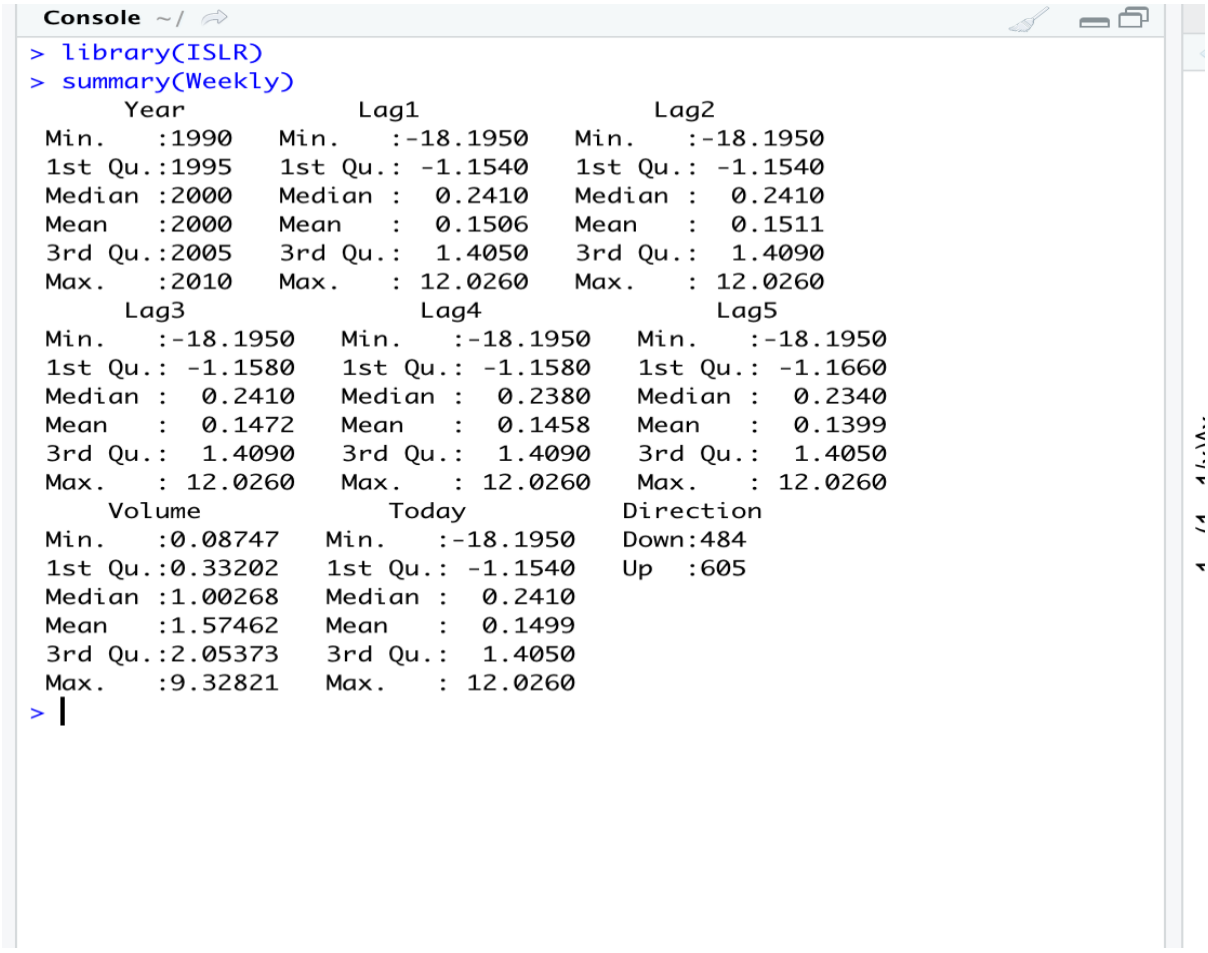
Anusha muppalla
16286311

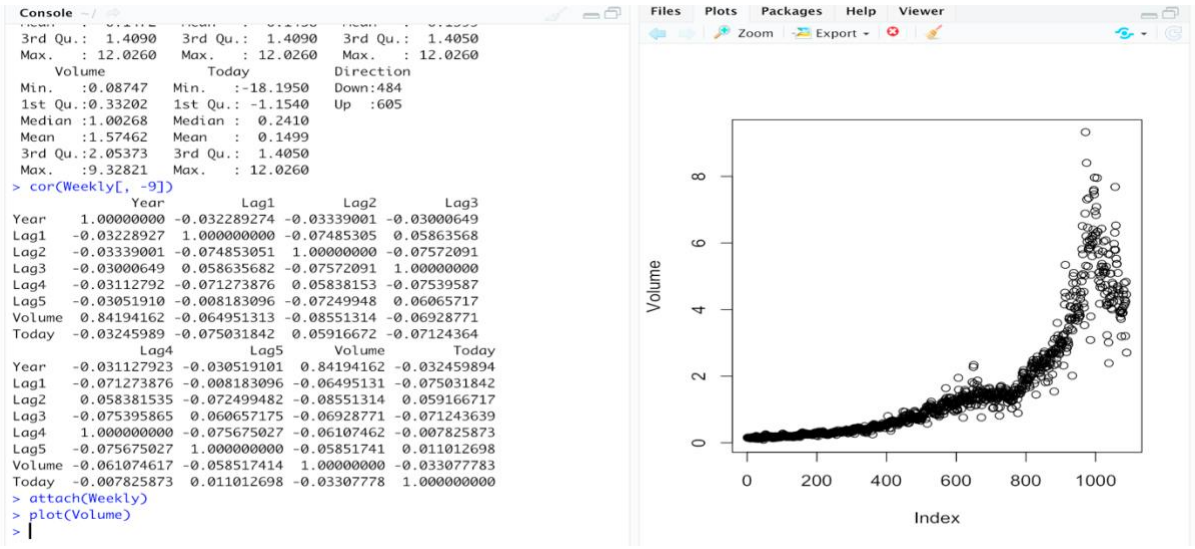
LAB ASSIGNMENT3

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?



```
Console ~/
 Median :  0.2410   Median :  0.2380   Median :  0.2340
 Mean   :  0.1472   Mean   :  0.1458   Mean   :  0.1399
 3rd Qu.:  1.4090   3rd Qu.:  1.4090   3rd Qu.:  1.4050
 Max.   : 12.0260   Max.   : 12.0260   Max.   : 12.0260
     Volume             Today          Direction
 Min.   :0.08747   Min.   :-18.1950   Down:484
 1st Qu.:0.33202   1st Qu.: -1.1540   Up   :605
 Median :1.00268   Median :  0.2410
 Mean   :1.57462   Mean   :  0.1499
 3rd Qu.:2.05373   3rd Qu.:  1.4050
 Max.   :9.32821   Max.   : 12.0260
> cor(Weekly[, -9])
              Year          Lag1         Lag2         Lag3
Year     1.00000000 -0.032289274 -0.03339001 -0.03000649
Lag1    -0.03228927  1.000000000 -0.07485305  0.05863568
Lag2    -0.03339001 -0.074853051  1.00000000 -0.07572091
Lag3    -0.03000649  0.058635682 -0.07572091  1.00000000
Lag4    -0.03112792 -0.071273876  0.05838153 -0.07539587
Lag5    -0.03051910 -0.008183096 -0.07249948  0.06065717
Volume   0.84194162 -0.064951313 -0.08551314 -0.06928771
Today   -0.03245989 -0.075031842  0.05916672 -0.07124364
              Lag4         Lag5       Volume        Today
Year    -0.031127923 -0.030519101  0.84194162 -0.032459894
Lag1    -0.071273876 -0.008183096 -0.06495131 -0.075031842
Lag2     0.058381535 -0.072499482 -0.08551314  0.059166717
Lag3    -0.075395865  0.060657175 -0.06928771 -0.071243639
Lag4     1.000000000 -0.075675027 -0.06107462 -0.007825873
Lag5    -0.075675027  1.000000000 -0.05851741  0.011012698
Volume  -0.061074617 -0.058517414  1.00000000 -0.033077783
Today   -0.007825873  0.011012698 -0.03307778  1.000000000
>
```



