Homework 1

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Question 1 (P52-Q1)

Solutions:

(a) A Flexible Method could be better for this situation. Because the extremely large capacity of the sample, it is better to use a more complicated and flexible method to fit the data, which will be more accurate than use an inflexible method under this circumstance.

(b) An inflexible Method could be better for this situation. Because the observation capacity is much smaller than the predictors, it is better to use a simpler and inflexible method to cater the basic need. The Flexible Method is better to adopt when condition the number of sample (or observation) is equal or larger than the number of predictors, otherwise it will be inefficient and overfitting the data.

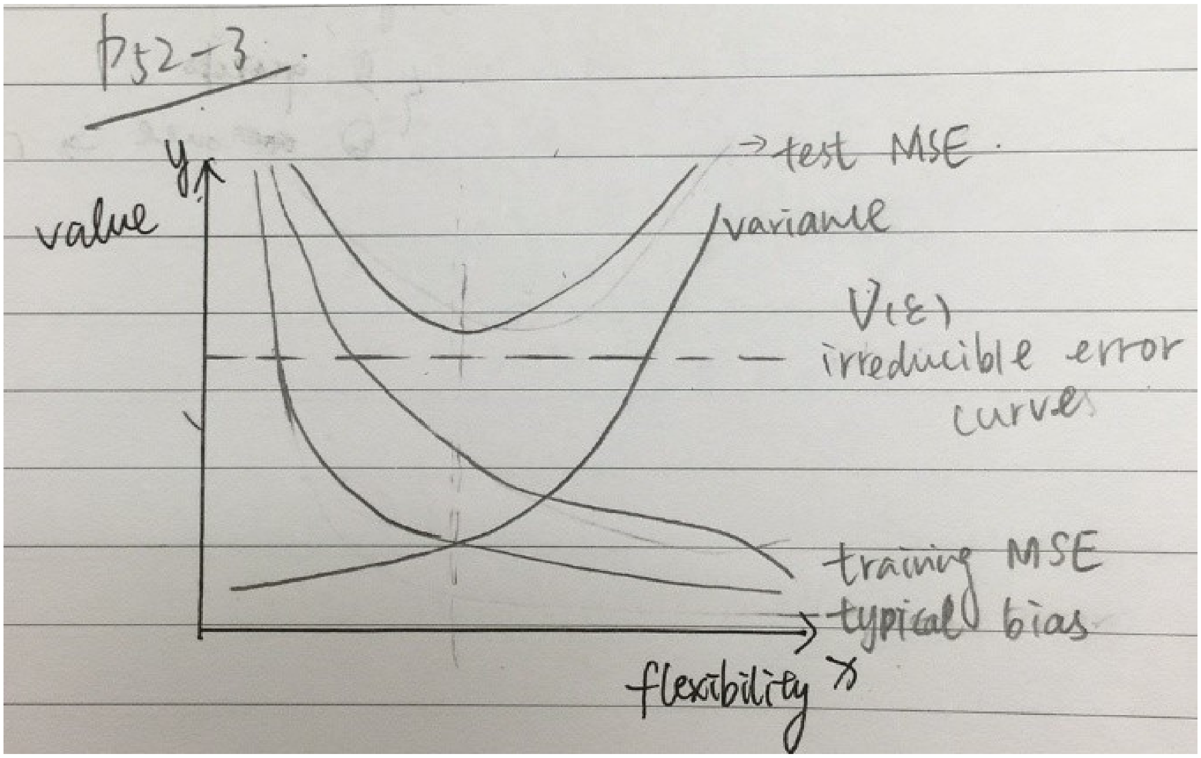
(c) A Flexible Method could be better for this situation. No-linear Relationship (or Regression) means the simple-inflexible method would fail to cater the need of the expression. For a more accurate expression, the Flexible Method with higher degree of freedom would fit the data better.

(d) Flexible Methods could worsen the situation. With the extremely high variance, A very flexible methods would be fit here and cause the overfitting. An inflexible model here may avoid this situation and get the key features of the data.

Question 2 (P52-Q3)

Solutions:

(a)



(b)

For Test Error and Training Error (Corresponding to Test MSE and Training MSE in the figure 1): as the increase of the flexibility, the training MSE will decrease but the test MSE will show a trend of parabola (a>0) above irreducible error (the dash line). That is because as flexibility increases, the f curve fits the observed data (training data) closer; in opposite, a large flexibility will cause Test data an overfitting, so the possibility of error increases after the lowest point. In real case, lower in test MSE is more important than training MSE.

For Typical bias and Variance: these two curves show the opposite trend. The bias will decrease because a flexible method will fit the sample closer. The variance will increase because a flexible method will overfit. In real case, a Bias-Variance Trade-off should be applied to find the appropriate degree of flexibility.

For Irreducible Error: The value of it should remain a constant as it is “irreducible” no matter which model is chosen. And it should be lower than the Test MSE as it is the lowest possible error.

Question 3 (P53-Q6)

The difference between Parametric Method and Non-Parametric Method: Parametric Method reduces the problem of estimating f down to one of estimating a set of parameters.

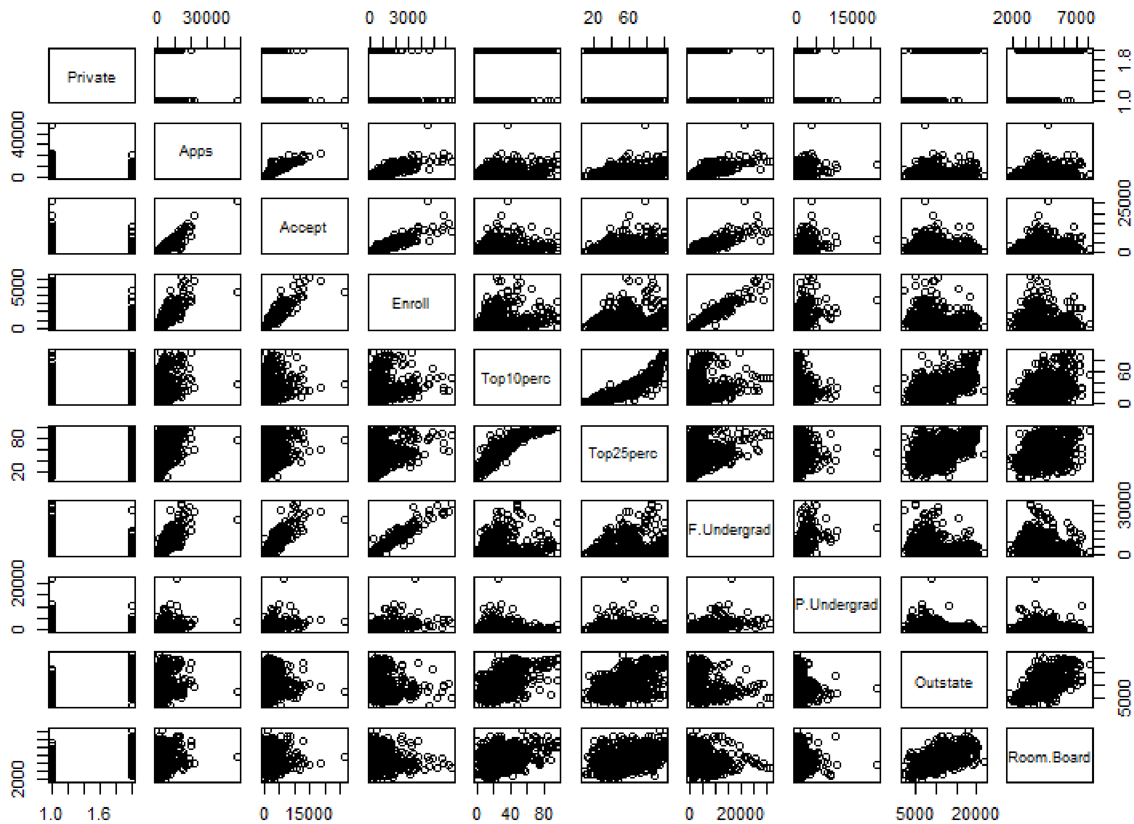
It needs a two-step model to make an assumption about the functional form of f and to uses training data to fit the model. Non-Parametric Method does not make explicit assumptions about the functional form of f and needs a large sample to accurate the estimate f.

