

# Quality of Wine

#Panel Data For this assignment, we examined the relationship between the variables “quality” and “fixed acidity”, “volatile acidity”, “citric acid”, “residual sugar”, “chlorides”, “free sulfur dioxide”, “total sulfur dioxide”, “density”, “pH”, “sulphates”, and “alcohol”. The variable we’re trying to predict, is the quality of wine based on our 11 predictors.

```
Wine_Quality<- read.csv("~/Downloads/WineQT.csv")
View(Wine_Quality)
```

## Question 1

### Histogram

In histograms 1 (fixed acidity), 2 (volatile acidity), 4 (residual sugar), 5 (chlorides), 6 (free sulfur dioxide), 7 (total sulfur dioxide), 10 (sulphates), and 11 (alcohol) the models are right-skewed, meaning there is a positive distribution. Histograms 8 (pH) and 9 (density) have a normal distribution. By fitting a distribution to the histogram, we can predict as well as understand the observations in a data set better. The red line, inputted as `curve()`, shows the distribution that best fits the data.

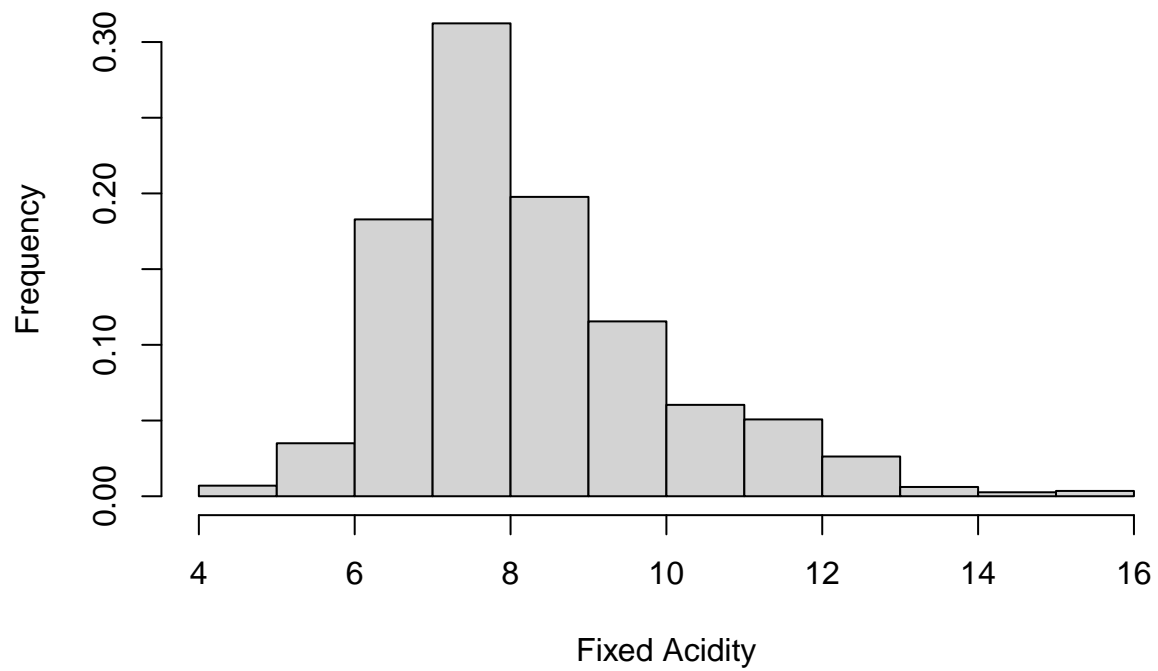
```
library(fitdistrplus)
```

```
## Loading required package: MASS
```

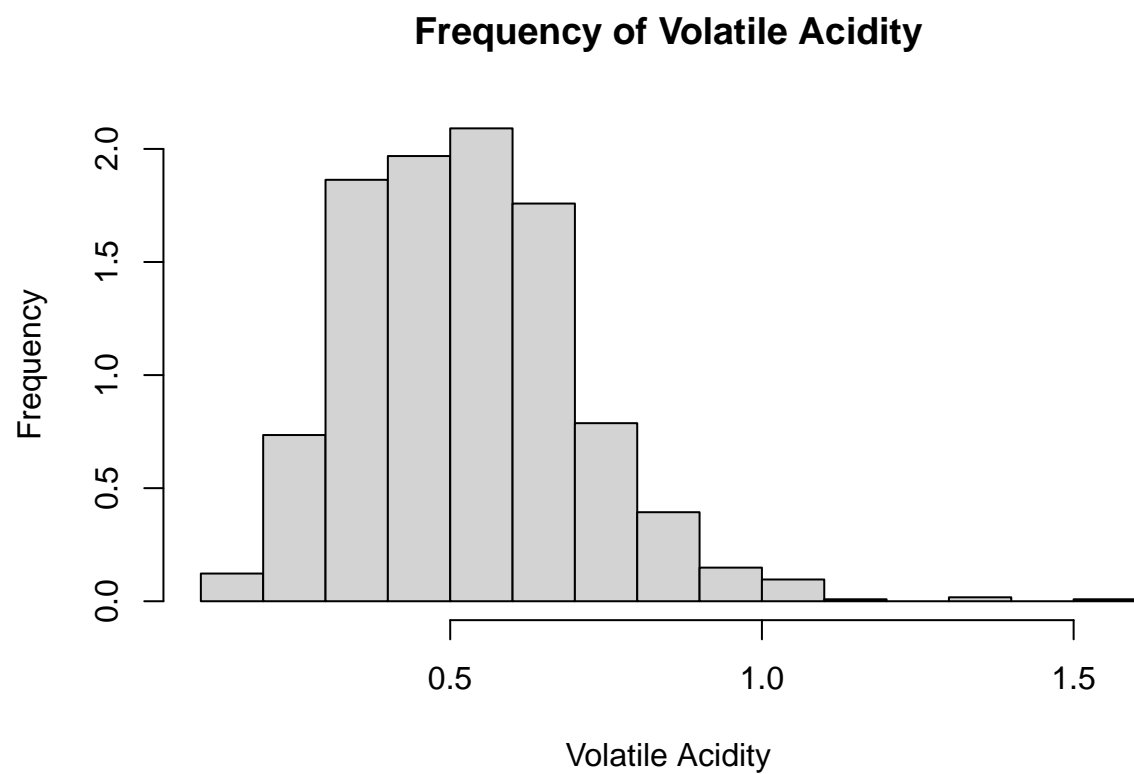
```
## Loading required package: survival
```

```
hist(Wine_Quality$fixed.acidity, prob = TRUE, xlab = "Fixed Acidity", ylab = "Frequency", main = "Frequency of Fixed Acidity")
```

