R Notebook

13. 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 chapter's lab, except that it contains 1,089 weekly returns for 21 years, from the beginning of 1990 to the end of 2010.

```
library(ISLR)
```

```
head(Weekly)
```

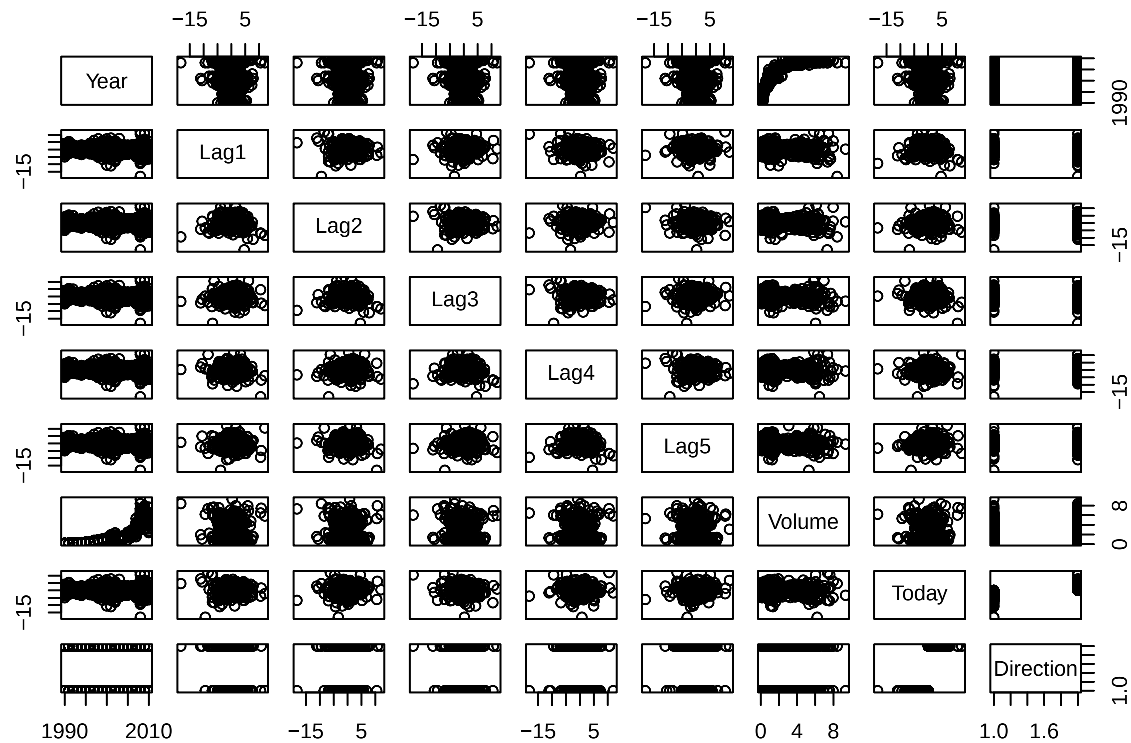
```
##   Year   Lag1   Lag2   Lag3   Lag4   Lag5    Volume  Today Direction
## 1 1990  0.816  1.572 -3.936 -0.229 -3.484 0.1549760 -0.270      Down
## 2 1990 -0.270  0.816  1.572 -3.936 -0.229 0.1485740 -2.576      Down
## 3 1990 -2.576 -0.270  0.816  1.572 -3.936 0.1598375  3.514        Up
## 4 1990  3.514 -2.576 -0.270  0.816  1.572 0.1616300  0.712        Up
## 5 1990  0.712  3.514 -2.576 -0.270  0.816 0.1537280  1.178        Up
## 6 1990  1.178  0.712  3.514 -2.576 -0.270 0.1544440 -1.372      Down
```

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

```
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            Today
##  Min.   :-18.1950   Min.   :-18.1950   Min.   :0.08747   Min.   :-18.1950
##  1st Qu.: -1.1580   1st Qu.: -1.1660   1st Qu.:0.33202   1st Qu.: -1.1540
##  Median :  0.2380   Median :  0.2340   Median :1.00268   Median :  0.2410
##  Mean   :  0.1458   Mean   :  0.1399   Mean   :1.57462   Mean   :  0.1499
##  3rd Qu.:  1.4090   3rd Qu.:  1.4050   3rd Qu.:2.05373   3rd Qu.:  1.4050
##  Max.   : 12.0260   Max.   : 12.0260   Max.   :9.32821   Max.   : 12.0260
##  Direction
##  Down:484
##  Up  :605
##
##
##
##
```

```r
pairs(Weekly)
```