(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?

```
Console ~/
> 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
```

P value is less than 0.05 for lag2

(c) (5 points) Compute the confusion matrix and overall fraction of correct predic- tions. Explain what the confusion matrix is telling you about the types of mistakes made by logistic regression.

```
Number of Fisher Scoring iterations: 4

> 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
>
```

(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).

```
    Up    430 557
> train <- (Year < 2009)
> Weekly.20092010 <- Weekly[!train, ]
> Direction.20092010 <- Direction[!train]
> fit.glm2 <- glm(Direction ~ Lag2, data = Weekly, family = binomial, su
bset = train)
> summary(fit.glm2)

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

>
```

```
Console ~/
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

> 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
>
```

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

```
> library(MASS)
> 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)
       Direction.20092010
        Down Up
  Down    9  5
  Up     34 56
> 
```

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

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

(g) (5 points) 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)
        Direction.20092010
pred.knn Down Up
    Down   21 30
    Up     22 31
>
```

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

Test error rates are minimum for logistic Regression and LDA and then 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.

```
    Up      22 31
> fit.glm3 <- glm(Direction ~ Lag2:Lag1, data = Weekly, family = binomia
l, 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
> fit.lda2 <- lda(Direction ~ Lag2:Lag1, data = Weekly, subset = train)
> pred.lda2 <- predict(fit.lda2, Weekly.20092010)
> mean(pred.lda2$class == Direction.20092010)
[1] 0.5769231
> fit.qda2 <- qda(Direction ~ Lag2 + sqrt(abs(Lag2)), data = Weekly, sub
set = train)
> pred.qda2 <- predict(fit.qda2, Weekly.20092010)
> table(pred.qda2$class, Direction.20092010)
      Direction.20092010
       Down Up
  Down   12 13
  Up     31 48
> mean(pred.qda2$class == Direction.20092010)
[1] 0.5769231
```

```
[1] 0.5865385
> fit.lda2 <- lda(Direction ~ Lag2:Lag1, data = Weekly, subset = train)
> pred.lda2 <- predict(fit.lda2, Weekly.20092010)
> mean(pred.lda2$class == Direction.20092010)
[1] 0.5769231
> fit.qda2 <- qda(Direction ~ Lag2 + sqrt(abs(Lag2)), data = Weekly, sub
set = train)
> pred.qda2 <- predict(fit.qda2, Weekly.20092010)
> table(pred.qda2$class, Direction.20092010)
      Direction.20092010
       Down Up
  Down   12 13
  Up     31 48
> mean(pred.qda2$class == Direction.20092010)
[1] 0.5769231
> 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
> 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
```

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.

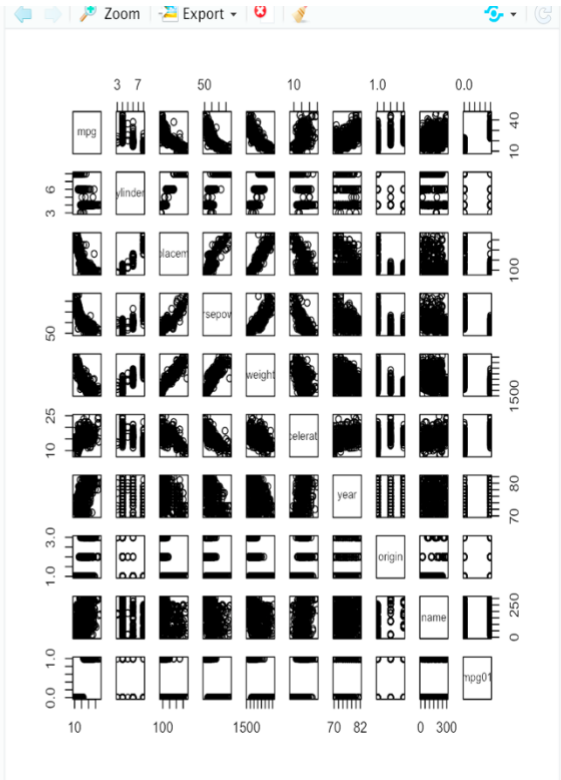
(a) (5 points) Create a binary variable, mpg01, that contains a 1 if mpg contains a value above its median, and a 0 if mpg contains a value below its median. You can compute the median using the median() function. Note you may find it helpful to use the data.frame() function to create a single data set containing both mpg01 and the other Auto variables.