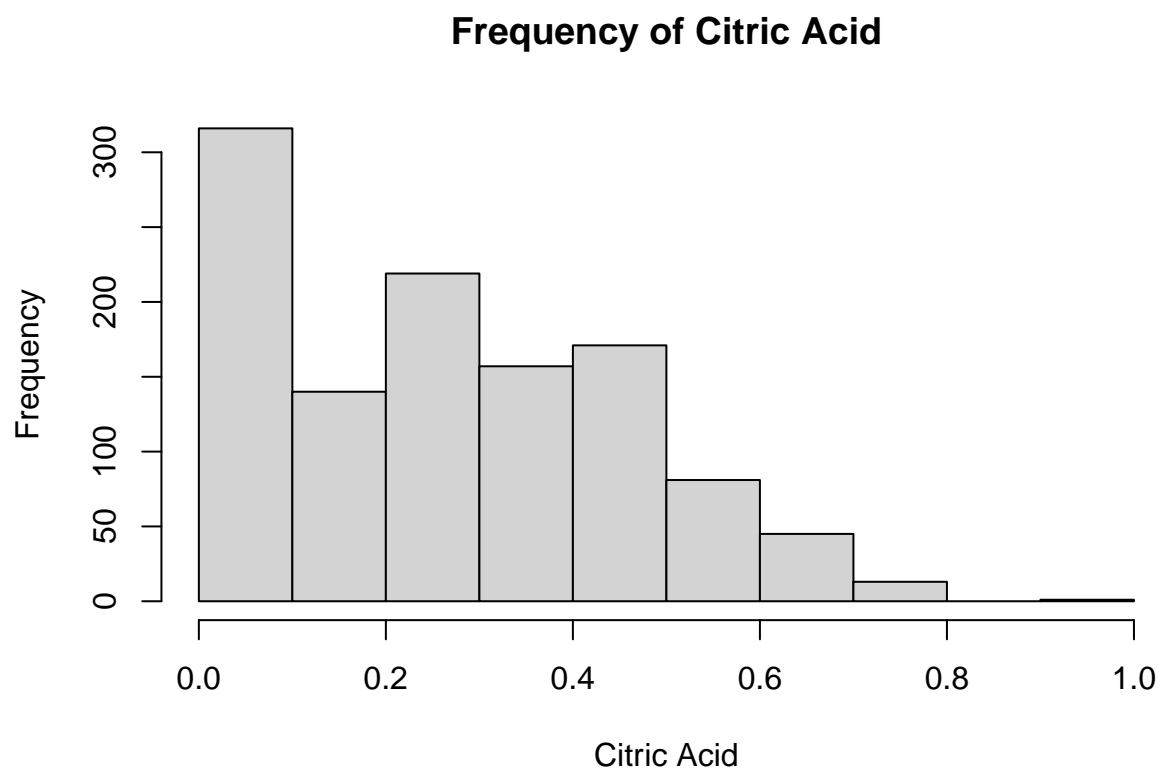
## Frequency of Fixed Acidity



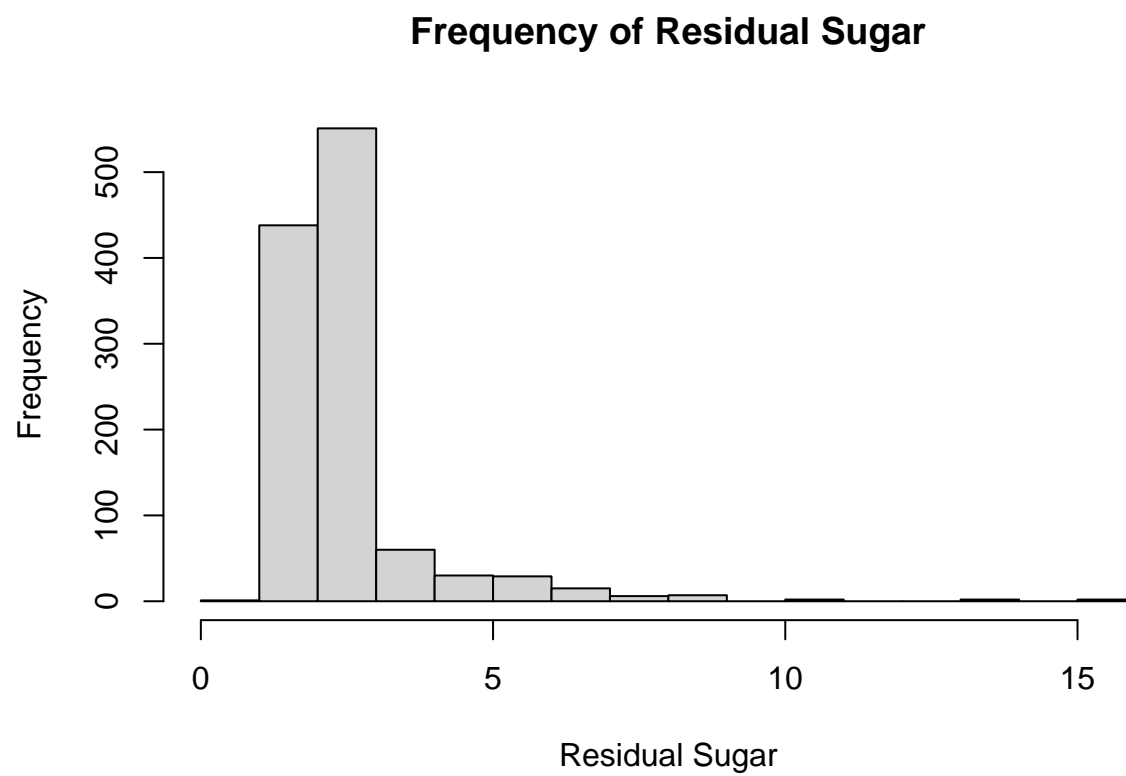
```
hist(Wine_Quality$volatile.acidity, prob = TRUE, xlab = "Volatile Acidity", ylab = "Frequency", main = "Frequency of Volatile Acidity")
```



```