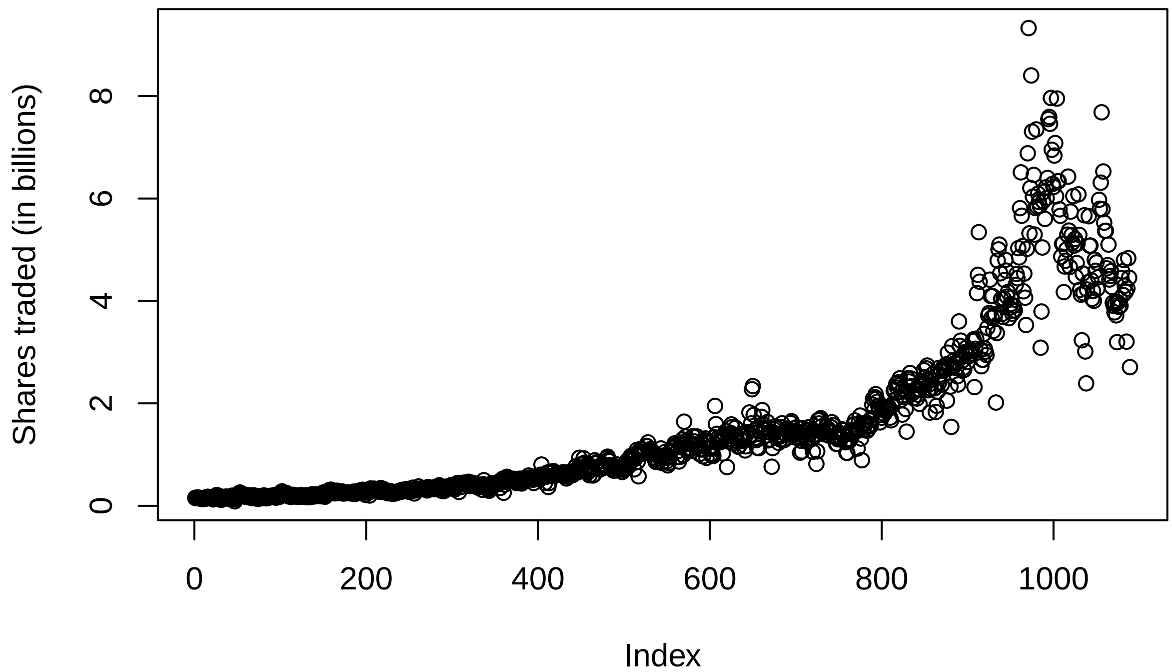



```r
cor(Weekly[, -9])
```

```
##               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
```

There seems to be a correlation between year and volume. There are no other noticeable patterns.

```r
plot(Weekly$Volume, ylab = "Shares traded (in billions)")
```



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. Use the summary function to print the results. Do any of the predictors appear to be statistically significant? If so, which ones?

```r
attach(Weekly)
glm.fit = glm(Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 + Volume, data = Weekly,
    family = binomial)
summary(glm.fit)
```

```
##
## 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
```

With a Pr(>|z|) = 3%, Lag 2 seems to have some statistical significance.

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.

```r
glm.probs = predict(glm.fit, type = "response")
glm.pred = rep("Down", length(glm.probs))
glm.pred[glm.probs > 0.5] = "Up"
table(glm.pred, Direction)
```

```
##         Direction
## glm.pred Down  Up
##     Down   54  48
##     Up    430 557
```

```r
mean(glm.pred == Weekly$Direction)
```

```
## [1] 0.5610652
```

The percentage of accurate predictions is (54 + 557)/(54 + 557 + 48 + 430) = 56.1%. 557/(557+48) = 92.1 percent of the time the logistic regression is accurate during market upswings. When the market rises, the logistic regression is frequently off by 11.2 percent, or 54/(430+54) weeks.

