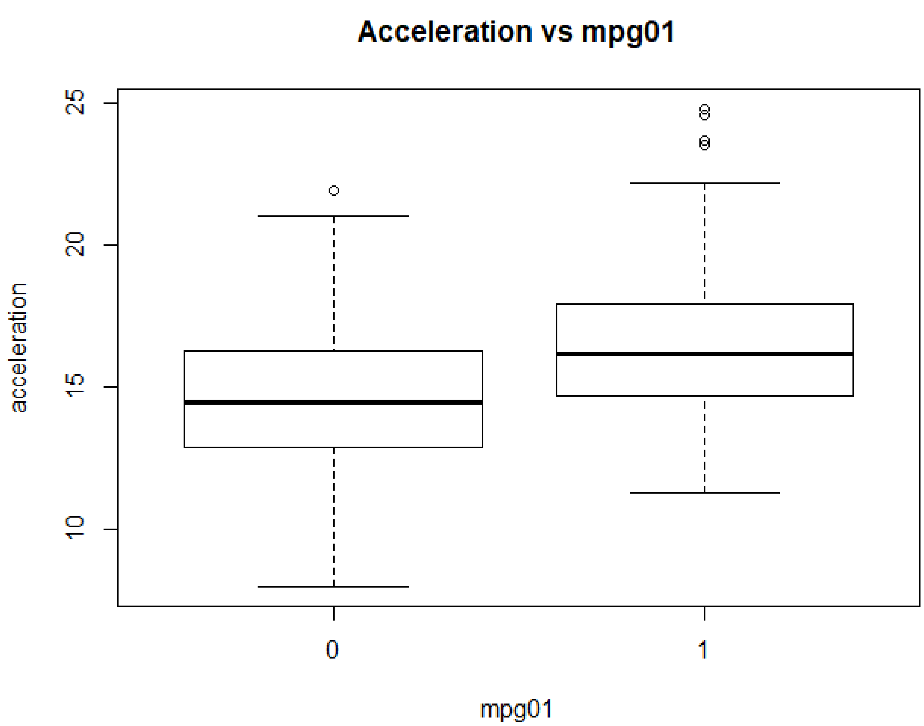

```
> boxplot(horsepower ~ mpg01, data = Auto, main = "Horsepower vs mpg01")
>
```



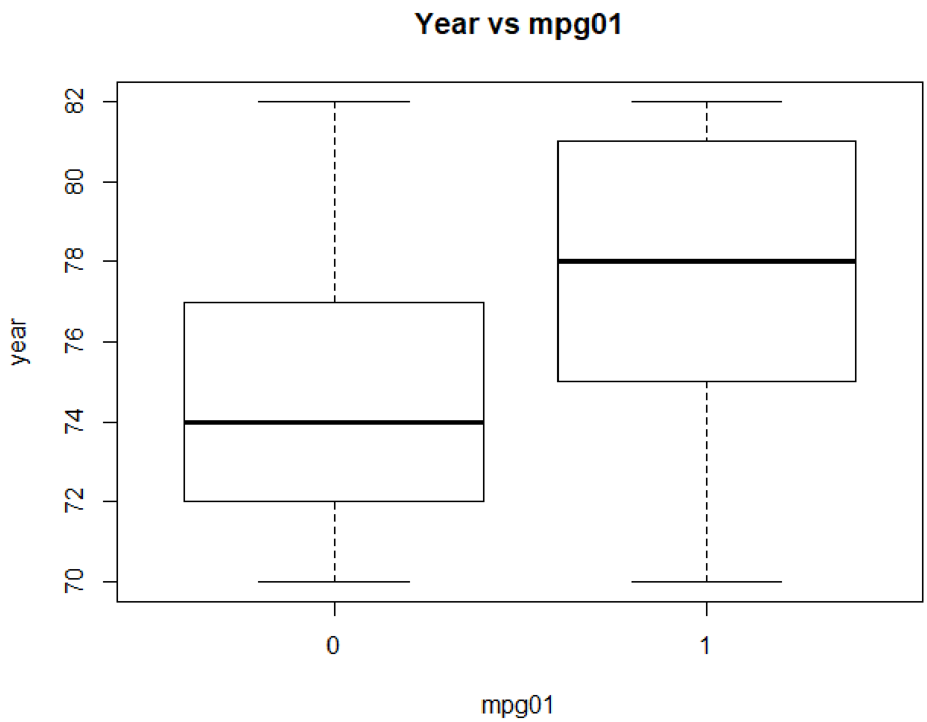

```
> boxplot(weight ~ mpg01, data = Auto, main = "Weight vs mpg01")
>
```




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




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



For predicting mpg01 I used box plot for all data against mpg01 and found that there exists some association between “mpg01” and “cylinders”, “weight”, “displacement” and “horsepower”.