```
> attach(Auto)
> mpg01 <- rep(0, length(mpg))
> mpg01[mpg > median(mpg)] <- 1
> Auto <- data.frame(Auto, mpg01)
```

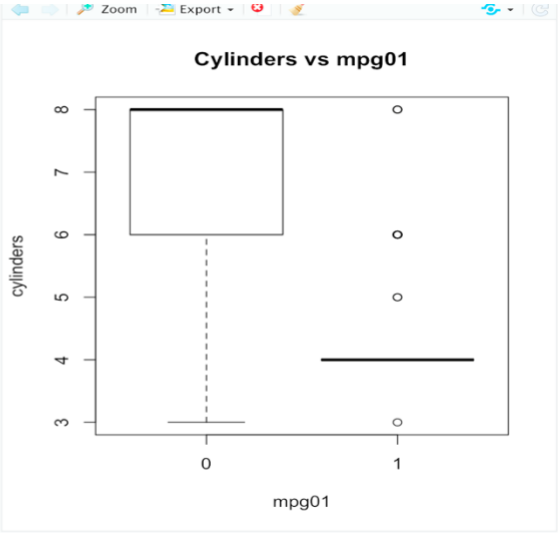
(b) (5 points) Explore the data graphically in order to investigate the association between mpg01 and the other features. Which of the other features seem most likely to be useful in predicting mpg01? Scatterplots and boxplots may be useful tools to answer this question. Describe your findings.

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

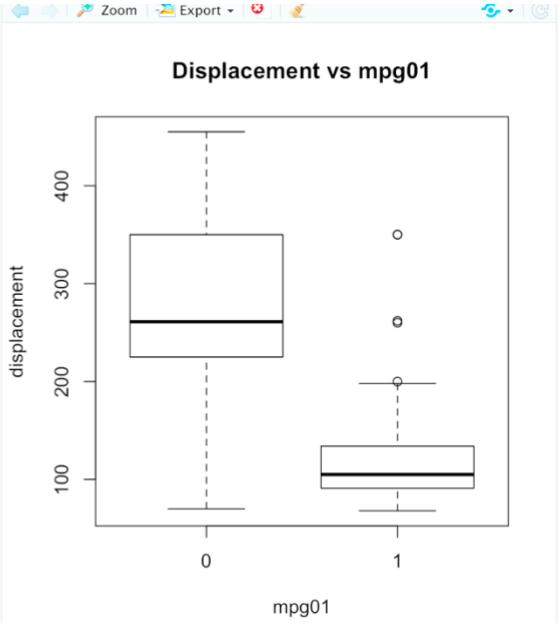
```
mpg           1.0000000 -0.7776175   -0.8051269 -0.7784268
cylinders    -0.7776175  1.0000000    0.9508233  0.8429834
displacement -0.8051269  0.9508233    1.0000000  0.8972570
horsepower   -0.7784268  0.8429834    0.8972570  1.0000000
weight       -0.8322442  0.8975273    0.9329944  0.8645377
acceleration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