hist(Wine_Quality$citric.acid, xlab = "Citric Acid", ylab = "Frequency", main = "Frequency of Citric Ac
```

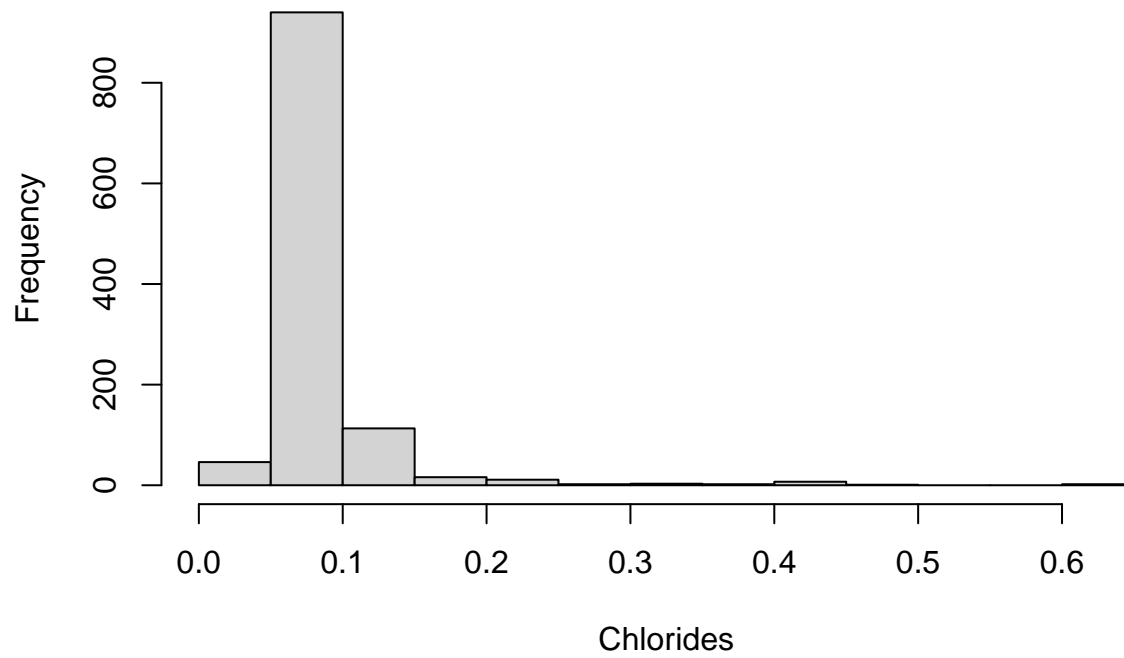


```
hist(Wine_Quality$residual.sugar, xlab = "Residual Sugar", ylab = "Frequency", main = "Frequency of Residual Sugar")
```