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 and 2010).

```r
train = (Year < 2009)
Weekly.0910 = Weekly[!train, ]
glm.fit = glm(Direction ~ Lag2, data = Weekly, family = binomial, subset = train)
glm.probs = predict(glm.fit, Weekly.0910, type = "response")
glm.pred = rep("Down", length(glm.probs))
glm.pred[glm.probs > 0.5] = "Up"
Direction.0910 = Direction[!train]
table(glm.pred, Direction.0910)
```

```
##          Direction.0910
## glm.pred Down Up
##     Down    9  5
##     Up     34 56
```

```
mean(glm.pred == Direction.0910)
```

```
## [1] 0.625
```

e. Repeat (d) using LDA.

```
library(MASS)
lda.fit = lda(Direction ~ Lag2, data = Weekly, subset = train)
lda.pred = predict(lda.fit, Weekly.0910)
table(lda.pred$class, Direction.0910)
```

```
##       Direction.0910
##         Down Up
##   Down    9  5
##   Up     34 56
```

```
mean(lda.pred$class == Direction.0910)
```

```
## [1] 0.625
```

f. Repeat (d) using QDA.

```
qda.fit = qda(Direction ~ Lag2, data = Weekly, subset = train)
qda.class = predict(qda.fit, Weekly.0910)$class
table(qda.class, Direction.0910)
```

```
##           Direction.0910
## qda.class Down Up
##      Down    0  0
##      Up     43 61
```

```
mean(qda.class == Direction.0910)
```

```
## [1] 0.5865385
```

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)
knn.pred = knn(train.X, test.X, train.Direction, k = 1)
table(knn.pred, Direction.0910)
```

```
##          Direction.0910
## knn.pred Down Up
##     Down   21 30
##     Up     22 31
```

```
mean(knn.pred == Direction.0910)
```

```
## [1] 0.5
```

h) Repeat (d) using naive Bayes.

i. Which of these methods appears to provide the best results on this data?

Logistic regression and LDA methods provide similar test error rates.

j. 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
glm.fit = glm(Direction ~ Lag2:Lag1, data = Weekly, family = binomial, subset = train)
glm.probs = predict(glm.fit, Weekly.0910, type = "response")
glm.pred = rep("Down", length(glm.probs))
glm.pred[glm.probs > 0.5] = "Up"
Direction.0910 = Direction[!train]
table(glm.pred, Direction.0910)
```

```
##          Direction.0910
## glm.pred Down Up
##     Down    1  1
##     Up     42 60
```

```
mean(glm.pred == Direction.0910)
```

```
## [1] 0.5865385
```

```
# LDA with Lag2 interaction with Lag1
lda.fit = lda(Direction ~ Lag2:Lag1, data = Weekly, subset = train)
lda.pred = predict(lda.fit, Weekly.0910)
mean(lda.pred$class == Direction.0910)
```

```
## [1] 0.5769231
```

```
# QDA with sqrt(abs(Lag2))
qda.fit = qda(Direction ~ Lag2 + sqrt(abs(Lag2)), data = Weekly, subset = train)
qda.class = predict(qda.fit, Weekly.0910)$class
table(qda.class, Direction.0910)
```

```
##          Direction.0910
## qda.class Down Up
##      Down   12 13
##      Up     31 48
```

```r
mean(qda.class == Direction.0910)
```

```
## [1] 0.5769231
```

```r
# KNN k =10
knn.pred = knn(train.X, test.X, train.Direction, k = 10)
table(knn.pred, Direction.0910)
```

```
##         Direction.0910
## knn.pred Down Up
##     Down   17 18
##     Up     26 43
```

```r
mean(knn.pred == Direction.0910)
```

```
## [1] 0.5769231
```

```r
# KNN k = 100
knn.pred = knn(train.X, test.X, train.Direction, k = 100)
table(knn.pred, Direction.0910)
```

```
##         Direction.0910
## knn.pred Down Up
##     Down    9 12
##     Up     34 49
```

```r
mean(knn.pred == Direction.0910)
```

```
## [1] 0.5576923
```