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

```
> #3. c) Split the data into a training set and a test set.
> train <- (year %% 2 == 0)
> Auto.train <- Auto[train, ]
> Auto.test <- Auto[!train, ]
> mpg01.test <- mpg01[!train]
>
```

(d) (5 points) 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?

```
#3. 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?

fit.lda <- lda(mpg01 ~ cylinders + weight + displacement + horsepower, data = Auto, subset = train)
fit.lda
```

131:1 (Top Level) R Script

Console Terminal

```
> fit.lda <- lda(mpg01 ~ cylinders + weight + displacement + horsepower, data = Auto, subset = train)
> fit.lda
Call:
lda(mpg01 ~ cylinders + weight + displacement + horsepower, data = Auto,
    subset = train)

Prior probabilities of groups:
        0         1
0.4571429 0.5428571

Group means:
  cylinders   weight displacement horsepower
0  6.812500 3604.823     271.7396  133.14583
1  4.070175 2314.763     111.6623   77.92105

Coefficients of linear discriminants:
                       LD1
cylinders    -0.6741402638
weight       -0.0011465750
displacement  0.0004481325
horsepower    0.0059035377
>
```

```
> pred.lda <- predict(fit.lda, Auto.test)
> table(pred.lda$class, mpg01.test)
   mpg01.test
     0  1
  0 86  9
  1 14 73
```

```
> mean(pred.lda$class != mpg01.test)
[1] 0.1263736
>
```

From above it is clear that the test error rate is 12.637%

(e) (5 points) Perform QDA 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?

```
> #3. e) Perform QDA 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 ?
>
> fit.qda <- qda(mpg01 ~ cylinders + weight + displacement + horsepower, data = Auto, subset = train)
> fit.qda
Call:
qda(mpg01 ~ cylinders + weight + displacement + horsepower, data = Auto,
    subset = train)

Prior probabilities of groups:
        0         1
0.4571429 0.5428571

Group means:
  cylinders   weight displacement horsepower
0  6.812500 3604.823     271.7396  133.14583
1  4.070175 2314.763     111.6623   77.92105
>
```

```
> pred.qda <- predict(fit.qda, Auto.test)
> table(pred.qda$class, mpg01.test)
   mpg01.test
     0  1
  0 89 13
  1 11 69
>
```

```
> mean(pred.qda$class != mpg01.test)
[1] 0.1318681
>
```

From above it is clear that test error rate is 13.186%

(f) (5 points) Perform logistic regression 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?

```
> #3. f)Perform logistic regression 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 ?
>
> fit.glm <- glm(mpg01 ~ cylinders + weight + displacement + horsepower, data = Auto, family = binomial, subset = train)
> summary(fit.glm)

Call:
glm(formula = mpg01 ~ cylinders + weight + displacement + horsepower,
    family = binomial, data = Auto, subset = train)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.48027  -0.03413   0.10583   0.29634   2.57584

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  17.658730   3.409012   5.180 2.22e-07 ***
cylinders    -1.028032   0.653607  -1.573   0.1158
weight       -0.002922   0.001137  -2.569   0.0102 *
displacement  0.002462   0.015030   0.164   0.8699
horsepower   -0.050611   0.025209  -2.008   0.0447 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 289.58  on 209  degrees of freedom
Residual deviance:  83.24  on 205  degrees of freedom
AIC: 93.24

Number of Fisher Scoring iterations: 7
```

```
> probs <- predict(fit.glm, Auto.test, type = "response")
> pred.glm <- rep(0, length(probs))
> pred.glm[probs > 0.5] <- 1
> table(pred.glm, mpg01.test)
        mpg01.test
pred.glm  0  1
       0 89 11
       1 11 71
>
```

```
> mean(pred.glm != mpg01.test)
[1] 0.1208791
>
```

From above it is clear that test error rate is 12.08791%

(g) (5 points) Perform KNN on the training data, with several values of K, in order to predict mpg01. Use only the variables that seemed most associated with mpg01 in (b). What test errors do you obtain? Which value of K seems to perform the best on this data set?

```
#3. g) Perform KNN on the training data, with several values of K, in order to predict "mpg01"
#using the variables that seemed most associated with "mpg01" in (b). What test errors do you obtain ?
#Which value of K seems to perform the best on this data set ?
train.X <- cbind(cylinders, weight, displacement, horsepower)[train, ]
test.X <- cbind(cylinders, weight, displacement, horsepower)[!train, ]
train.mpg01 <- mpg01[train]
set.seed(1)
pred.knn <- knn(train.X, test.X, train.mpg01, k = 1)
table(pred.knn, mpg01.test)
```

179:1 (Top Level)

Console Terminal

~/

```
        mpg01.test
pred.knn  0  1
       0 83 11
       1 17 71
>
```

```
> mean(pred.knn != mpg01.test)
[1] 0.1538462
>
```

For K=1 the test error rate is 15.38462%

```
> pred.knn <- knn(train.X, test.X, train.mpg01, k = 10)
> table(pred.knn, mpg01.test)
        mpg01.test
pred.knn  0  1
       0 77  7
       1 23 75
>
```

```
> mean(pred.knn != mpg01.test)
[1] 0.1648352
>
```

Foe K=10 the test error rate is 16.48352%

```
> pred.knn <- knn(train.X, test.X, train.mpg01, k = 100)
> table(pred.knn, mpg01.test)
        mpg01.test
pred.knn  0  1
       0 81  7
       1 19 75
```

```
> mean(pred.knn != mpg01.test)
[1] 0.1428571
>
```

From above for K=100 the test error rate is 14.28571%