The advantage of using Parametric Method for regression or classification: simplify the problem of estimating f; reduce the requirements for the large sample number comparing to Non-Parametric Methods. the potential disadvantage of the Parametric Method is that the model we choose will usually not match the true unknown form of f, the estimate f might very different from the true f which will cause the resulting model fail to fit the data well.

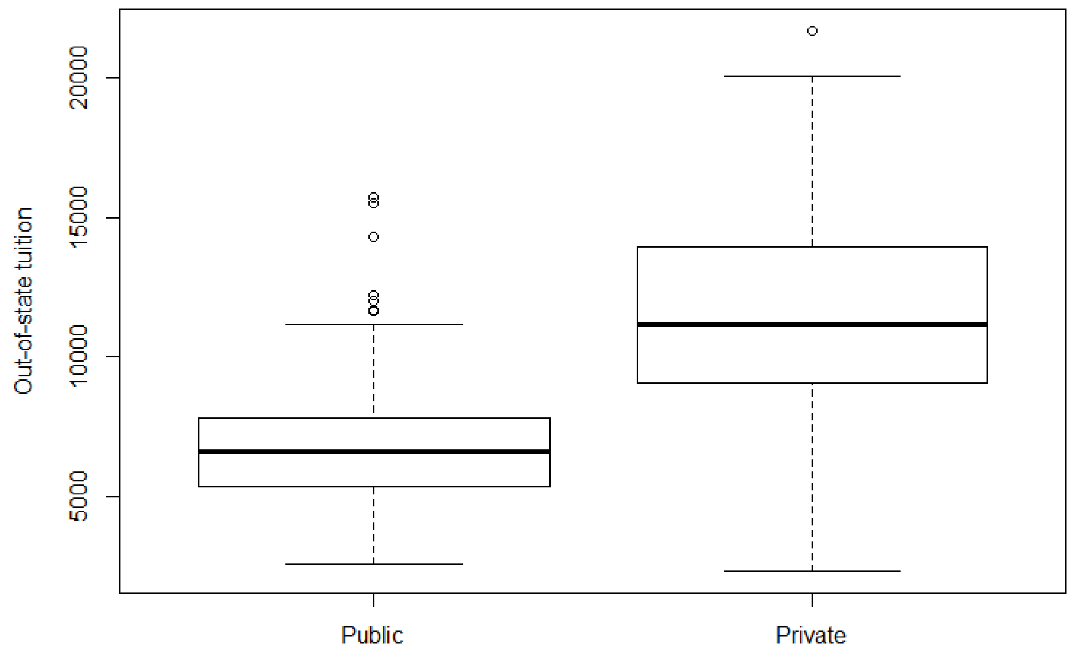
Question 4

```r
# Author: Tianyu Li
# Created on Jan 21st 2019
# Edited on Jan 28th 2019
#
# R script for Homework 1 Question 4(Section 2.4, page 54-55, question 8)
# The College.csv file should be in working direction
setwd('Z:/R_working_directory/DS502HW1');

#(a) Read the file
college = read.csv(file = 'College.csv', header = TRUE);

#(b) Give row names
rownames(college) = college[,1];
fix(college);

college = college[,-1];
fix(college);

#(c) i.Summary function
summary(college);

##  Private        Apps           Accept          Enroll       Top10perc
##  No :212   Min.   :   81   Min.   :   72   Min.   :  35   Min.   : 1.00
##  Yes:565   1st Qu.:  776   1st Qu.:  604   1st Qu.: 242   1st Qu.:15.00
##            Median : 1558   Median : 1110   Median : 434   Median :23.00
##            Mean   : 3002   Mean   : 2019   Mean   : 780   Mean   :27.56
##            3rd Qu.: 3624   3rd Qu.: 2424   3rd Qu.: 902   3rd Qu.:35.00
```