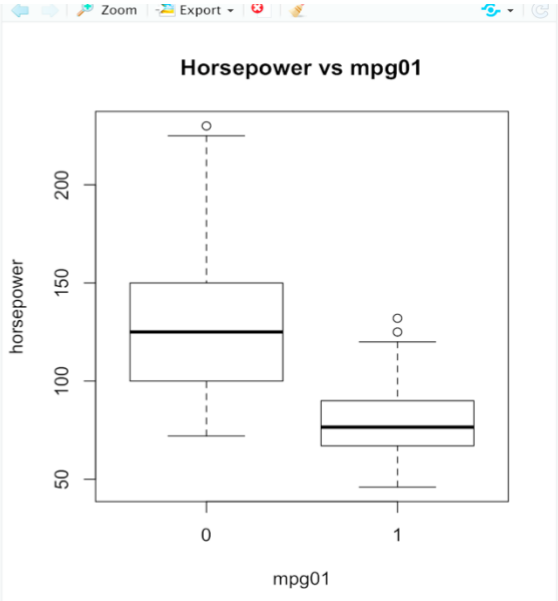
```
cylinders    -0.7776175  1.0000000    0.9508233  0.8429834
displacement -0.8051269  0.9508233    1.0000000  0.8972570
horsepower   -0.7784268  0.8429834    0.8972570  1.0000000
weight       -0.8322442  0.8975273    0.9329944  0.8645377
acceleration  0.4233285 -0.5046834   -0.5438005 -0.6891955
year          0.5805410 -0.3456474   -0.3698552 -0.4163615
origin        0.5652088 -0.5689316   -0.6145351 -0.4551715
mpg01         0.8369392 -0.7591939   -0.7534766 -0.6670526
                 weight acceleration       year     origin
mpg          -0.8322442    0.4233285  0.5805410  0.5652088
cylinders     0.8975273   -0.5046834 -0.3456474 -0.5689316
displacement  0.9329944   -0.5438005 -0.3698552 -0.6145351
horsepower    0.8645377   -0.6891955 -0.4163615 -0.4551715
weight        1.0000000   -0.4168392 -0.3091199 -0.5850054
acceleration -0.4168392    1.0000000  0.2903161  0.2127458
year         -0.3091199    0.2903161  1.0000000  0.1815277
origin       -0.5850054    0.2127458  0.1815277  1.0000000
mpg01        -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")
>
```



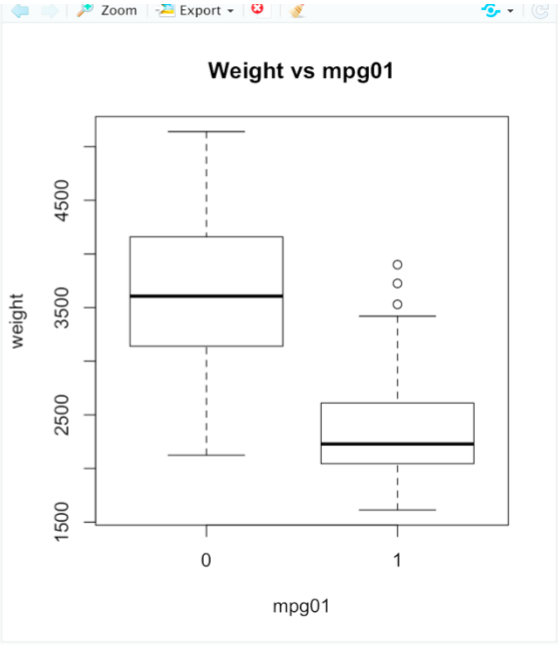

```
horsepower   -0.7784268  0.8429834    0.8972570  1.0000000
weight       -0.8322442  0.8975273    0.9329944  0.8645377
acceleration  0.4233285 -0.5046834   -0.5438005 -0.6891955
year          0.5805410 -0.3456474   -0.3698552 -0.4163615
origin        0.5652088 -0.5689316   -0.6145351 -0.4551715
mpg01         0.8369392 -0.7591939   -0.7534766 -0.6670526
                 weight acceleration       year     origin
mpg          -0.8322442    0.4233285  0.5805410  0.5652088
cylinders     0.8975273   -0.5046834 -0.3456474 -0.5689316
displacement  0.9329944   -0.5438005 -0.3698552 -0.6145351
horsepower    0.8645377   -0.6891955 -0.4163615 -0.4551715
weight        1.0000000   -0.4168392 -0.3091199 -0.5850054
acceleration -0.4168392    1.0000000  0.2903161  0.2127458
year         -0.3091199    0.2903161  1.0000000  0.1815277
origin       -0.5850054    0.2127458  0.1815277  1.0000000
mpg01        -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 mpg
01")
>
```