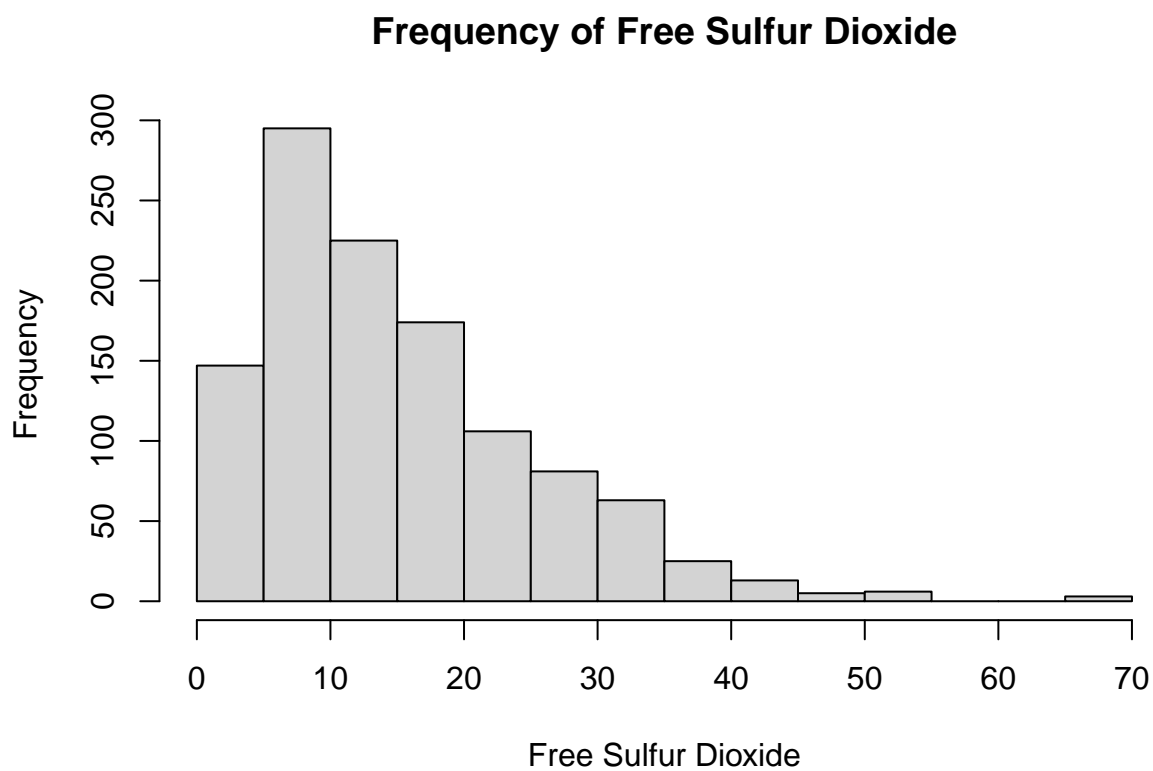


```
hist(Wine_Quality$chlorides, xlab = "Chlorides", ylab = "Frequency", main = "Frequency of Chlorides")
```

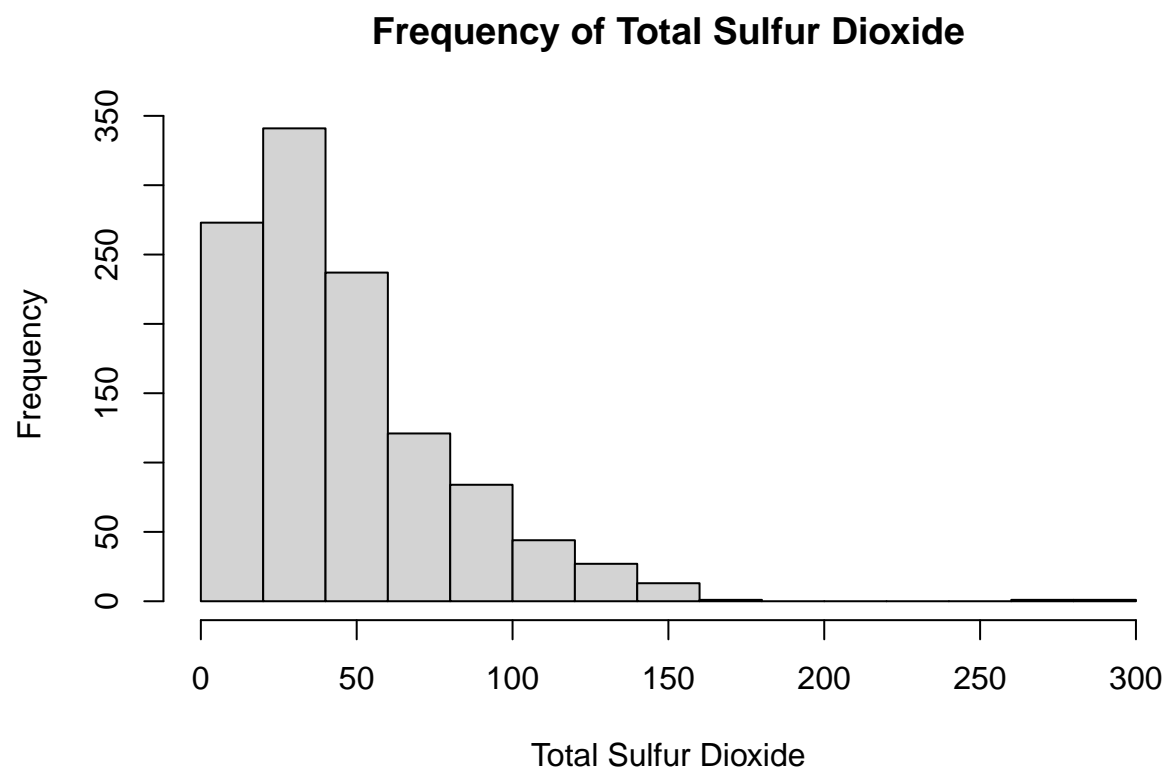
## Frequency of Chlorides



```
hist(Wine_Quality$free.sulfur.dioxide, xlab = "Free Sulfur Dioxide", ylab = "Frequency", main = "Frequency of Free Sulfur Dioxide")
```