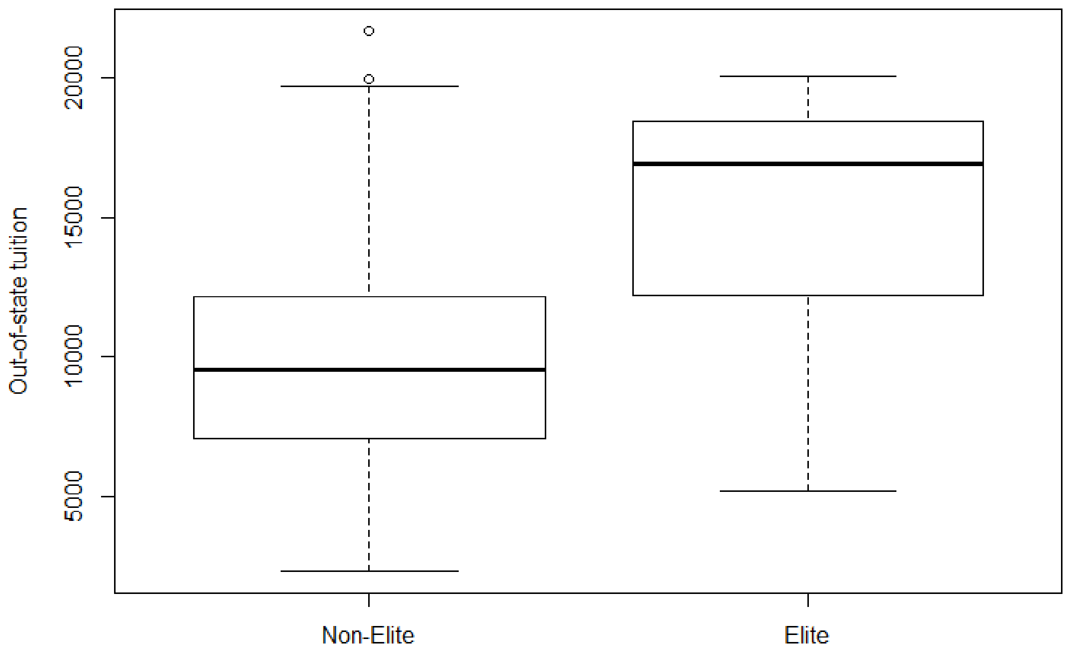
```
##             Max.   :48094   Max.   :26330   Max.   :6392   Max.   :96.00  
##    Top25perc      F.Undergrad     P.Undergrad         Outstate    
##  Min.   :  9.0   Min.   :  139   Min.   :    1.0   Min.   : 2340  
##  1st Qu.: 41.0   1st Qu.:  992   1st Qu.:   95.0   1st Qu.: 7320  
##  Median : 54.0   Median : 1707   Median :  353.0   Median : 9990  
##  Mean   : 55.8   Mean   : 3700   Mean   :  855.3   Mean   :10441  
##  3rd Qu.: 69.0   3rd Qu.: 4005   3rd Qu.:  967.0   3rd Qu.:12925  
##  Max.   :100.0   Max.   :31643   Max.   :21836.0   Max.   :21700  
##    Room.Board       Books           Personal         PhD        
##  Min.   :1780   Min.   :  96.0   Min.   : 250   Min.   :  8.00  
##  1st Qu.:3597   1st Qu.: 470.0   1st Qu.: 850   1st Qu.: 62.00  
##  Median :4200   Median : 500.0   Median :1200   Median : 75.00  
##  Mean   :4358   Mean   : 549.4   Mean   :1341   Mean   : 72.66  
##  3rd Qu.:5050   3rd Qu.: 600.0   3rd Qu.:1700   3rd Qu.: 85.00  
##  Max.   :8124   Max.   :2340.0   Max.   :6800   Max.   :103.00  
##     Terminal       S.F.Ratio      perc.alumni        Expend     
##  Min.   : 24.0   Min.   : 2.50   Min.   : 0.00   Min.   : 3186  
##  1st Qu.: 71.0   1st Qu.:11.50   1st Qu.:13.00   1st Qu.: 6751  
##  Median : 82.0   Median :13.60   Median :21.00   Median : 8377  
##  Mean   : 79.7   Mean   :14.09   Mean   :22.74   Mean   : 9660  
##  3rd Qu.: 92.0   3rd Qu.:16.50   3rd Qu.:31.00   3rd Qu.:10830  
##  Max.   :100.0   Max.   :39.80   Max.   :64.00   Max.   :56233  
##    Grad.Rate     
##  Min.   : 10.00  
##  1st Qu.: 53.00  
##  Median : 65.00  
##  Mean   : 65.46  
##  3rd Qu.: 78.00  
##  Max.   :118.00

#(c) ii.Pairs function
pairs(college[,1:10]);
```



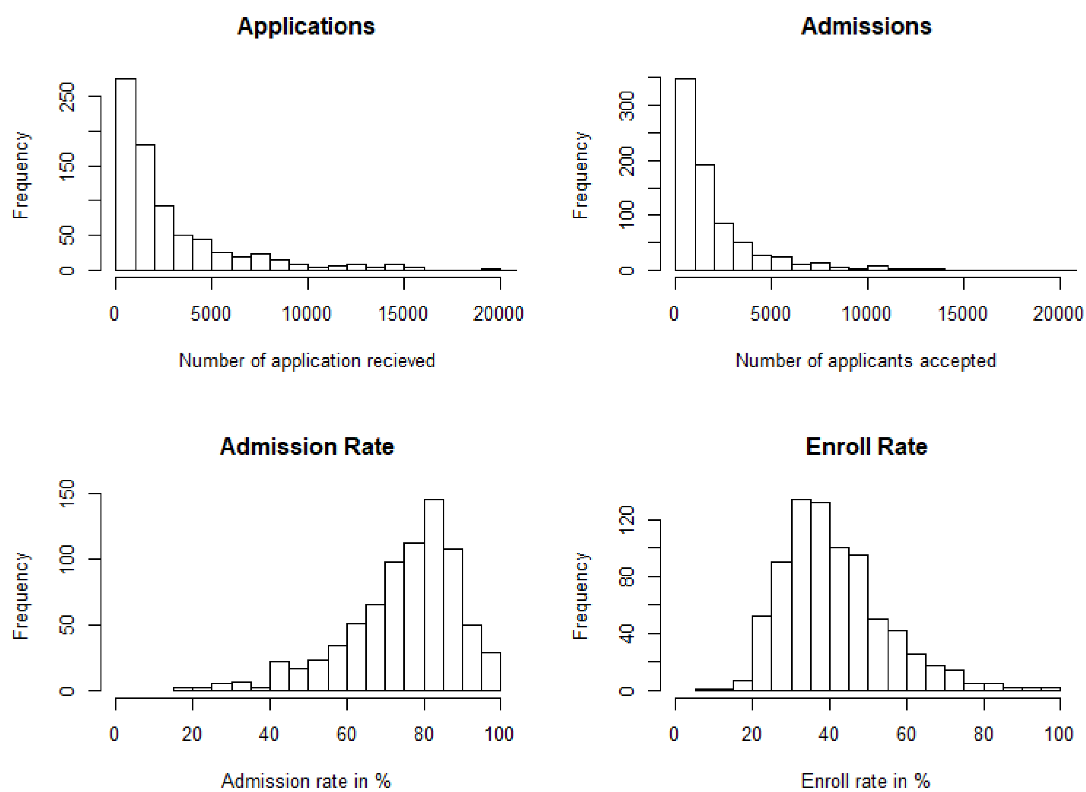

```r
#(c) iii.Plot function
boxplot(college$Outstate ~ college$Private, names = c("Public", "Private"),
        ylab = "Out-of-state tuition");
```




```r
#(c) iv.Factor function
Elite = rep("No", nrow(college));
Elite[college$Top10perc > 50] = "Yes";
Elite = as.factor(Elite);
college = data.frame(college, Elite);

summary(college$Elite);

##   No Yes
## 699  78

boxplot(college$Outstate ~ college$Elite, names = c("Non-Elite", "Elite"),
        ylab = "Out-of-state tuition");
```




```r
#(c) v.Hist function
par(mfrow=c(2,2));

hist(college$Apps, breaks = 40, xlim = range(0, 20000), main =
"Applications",
     xlab = "Number of application recieved");
hist(college$Accept, breaks = 20, xlim = range(0, 20000), main =
"Admissions",
     xlab = "Number of applicants accepted");
hist(100 * college$Accept / college$Apps, breaks = 20, xlim = range(0, 100),
     main = "Admission Rate", xlab = "Admission rate in %");
hist(100 * college$Enroll / college$Accept, breaks = 20, xlim = range(0,
100),
     main = "Enroll Rate", xlab = "Enroll rate in %");
```




```r
#(c) vi.Continue exploring
summary(lm(Grad.Rate ~ . , data = college));

##
## Call:
## lm(formula = Grad.Rate ~ ., data = college)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -53.991  -7.100  -0.300   7.174  54.034
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 33.8925541  4.8522723   6.985 6.24e-12 ***
## PrivateYes   3.4262050  1.7151733   1.998 0.046119 *
## Apps         0.0012936  0.0004428   2.921 0.003588 **
## Accept      -0.0006909  0.0008638  -0.800 0.424030
## Enroll       0.0021440  0.0023111   0.928 0.353840
## Top10perc    0.0465274  0.0851268   0.547 0.584838
## Top25perc    0.1374511  0.0564462   2.435 0.015118 *
## F.Undergrad -0.0004648  0.0004026  -1.155 0.248635
## P.Undergrad -0.0014809  0.0003907  -3.790 0.000162 ***
```

```
## Outstate     0.0010197  0.0002339   4.360 1.48e-05 ***
## Room.Board   0.0019067  0.0005926   3.217 0.001348 **
## Books       -0.0022140  0.0029189  -0.758 0.448388
## Personal    -0.0016620  0.0007703  -2.158 0.031270 *
## PhD          0.0882924  0.0571134   1.546 0.122543
## Terminal    -0.0751566  0.0624063  -1.204 0.228845
## S.F.Ratio    0.0746163  0.1595478   0.468 0.640153
## perc.alumni  0.2796432  0.0492353   5.680 1.92e-08 ***
## Expend      -0.0004596  0.0001552  -2.961 0.003158 **
## EliteYes     0.4618984  2.5235781   0.183 0.854821
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.75 on 758 degrees of freedom
## Multiple R-squared:  0.4616, Adjusted R-squared:  0.4488
## F-statistic:  36.1 on 18 and 758 DF,  p-value: < 2.2e-16

# We chose graduate rate as the dependent variable and tried to fit in a linear model of other columns.
# We found that the Number of part-time student is negatively correlated to the graduate rate significantly and
# the outstate tuition and percent of alumni who donate are postively correlated to the graduate rate significantly.
# Besides, the number of applicants, room and board costs and instructional expenditure per student are
# also correlated to the graduate rate.
```