R Notebook

Q5. In Chapter 4, we used logisitc regression to predict the probability of "default" using "income" and "balance" on the "Default" data set. We will now estimate the test error of this logistic regression model using the validation set approach. Do not forget to set a random seed before beginning your analysis.

```
library(ISLR)
summary(Default)

##  default    student       balance           income     
##  No :9667   No :7056   Min.   :   0.0   Min.   :  772  
##  Yes: 333   Yes:2944   1st Qu.: 481.7   1st Qu.:21340  
##                        Median : 823.6   Median :34553  
##                        Mean   : 835.4   Mean   :33517  
##                        3rd Qu.:1166.3   3rd Qu.:43808  
##                        Max.   :2654.3   Max.   :73554

attach(Default)
```

a. Fit a logistic regression model that uses "income" and "balance" to predict "default".

```
set.seed(1)
glm.fit = glm(default ~ income + balance, data = Default, family = binomial)
summary(glm.fit)

## 
## Call:
## glm(formula = default ~ income + balance, family = binomial, 
##     data = Default)
## 
## Deviance Residuals: 
##     Min       1Q   Median       3Q      Max  
## -2.4725  -0.1444  -0.0574  -0.0211   3.7245  
## 
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)    
## (Intercept) -1.154e+01  4.348e-01 -26.545  < 2e-16 ***
## income       2.081e-05  4.985e-06   4.174 2.99e-05 ***
## balance      5.647e-03  2.274e-04  24.836  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for binomial family taken to be 1)
## 
##     Null deviance: 2920.6  on 9999  degrees of freedom
## Residual deviance: 1579.0  on 9997  degrees of freedom
## AIC: 1585
```

```
##
## Number of Fisher Scoring iterations: 8
```

b. Using the validation set approach, estimate the test error of this model. In order to do this, you must perform the following steps:

c. Split the sample set into a training set and a validation set.

```
train = sample(dim(Default)[1], dim(Default)[1] / 2)
```

ii. Fit a multiple logistic regression model using only the training observations.

```
glm.fit = glm(default ~ income + balance, data = Default, family = binomial,
subset = train)
summary(glm.fit)

##
## Call:
## glm(formula = default ~ income + balance, family = binomial,
##     data = Default, subset = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.5830  -0.1428  -0.0573  -0.0213   3.3395
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.194e+01  6.178e-01 -19.333  < 2e-16 ***
## income       3.262e-05  7.024e-06   4.644 3.41e-06 ***
## balance      5.689e-03  3.158e-04  18.014  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1523.8  on 4999  degrees of freedom
## Residual deviance:  803.3  on 4997  degrees of freedom
## AIC: 809.3
##
## Number of Fisher Scoring iterations: 8
```

iii. Obtain a prediction of default status for each individual in the validation set by computing the posterior probability of default for that individual, and classifying the individual to the “default” category if the posterior probability is greater than 0.5.

```
glm.pred = rep("No", dim(Default)[1]/2)
glm.probs = predict(glm.fit, Default[-train, ], type = "response")
glm.pred[glm.probs > 0.5] = "Yes"
```

iv. Compute the validation set error, which is the fraction of the observations in the validation set that are misclassified.

```
mean(glm.pred != Default[-train, ]$default)
```

```
## [1] 0.0254
```

2.54% test error rate from validation set approach.

c. Repeat the process in (b) three times, using three different splits of the observations into a training set and a validation set. Comment on the results obtained.

```
train = sample(dim(Default)[1], dim(Default)[1] / 2)
glm.fit = glm(default ~ income + balance, data = Default, family = binomial,
subset = train)
glm.pred = rep("No", dim(Default)[1]/2)
glm.probs = predict(glm.fit, Default[-train, ], type = "response")
glm.pred[glm.probs > 0.5] = "Yes"
mean(glm.pred != Default[-train, ]$default)

## [1] 0.0274

train = sample(dim(Default)[1], dim(Default)[1] / 2)
glm.fit = glm(default ~ income + balance, data = Default, family = binomial,
subset = train)
glm.pred = rep("No", dim(Default)[1]/2)
glm.probs = predict(glm.fit, Default[-train, ], type = "response")
glm.pred[glm.probs > 0.5] = "Yes"
mean(glm.pred != Default[-train, ]$default)

## [1] 0.0244

train = sample(dim(Default)[1], dim(Default)[1] / 2)
glm.fit = glm(default ~ income + balance, data = Default, family = binomial,
subset = train)
glm.pred = rep("No", dim(Default)[1]/2)
glm.probs = predict(glm.fit, Default[-train, ], type = "response")
glm.pred[glm.probs > 0.5] = "Yes"
mean(glm.pred != Default[-train, ]$default)

## [1] 0.0244
```