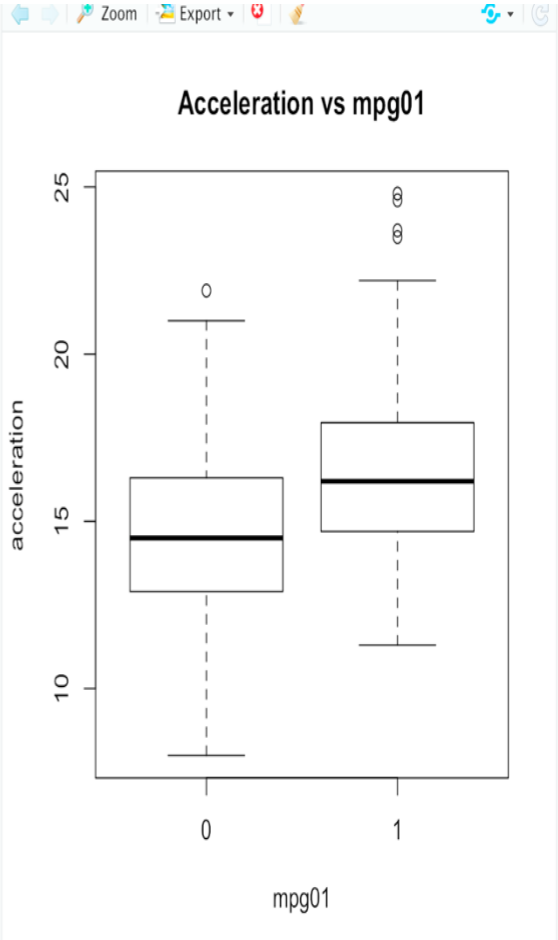

```
weight       -0.8322442  0.8975273    0.9329944  0.8645377
acceleration  0.4233285 -0.5046834   -0.5438005 -0.6891955
year          0.5805410 -0.3456474   -0.3698552 -0.4163615
origin        0.5652088 -0.5689316   -0.6145351 -0.4551715
mpg01         0.8369392 -0.7591939   -0.7534766 -0.6670526
                 weight acceleration       year     origin
mpg          -0.8322442    0.4233285  0.5805410  0.5652088
cylinders     0.8975273   -0.5046834 -0.3456474 -0.5689316
displacement  0.9329944   -0.5438005 -0.3698552 -0.6145351
horsepower    0.8645377   -0.6891955 -0.4163615 -0.4551715
weight        1.0000000   -0.4168392 -0.3091199 -0.5850054
acceleration -0.4168392    1.0000000  0.2903161  0.2127458
year         -0.3091199    0.2903161  1.0000000  0.1815277
origin       -0.5850054    0.2127458  0.1815277  1.0000000
mpg01        -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 mpg
01")
> boxplot(horsepower ~ mpg01, data = Auto, main = "Horsepower vs mpg01")
>
```