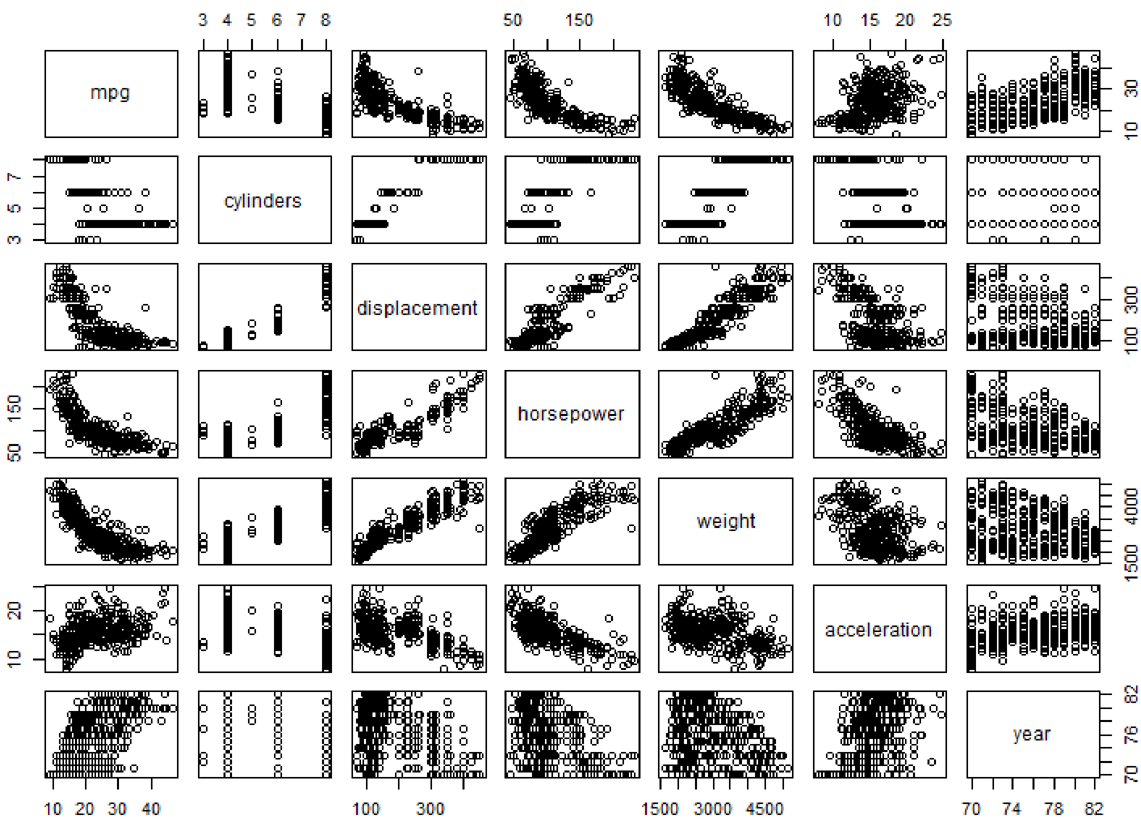
Question 5

```
# Author: Tianyu Li
# Created on Jan 28th 2019
# Edited on Jan 29th 2019
#
# R script for Homework 1 Question 5(Section 2.4, page 56, question 9)
# The Auto.csv file should be in working direction
setwd('Z:/R_working_directory/DS502HW1');

# Read the file
auto = read.csv(file = 'Auto.csv', header = TRUE);

# Remove missing values
```