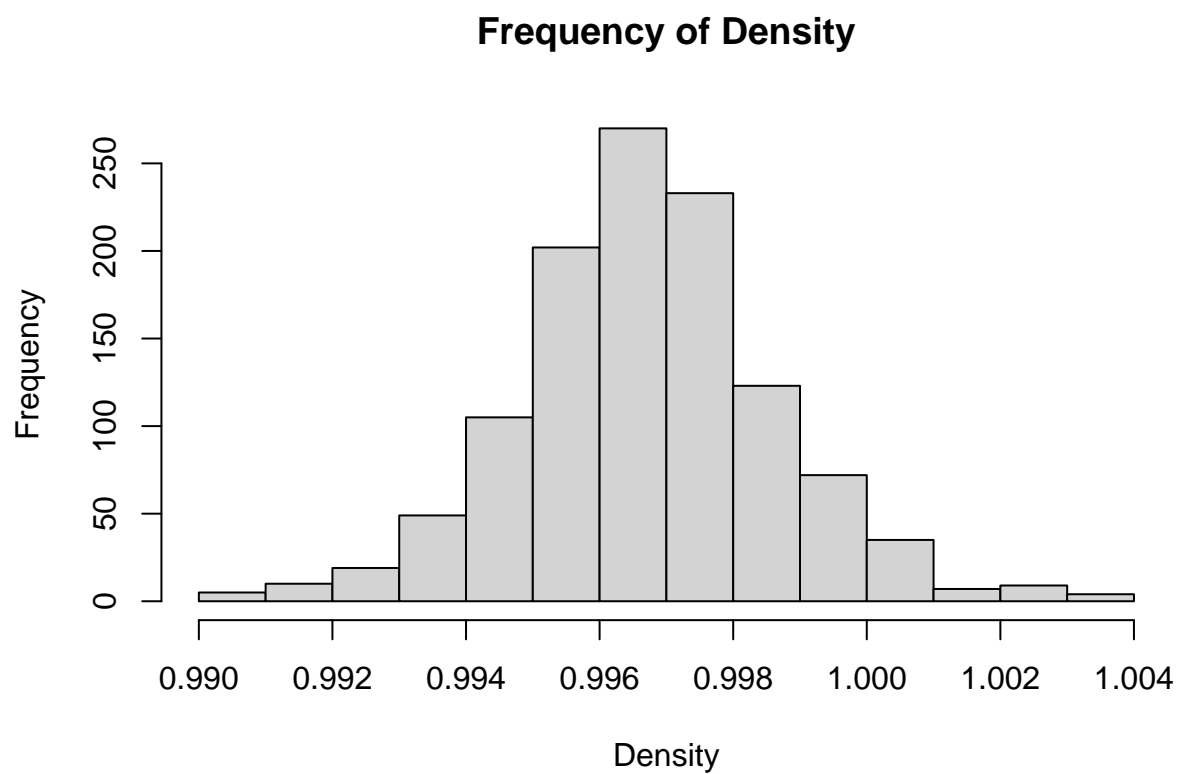


```
hist(Wine_Quality$total.sulfur.dioxide, xlab = "Total Sulfur Dioxide", ylab = "Frequency", main = "Frequency of Total Sulfur Dioxide")
```

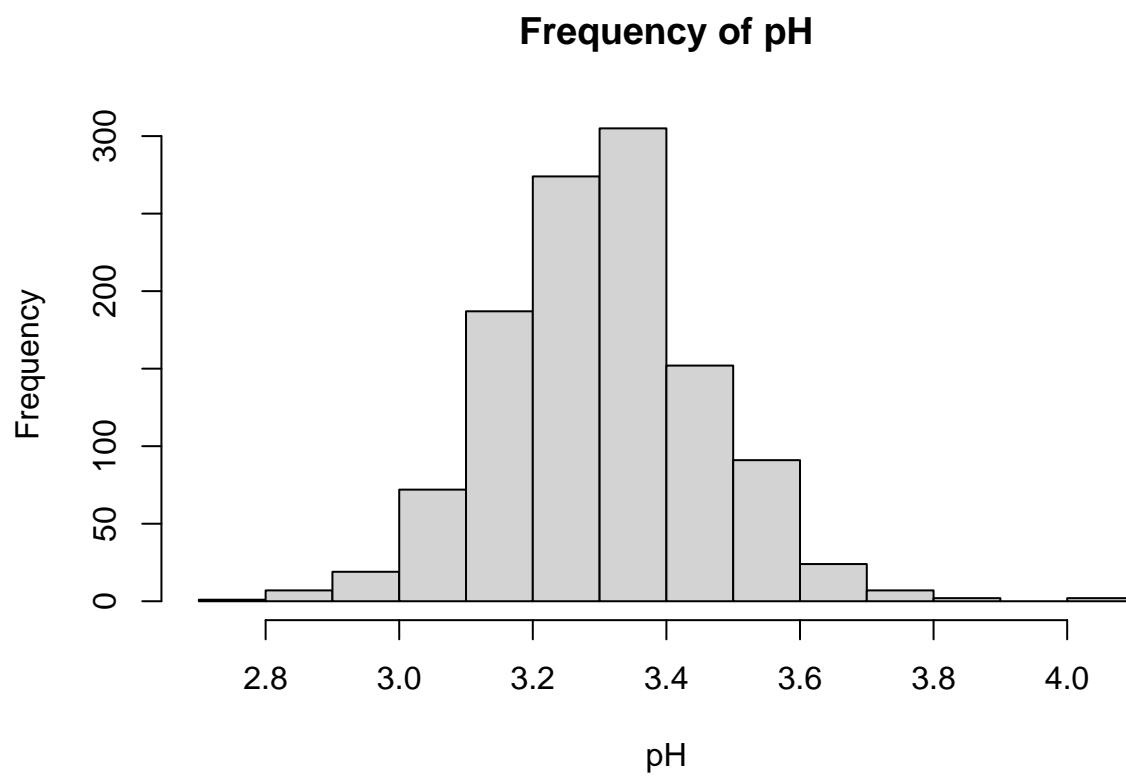


```
hist(Wine_Quality$density, xlab = "Density", ylab = "Frequency", main = "Frequency of Density")
```