It seems to average around 2.7% test error rate.

d. Now consider a logistic regression model that predicts the probability of default using income, balance, and a dummy variable for student. Estimate the test error for this model using the validation set approach. Comment on whether or not including a dummyvariable for student leads to a reduction in the test error rate.

```
train = sample(dim(Default)[1], dim(Default)[1]/2)
glm.fit = glm(default ~ income + balance + student, data = Default, family =
binomial,
    subset = train)
glm.pred = rep("No", dim(Default)[1]/2)
glm.probs = predict(glm.fit, Default[-train, ], type = "response")
glm.pred[glm.probs > 0.5] = "Yes"
mean(glm.pred != Default[-train, ]$default)
```

```
## [1] 0.0278
```

Test error rate of 2.64 percent using student dummy variable. Using the validation set method, it doesn't seem like including the student dummy variable causes the test error rate to go down.

Q6. We continue to consider the use of a logistic regression model to predict the probability of "default" using "income" and "balance" on the "Default" data set. In particular, we will now computes estimates for the standard errors of the "income" and "balance" logistic regression coefficients in two different ways : (1) using the bootstrap, and (2) using the standard formula for computing the standard errors in the glm() function. Do not forget to set a random seed before beginning your analysis.

a. Using the summary() and glm() functions, determine the estimated standard errors for the coefficients associated with "income" and "balance" in a multiple logistic regression model that uses both predictors.

```
set.seed(1)
glm.fit = glm(default ~ income + balance, data = Default, family = binomial)
summary(glm.fit)

##
## Call:
## glm(formula = default ~ income + balance, family = binomial,
##     data = Default)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4725  -0.1444  -0.0574  -0.0211   3.7245
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.154e+01  4.348e-01 -26.545  < 2e-16 ***
## income       2.081e-05  4.985e-06   4.174 2.99e-05 ***
## balance      5.647e-03  2.274e-04  24.836  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2920.6  on 9999  degrees of freedom
## Residual deviance: 1579.0  on 9997  degrees of freedom
## AIC: 1585
##
## Number of Fisher Scoring iterations: 8
```

b. Write a function, boot.fn(), that takes as input the "Default" data set as well as an index of the observations, and that outputs the coefficient estimates for "income" and "balance" in the multiple logistic regression model.

```r
boot.fn = function(data, index) return(coef(glm(default ~ income + balance,
    data = data, family = binomial, subset = index)))
```

c. Use the boot() function together with your boot.fn() function to estimate the standard errors of the logistic regression coefficients for "income" and "balance".

```r
library(boot)
boot(Default, boot.fn, 50)

##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = Default, statistic = boot.fn, R = 50)
##
##
## Bootstrap Statistics :
##          original        bias     std. error
## t1* -1.154047e+01 -5.661486e-02 4.847786e-01
## t2*  2.080898e-05 -7.436578e-08 4.456965e-06
## t3*  5.647103e-03  1.854126e-05 2.639029e-04
```

d. Comment on the estimated standard errors obtained using the glm() function and using your bootstrap function.

Similar answers to the second and third significant digits.