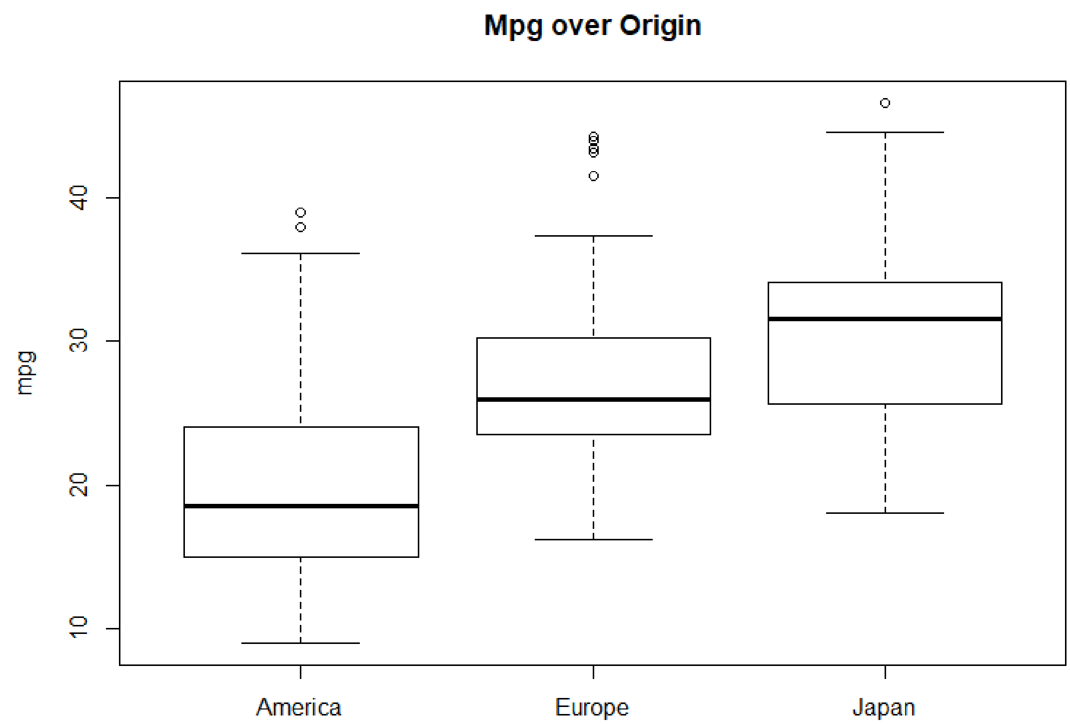
```r
auto[auto == '?'] <- NA;
auto = na.omit(auto);
auto$horsepower = as.numeric(as.character(auto$horsepower));

#(a) The last 2 predictors are qualitative, the others are quantative.
#    The "origin" should stands for the continent so it is qualitative.

#(b) Range of each quantitative predictor
sapply(auto[, 1:7], range);

##       mpg cylinders displacement horsepower weight acceleration year
## [1,]  9.0         3           68         46   1613          8.0   70
## [2,] 46.6         8          455        230   5140         24.8   82

#(c) Mean and standard deviation of each quantitative predictor
sapply(auto[, 1:7], mean);

##          mpg    cylinders displacement   horsepower       weight
##    23.445918     5.471939   194.411990   104.469388  2977.584184
## acceleration         year
##    15.541327    75.979592

sapply(auto[, 1:7], sd);

##          mpg    cylinders displacement   horsepower       weight
##     7.805007     1.705783   104.644004    38.491160   849.402560
## acceleration         year
##     2.758864     3.683737

#(d) Remove the 10th through 85th observations.
subAuto = auto[-(10:85),];
sapply(subAuto[, 1:7], range);

##       mpg cylinders displacement horsepower weight acceleration year
## [1,] 11.0         3           68         46   1649          8.5   70
## [2,] 46.6         8          455        230   4997         24.8   82

sapply(subAuto[, 1:7], mean);

##          mpg    cylinders displacement   horsepower       weight
##    24.404430     5.373418   187.240506   100.721519  2935.971519
## acceleration         year
##    15.726899    77.145570

sapply(subAuto[, 1:7], sd);
```

```
##          mpg     cylinders displacement   horsepower       weight
##     7.867283      1.654179    99.678367    35.708853   811.300208
## acceleration          year
##     2.693721      3.106217
```

```r
#(e) Create some plots
pairs(auto[, 1:7]);
```




```r
# We found that the displacement and weight look postively correlated to the horsepower.

#(f) Predictors that might be useful in predicting mpg
# From the figures of last question, we found that mpg is postively correlated to year and
# negatively correlated to displacement, horsepower and weight.
boxplot(auto$mpg ~ auto$origin, names = c("America", "Europe", "Japan"), ylab = "mpg",
        main = "Mpg over Origin");
```




```
# We also found that for the origin column, 1 should stands for America, 2 stands for Europe
# and 3 stands for Asia. In general, asian cars is highest on mpg while american cars is lowest.
```

Question 6 (P120-Q1)

Solutions:

In this case, we can assume the advertising budgets of TV, Radio and Newspaper do not affect the sales. Multiple Linear Regression Model is $Sales = \beta_0 + \beta_1 \times TV + \beta_2 \times Radio + \beta_3 \times Newspaper + error$

The null hypothesis with $H_0 \begin{cases} H_0': \beta_1 = 0 \\ H_0'': \beta_2 = 0 \\ H_0''': \beta_3 = 0 \end{cases}$, $(\beta_1 - TV, \beta_2 - Radio, \beta_3 - Newpaper)$.

Since the corresponding p-value for TV and Radio are highly significant but not significant for Newspaper, we reject the $H_0'$and H_0'', and accept H_0'''. Which means in this case, the TV and Radio advertising could affect the sales, but the Newspaper advertising do not affect sales significantly.

Question 7 (P121-Q5)

Solutions:

1. When $\mathrm{i} = 1$ to n, substitute $\hat{\beta}$ into $\hat{y_i}$:

$$\hat{y_i} = x_i \times \frac{\sum_{i=1}^{n} x_i \times y_i}{\sum_{i'=1}^{n} x_{i'}^2}$$

$$\hat{y_i} = \sum_{i=1}^{n} \frac{x_i}{n} \times x_i \times \frac{1}{x_i^2} \times y_i$$

$$\hat{y_i} = \sum_{i=1}^{n} \frac{1}{n} \times y_i\text{-----eqn.1}$$

2. When $i' = 1$ to n, let eqn.1 equivalent to $\hat{y_i}$ function in terms of $a_{i'}$:

$$\hat{y_i} = \sum_{i=1}^{n} \frac{1}{n} \times y_i = \sum_{i'=1}^{n} a_{i'} \times y_{i'}$$

$$a_{i'} = \frac{1}{n}$$

Question 8 (P121-Q6)

Solutions:

Reminds the Eqn.3.4 on textbook is $\widehat{\beta_0} = y - \widehat{\beta_1} \times x$