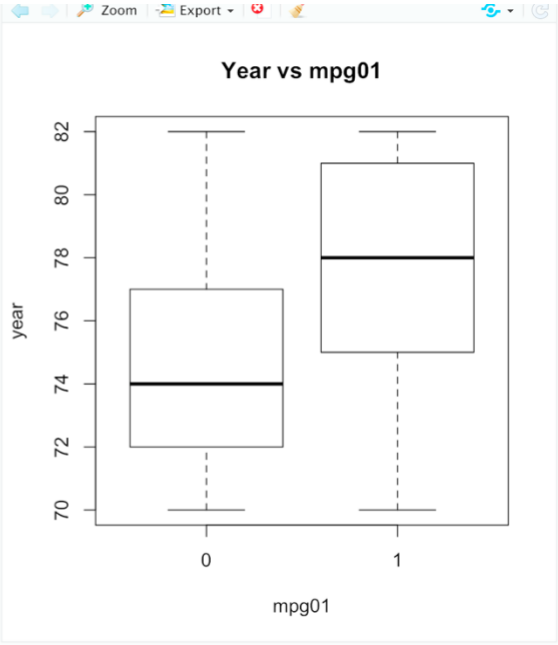
```
acceleration  0.4233285 -0.5046834   -0.5438005 -0.6891955
year          0.5805410 -0.3456474   -0.3698552 -0.4163615
origin        0.5652088 -0.5689316   -0.6145351 -0.4551715
mpg01         0.8369392 -0.7591939   -0.7534766 -0.6670526
                 weight acceleration       year     origin
mpg          -0.8322442    0.4233285  0.5805410  0.5652088
cylinders     0.8975273   -0.5046834 -0.3456474 -0.5689316
displacement  0.9329944   -0.5438005 -0.3698552 -0.6145351
horsepower    0.8645377   -0.6891955 -0.4163615 -0.4551715
weight        1.0000000   -0.4168392 -0.3091199 -0.5850054
acceleration -0.4168392    1.0000000  0.2903161  0.2127458
year         -0.3091199    0.2903161  1.0000000  0.1815277
origin       -0.5850054    0.2127458  0.1815277  1.0000000
mpg01        -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 mpg
01")
> boxplot(horsepower ~ mpg01, data = Auto, main = "Horsepower vs mpg01")
> boxplot(weight ~ mpg01, data = Auto, main = "Weight vs mpg01")
>
```




```
origin        0.5652088 -0.5689316   -0.6145351 -0.4551715
mpg01         0.8369392 -0.7591939   -0.7534766 -0.6670526
                 weight acceleration       year     origin
mpg          -0.8322442    0.4233285  0.5805410  0.5652088
cylinders     0.8975273   -0.5046834 -0.3456474 -0.5689316
displacement  0.9329944   -0.5438005 -0.3698552 -0.6145351
horsepower    0.8645377   -0.6891955 -0.4163615 -0.4551715
weight        1.0000000   -0.4168392 -0.3091199 -0.5850054
acceleration -0.4168392    1.0000000  0.2903161  0.2127458
year         -0.3091199    0.2903161  1.0000000  0.1815277
origin       -0.5850054    0.2127458  0.1815277  1.0000000
mpg01        -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 mpg
01")
> 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 mpg
01")
>
```



```
mpg01         0.8369392 -0.7591939   -0.7534766 -0.6670526
                 weight acceleration       year     origin
mpg          -0.8322442    0.4233285  0.5805410  0.5652088
cylinders     0.8975273   -0.5046834 -0.3456474 -0.5689316
displacement  0.9329944   -0.5438005 -0.3698552 -0.6145351
horsepower    0.8645377   -0.6891955 -0.4163615 -0.4551715
weight        1.0000000   -0.4168392 -0.3091199 -0.5850054
acceleration -0.4168392    1.0000000  0.2903161  0.2127458
year         -0.3091199    0.2903161  1.0000000  0.1815277
origin       -0.5850054    0.2127458  0.1815277  1.0000000
mpg01        -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 mpg
01")
> 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 mpg
01")
> boxplot(year ~ mpg01, data = Auto, main = "Year vs mpg01")
>
```



(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?

```
> train <- (year %% 2 == 0)
> Auto.train <- Auto[train, ]
> Auto.test <- Auto[!train, ]
> mpg01.test <- mpg01[!train]
> 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
>
```

(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?

```
> fit.qda <- qda(mpg01 ~ cylinders + weight + displacement + horsepow
er, data = Auto, subset = train)
> fit.qda
Call:
qda(mpg01 ~ cylinders + weight + displacement + horsepower, data = Au
to,
    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
>
```

(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?

```
> fit.glm <- glm(mpg01 ~ cylinders + weight + displacement + horsepow
er, 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
```

```
> 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
>
```

(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?

```
> 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)
        mpg01.test
pred.knn  0  1
       0 83 11
       1 17 71
> mean(pred.knn != mpg01.test)
[1] 0.1538462
> 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
> 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
>
```