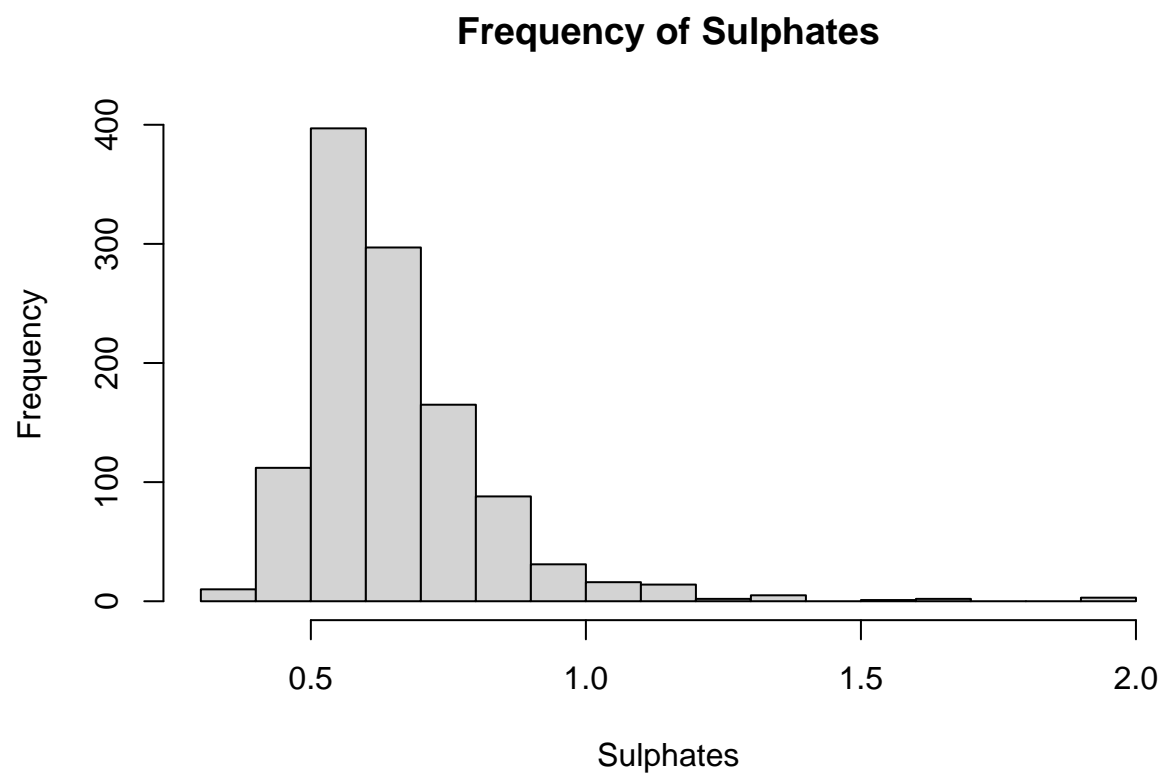




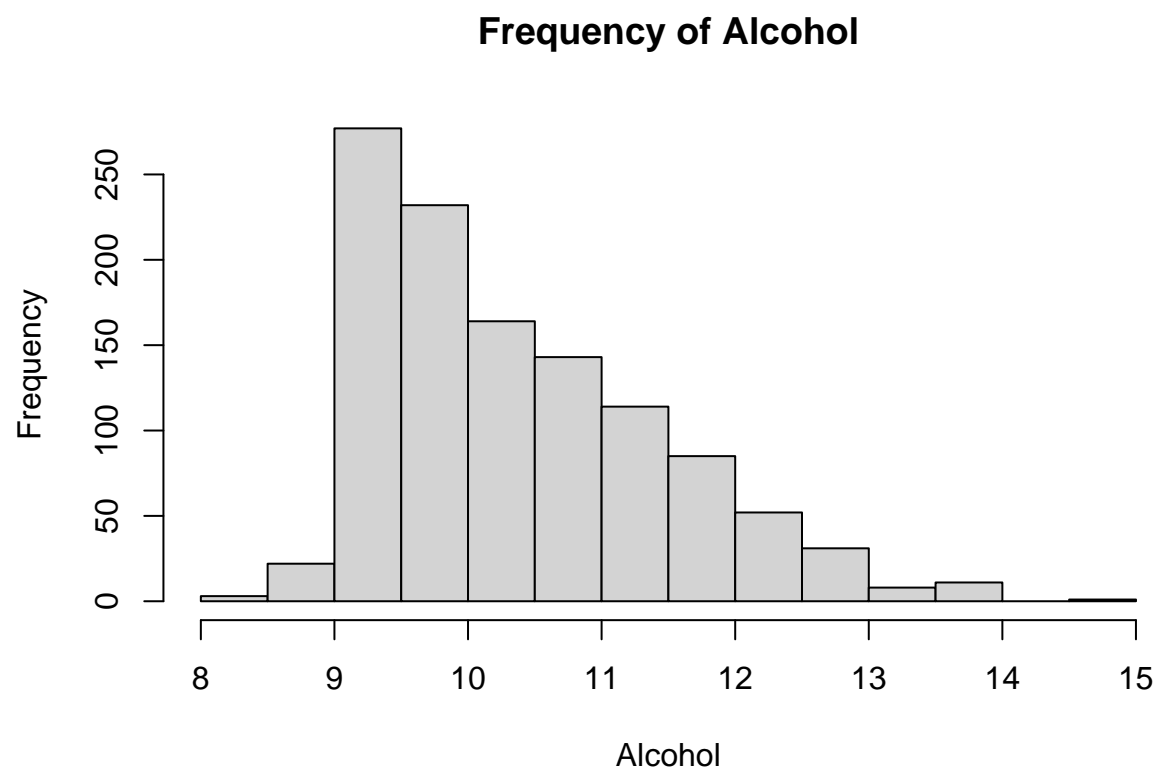
```
hist(Wine_Quality$pH, xlab = "pH", ylab = "Frequency", main = "Frequency of pH")
```



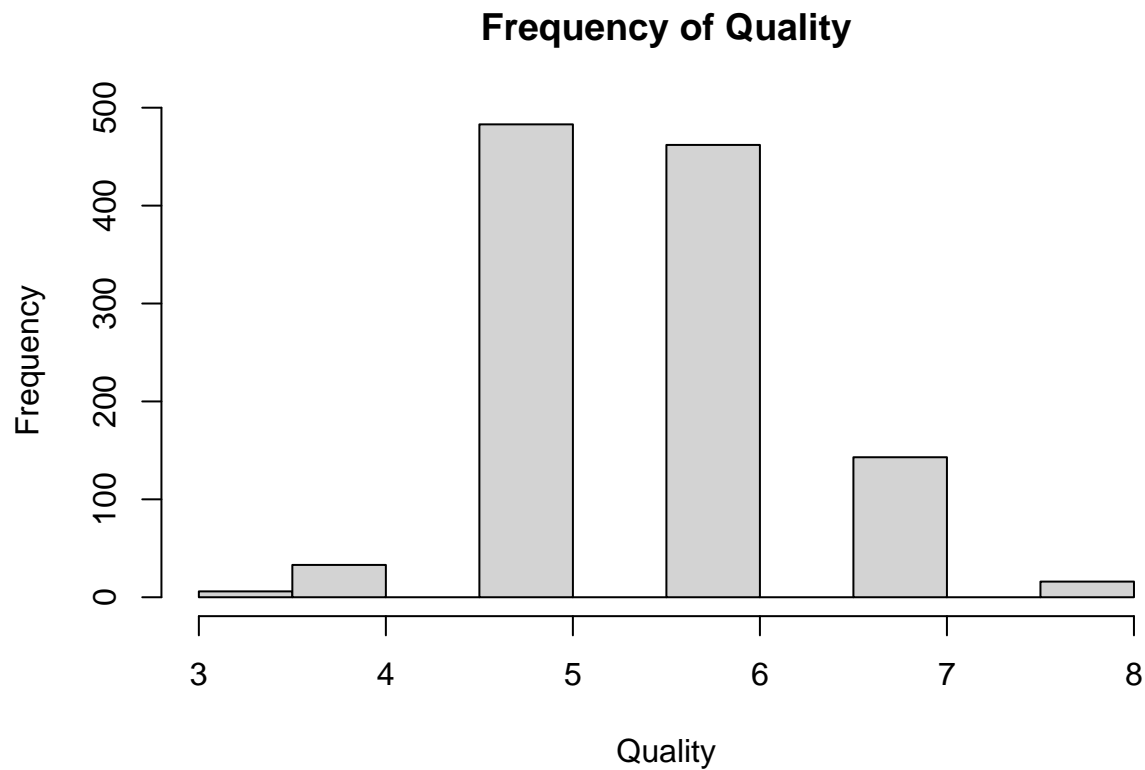
```
hist(Wine_Quality$sulphates, xlab = "Sulphates", ylab = "Frequency", main = "Frequency of Sulphates")
```



```
hist(Wine_Quality$alcohol, xlab = "Alcohol", ylab = "Frequency", main = "Frequency of Alcohol")
```



```
hist(Wine_Quality$quality, xlab = "Quality", ylab = "Frequency", main = "Frequency of Quality")
```