The function of y is

$y = \widehat{\beta_0} + \widehat{\beta_1} \times x$

Assume the point $(\bar{x}, \bar{y})$, substitute the $\bar{x}$

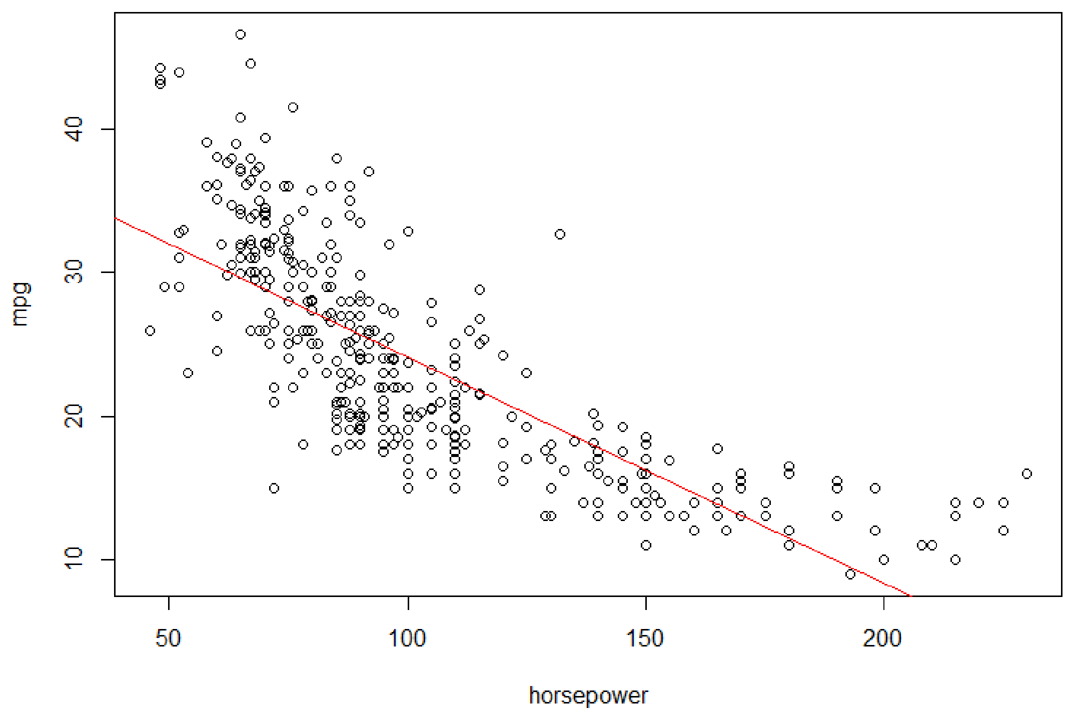
$$y = \widehat{\beta_0} + \widehat{\beta_1} \times \bar{x} = \widehat{\beta_0} + \widehat{\beta_1} \times \frac{\bar{y} - \widehat{\beta_0}}{\widehat{\beta_1}} = \bar{y}$$

So, we conclude that the point $(\bar{x}, \bar{y})$ always on the least square line.

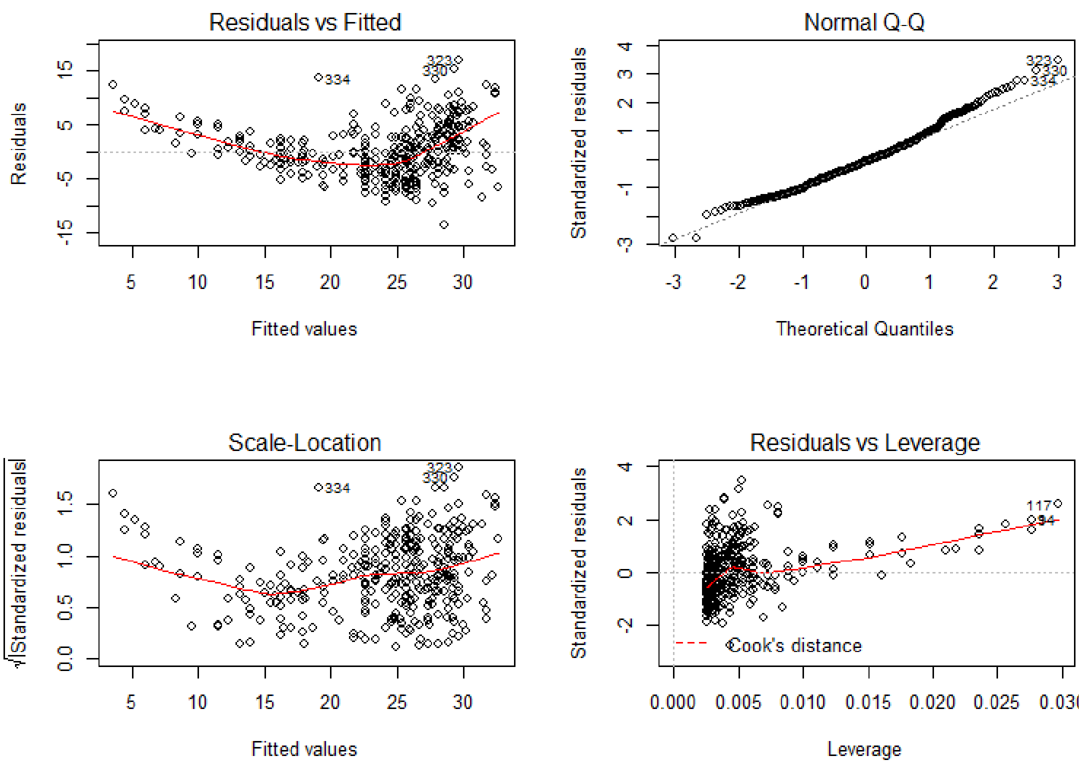
Question 9

```r
# Author: Tianyu Li
# Created on Jan 29th 2019
#
# R script for Homework 1 Question 9(Section 3.7, page 121-122, question 8)
# The Auto.csv file should be in working direction
setwd('Z:/R_working_directory/DS502HW1');

# Read the file
auto = read.csv(file = 'Auto.csv', header = TRUE);

# Remove missing values
auto[auto == '?'] <- NA;
auto = na.omit(auto);
auto$horsepower = as.numeric(as.character(auto$horsepower));

#(a) Perform a simple linear regression
temp = lm(mpg ~ horsepower, data = auto);
summary(temp);

##
## Call:
## lm(formula = mpg ~ horsepower, data = auto)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.5710  -3.2592  -0.3435   2.7630  16.9240
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 39.935861   0.717499   55.66   <2e-16 ***
## horsepower  -0.157845   0.006446  -24.49   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.906 on 390 degrees of freedom
## Multiple R-squared:  0.6059, Adjusted R-squared:  0.6049
## F-statistic: 599.7 on 1 and 390 DF,  p-value: < 2.2e-16

# i Yes
# ii The relationship is strong as the value of R^2 is 0.6059
```

```r
# iii Negative, the coefficient is -0.157845.
# iv Predict mpg associated with a horsepower of 98
predict(temp, data.frame(horsepower = 98), interval = "confidence");

##        fit      lwr      upr
## 1 24.46708 23.97308 24.96108

predict(temp, data.frame(horsepower = 98), interval = "prediction");

##        fit     lwr      upr
## 1 24.46708 14.8094 34.12476

#(b) Plot the response and the predictor
par(mfrow=c(1,1));
plot(mpg ~ horsepower, data = auto);
abline(temp, col = 'red');
```




```r
#(c) Produce diagnostic plots of the least squares regression fit
par(mfrow = c(2, 2))
plot(temp);
```