Q9. We will now consider the "Boston" housing data set, from the "MASS" library.

```r
library(MASS)
summary(Boston)

##       crim                zn             indus            chas
##  Min.   : 0.00632   Min.   :  0.00   Min.   : 0.46   Min.   :0.00000
##  1st Qu.: 0.08205   1st Qu.:  0.00   1st Qu.: 5.19   1st Qu.:0.00000
##  Median : 0.25651   Median :  0.00   Median : 9.69   Median :0.00000
##  Mean   : 3.61352   Mean   : 11.36   Mean   :11.14   Mean   :0.06917
##  3rd Qu.: 3.67708   3rd Qu.: 12.50   3rd Qu.:18.10   3rd Qu.:0.00000
##  Max.   :88.97620   Max.   :100.00   Max.   :27.74   Max.   :1.00000
##       nox               rm             age              dis
##  Min.   :0.3850   Min.   :3.561   Min.   :  2.90   Min.   : 1.130
##  1st Qu.:0.4490   1st Qu.:5.886   1st Qu.: 45.02   1st Qu.: 2.100
##  Median :0.5380   Median :6.208   Median : 77.50   Median : 3.207
##  Mean   :0.5547   Mean   :6.285   Mean   : 68.57   Mean   : 3.795
##  3rd Qu.:0.6240   3rd Qu.:6.623   3rd Qu.: 94.08   3rd Qu.: 5.188
##  Max.   :0.8710   Max.   :8.780   Max.   :100.00   Max.   :12.127
##       rad              tax           ptratio          black
##  Min.   : 1.000   Min.   :187.0   Min.   :12.60   Min.   :  0.32
##  1st Qu.: 4.000   1st Qu.:279.0   1st Qu.:17.40   1st Qu.:375.38
##  Median : 5.000   Median :330.0   Median :19.05   Median :391.44
##  Mean   : 9.549   Mean   :408.2   Mean   :18.46   Mean   :356.67
```

```
##  3rd Qu.:24.000   3rd Qu.:666.0   3rd Qu.:20.20   3rd Qu.:396.23
##  Max.   :24.000   Max.   :711.0   Max.   :22.00   Max.   :396.90
##      lstat            medv
##  Min.   : 1.73   Min.   : 5.00
##  1st Qu.: 6.95   1st Qu.:17.02
##  Median :11.36   Median :21.20
##  Mean   :12.65   Mean   :22.53
##  3rd Qu.:16.95   3rd Qu.:25.00
##  Max.   :37.97   Max.   :50.00

set.seed(1)
attach(Boston)
```

a. Based on this data set, provide an estimate for the population mean of "medv". Call this estimate μ^.

```
medv.mean = mean(medv)
medv.mean

## [1] 22.53281
```

b. Provide an estimate of the standard error of μ^. Interpret this result.

```
medv.err = sd(medv)/sqrt(length(medv))
medv.err

## [1] 0.4088611
```

c. Now estimate the standard error of μ^ using the bootstrap. How does this compare to your answer from (b) ?

```
boot.fn = function(data, index) return(mean(data[index]))
library(boot)
bstrap = boot(medv, boot.fn, 1000)
bstrap

##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = medv, statistic = boot.fn, R = 1000)
##
##
## Bootstrap Statistics :
##     original      bias    std. error
## t1* 22.53281 0.007650791   0.4106622
```

Similar to answer from (b) up to two significant digits. (0.4106 vs 0.4089)

d. Based on your bootstrap estimate from (c), provide a 95% confidence interval for the mean of "medv". Compare it to the results obtained using t.test(Boston$medv).

```
t.test(medv)
```

```
## 
##  One Sample t-test
## 
## data:  medv
## t = 55.111, df = 505, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  21.72953 23.33608
## sample estimates:
## mean of x 
##  22.53281
```

```
c(bstrap$t0 - 2 * 0.4106, bstrap$t0 + 2 * 0.4106)
```

```
## [1] 21.71161 23.35401
```

e. Based on this data set, provide an estimate, μ^med, for the median value of "medv" in the population.

```
medv.med = median(medv)
medv.med
```

```
## [1] 21.2
```

f. We now would like to estimate the standard error of μ^med. Unfortunately, there is no simple formula for computing the standard error of the median. Instead, estimate the standard error of the median using the bootstrap. Comment on your findings.

```
boot.fn = function(data, index) return(median(data[index]))
boot(medv, boot.fn, 1000)
```

```
## 
## ORDINARY NONPARAMETRIC BOOTSTRAP
## 
## 
## Call:
## boot(data = medv, statistic = boot.fn, R = 1000)
## 
## 
## Bootstrap Statistics :
##     original  bias    std. error
## t1*     21.2 -0.0386   0.3770241
```

Median of 21.2 with SE of 0.377. Small standard error relative to median value.

g. Based on this data set, provide an estimate for the tenth percentile of "medv" in Boston suburbs. Call this quantity μ^0.1.

```
medv.tenth = quantile(medv, c(0.1))
medv.tenth
```

```
##   10% 
## 12.75
```

h. Use the bootstrap to estimate the standard error of μ^0.1. Comment on your findings.

```
boot.fn = function(data, index) return(quantile(data[index], c(0.1)))
boot(medv, boot.fn, 1000)

##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = medv, statistic = boot.fn, R = 1000)
##
##
## Bootstrap Statistics :
##     original  bias    std. error
## t1*    12.75  0.0186   0.4925766
```

Tenth-percentile of 12.75 with SE of 0.4925. Small standard error relative to tenth-percentile value.