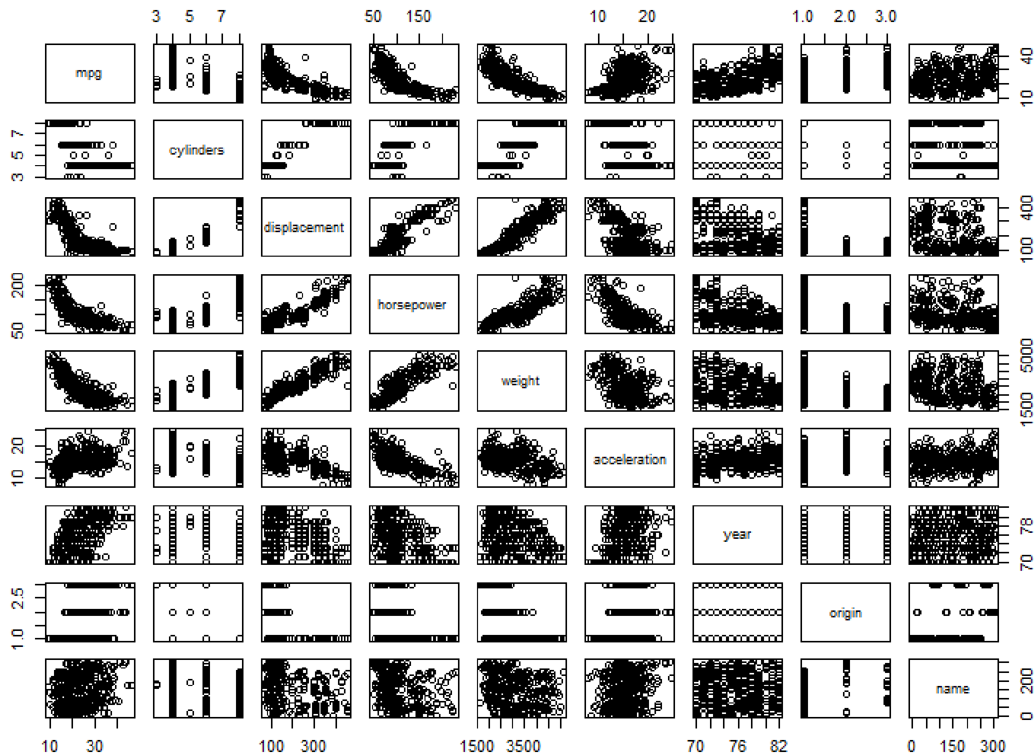



```
# The plots (the first and third one) show that the relationship is non-linear.
```

Question 10

```
# Author: Tianyu Li
# Created on Jan 29th 2019
#
# R script for Homework 1 Question 10(Section 3.7, page 122, question 9)
# The Auto.csv file should be in working direction
setwd('Z:/R_working_directory/DS502HW1');

# Read the file
auto = read.csv(file = 'Auto.csv', header = TRUE);

# Remove missing values
auto[auto == '?'] <- NA;
auto = na.omit(auto);
```

```r
auto$horsepower = as.numeric(as.character(auto$horsepower));

#(a) Produce a scatterplot matrix
pairs(auto);
```




```r
#(b) Compute the matrix of correlations
cor(auto[, 1:8]);
```

```
##                     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
##              acceleration       year     origin
## mpg             0.4233285  0.5805410  0.5652088
## cylinders      -0.5046834 -0.3456474 -0.5689316
## displacement   -0.5438005 -0.3698552 -0.6145351
## horsepower     -0.6891955 -0.4163615 -0.4551715
```

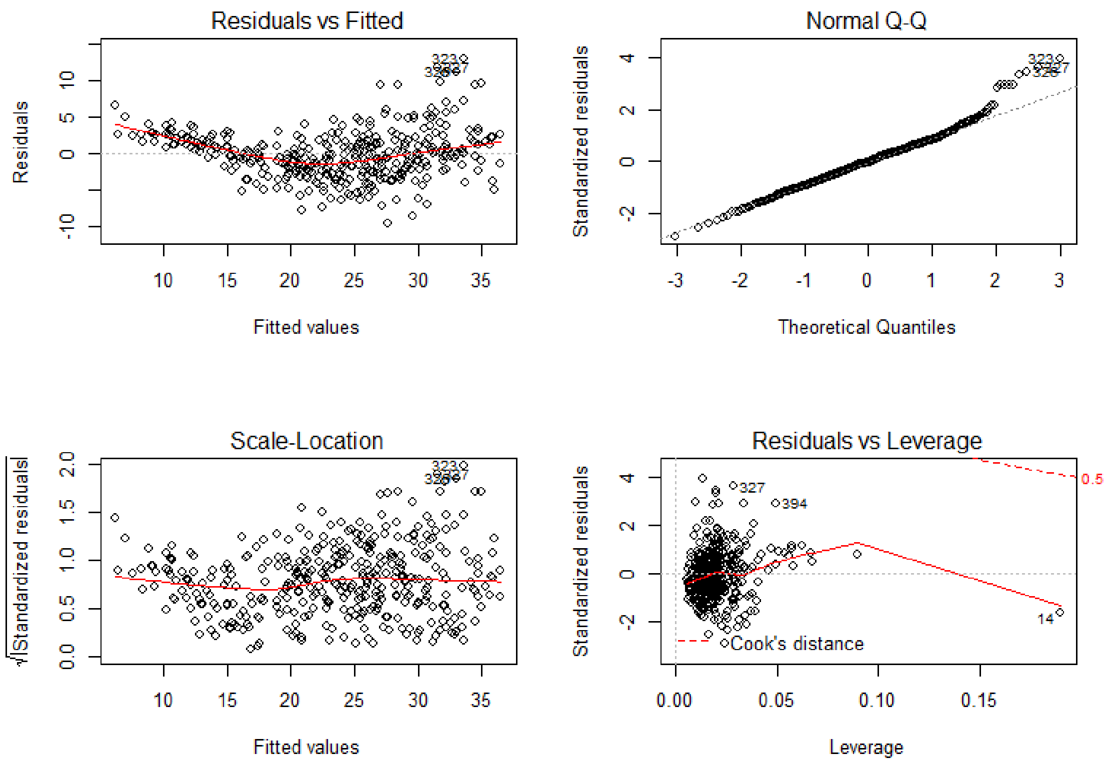
```
## weight         -0.4168392 -0.3091199 -0.5850054
## acceleration    1.0000000  0.2903161  0.2127458
## year            0.2903161  1.0000000  0.1815277
## origin          0.2127458  0.1815277  1.0000000
```

```r
#(c) Perform a multiple linear regression with mpg
temp = lm(mpg ~ . - name, data = auto);
summary(temp);
```

```
##
## Call:
## lm(formula = mpg ~ . - name, data = auto)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.5903 -2.1565 -0.1169  1.8690 13.0604
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -17.218435   4.644294  -3.707  0.00024 ***
## cylinders     -0.493376   0.323282  -1.526  0.12780
## displacement   0.019896   0.007515   2.647  0.00844 **
## horsepower    -0.016951   0.013787  -1.230  0.21963
## weight        -0.006474   0.000652  -9.929  < 2e-16 ***
## acceleration   0.080576   0.098845   0.815  0.41548
## year           0.750773   0.050973  14.729  < 2e-16 ***
## origin         1.426141   0.278136   5.127 4.67e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.328 on 384 degrees of freedom
## Multiple R-squared:  0.8215, Adjusted R-squared:  0.8182
## F-statistic: 252.4 on 7 and 384 DF,  p-value: < 2.2e-16
```

```r
#i Yes, the adjusted R-squared value is 0.8185, which is high.
#ii From the summary table, we may conclude that 'displacement', 'weight',
#   'year', 'origin' have a statistically significant relationship to the
response.
#iii It suggests that in average, 0.750773 mpg will increase as a year
increase.
#    Which means the fuel efficiency is improving.


#(d) Produce diagnostic plots of the linear regression fit.
```

```r
par(mfrow=c(2,2));
plot(temp);
```




```r
# No unusually large outliers are observed.
# The plot shows that the 14th data have a relatively high leverage.
temp2 = lm(mpg ~ . - name, data = auto[-(14),]);
summary(temp2);

##
## Call:
## lm(formula = mpg ~ . - name, data = auto[-(14), ])
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -9.551 -2.147 -0.048  1.889 13.056
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.771e+01  4.644e+00  -3.813  0.00016 ***
## cylinders    -5.469e-01  3.242e-01  -1.687  0.09247 .
## displacement  2.306e-02  7.745e-03   2.977  0.00309 **
## horsepower   -1.105e-02  1.422e-02  -0.777  0.43769
```

```
## weight       -6.916e-03  7.046e-04  -9.815  < 2e-16 ***
## acceleration  1.163e-01  1.010e-01   1.151  0.25043
## year          7.551e-01  5.093e-02  14.825  < 2e-16 ***
## origin        1.427e+00  2.775e-01   5.142 4.35e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.32 on 383 degrees of freedom
## Multiple R-squared:  0.822,  Adjusted R-squared:  0.8188
## F-statistic: 252.7 on 7 and 383 DF,  p-value: < 2.2e-16

# By removing the 14th data, the R-squared value increase for 0.0006

#(e) Fit linear regression models with interaction effects.
temp3 = lm(mpg ~ . - name + horsepower:weight + horsepower:displacement, data
= auto);
summary(temp3);

##
## Call:
## lm(formula = mpg ~ . - name + horsepower:weight + horsepower:displacement,
##     data = auto)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.5879 -1.5160 -0.0954  1.3493 11.9604
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)              1.364e+00  4.476e+00   0.305 0.760723
## cylinders                4.152e-01  3.143e-01   1.321 0.187275
## displacement            -4.432e-02  1.652e-02  -2.684 0.007596 **
## horsepower              -2.256e-01  2.339e-02  -9.646  < 2e-16 ***
## weight                  -6.623e-03  1.556e-03  -4.256 2.63e-05 ***
## acceleration            -1.770e-01  9.123e-02  -1.941 0.053037 .
## year                     7.515e-01  4.468e-02  16.818  < 2e-16 ***
## origin                   7.046e-01  2.511e-01   2.806 0.005276 **
## horsepower:weight        2.541e-05  1.036e-05   2.453 0.014625 *
## displacement:horsepower  3.194e-04  9.601e-05   3.327 0.000964 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.893 on 382 degrees of freedom
```

```
## Multiple R-squared:  0.8657, Adjusted R-squared:  0.8626
## F-statistic: 273.7 on 9 and 382 DF,  p-value: < 2.2e-16
```

```r
# The interaction between displacement and horsepower appear to be
statistically significant.


#(f) Try a few different transformations of the variables
cor(data.frame(auto$weight, log(auto$weight), sqrt(auto$weight),
(auto$weight)^2), auto$mpg);
```

```
##                          [,1]
## auto.weight       -0.8322442
## log.auto.weight.  -0.8441938
## sqrt.auto.weight. -0.8400951
## X.auto.weight..2  -0.8066816
```

```r
cor(data.frame(auto$horsepower, log(auto$horsepower), sqrt(auto$horsepower),
(auto$horsepower)^2), auto$mpg);
```

```
##                              [,1]
## auto.horsepower       -0.7784268
## log.auto.horsepower.  -0.8175174
## sqrt.auto.horsepower. -0.8023114
## X.auto.horsepower..2  -0.7122970
```

```r
cor(data.frame(auto$cylinders, log(auto$cylinders), sqrt(auto$cylinders),
(auto$cylinders)^2), auto$mpg);
```

```
##                             [,1]
## auto.cylinders       -0.7776175
## log.auto.cylinders.  -0.7768177
## sqrt.auto.cylinders. -0.7783516
## X.auto.cylinders..2  -0.7703552
```

```r
cor(data.frame(auto$displacement, log(auto$displacement),
sqrt(auto$displacement), (auto$displacement)^2), auto$mpg);
```

```
##                                [,1]
## auto.displacement       -0.8051269
## log.auto.displacement.  -0.8284533
## sqrt.auto.displacement. -0.8213314
## X.auto.displacement..2  -0.7523545
```

```r
cor(data.frame(auto$acceleration, log(auto$acceleration),
sqrt(auto$acceleration), (auto$acceleration)^2), auto$mpg);
```

```
##                                   [,1]
## auto.acceleration       0.4233285
## log.auto.acceleration.  0.4359007
## sqrt.auto.acceleration. 0.4306775
## X.auto.acceleration..2  0.4037617
```

```r
cor(data.frame(auto$origin, log(auto$origin), sqrt(auto$origin),
(auto$origin)^2), auto$mpg);
```

```
##                             [,1]
## auto.origin       0.5652088
## log.auto.origin.  0.5742758
## sqrt.auto.origin. 0.5708022
## X.auto.origin..2  0.5483534
```

```r
cor(data.frame(auto$year, log(auto$year), sqrt(auto$year), (auto$year)^2),
auto$mpg);
```

```
##                           [,1]
## auto.year       0.5805410
## log.auto.year.  0.5765192
## sqrt.auto.year. 0.5785682
## X.auto.year..2  0.5842529
```

```r
# Weight, horsepower, displacement, acceleration and origin fit the log
transformation best,
# Cylinders fit the square root transformation best and year fit square
transfromation best.
```