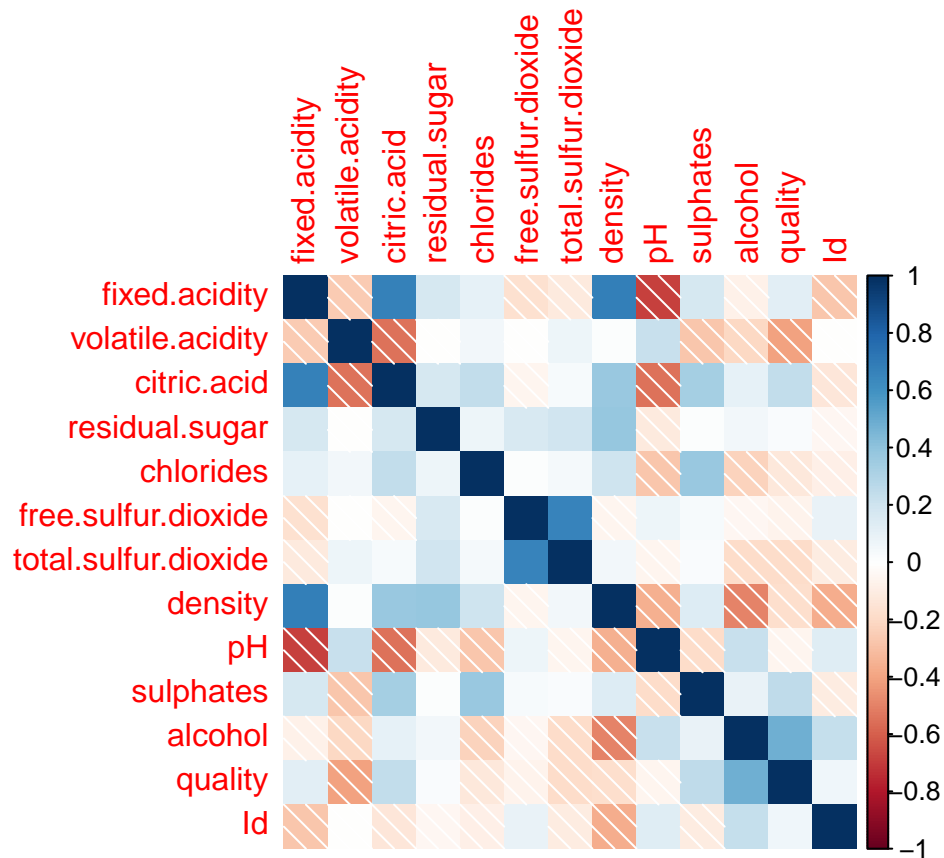
### Correlation Plot

Based on the correlation plot above, there is a positive correlation between the quality of wine and alcohol, sulphates, citric acid, and fixed acidity. However, there is a negative correlation between wine quality and volatile acidity, chlorides, free sulfur dioxide, total sulfur dioxide, density, and pH.

```
# Correlation Plot  
# uses cor() to make correlation matrix  
# uses corrplot() to make correlation plot  
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
M = cor(Wine_Quality)  
corrplot(M, method = 'shade')
```

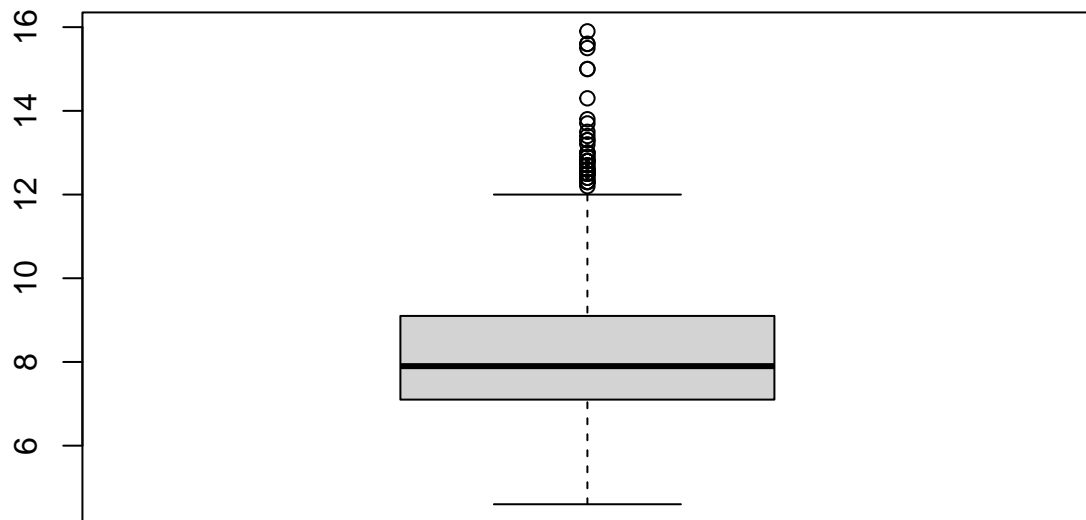


## Box Plot

Similar to a histogram, a box plot provides insight into the distribution of a data set. The box is the interquartile range of data, showing the values between the first and third quartile. The length of the box shows how spread out or concentrated the data is. It is evident by the models above that the data is moderately concentrated with the predictor variable citric acid having the largest spread and chlorides having the smallest spread. The points outside the box are outliers. Besides the predictor variables citric acid and alcohol, the rest have many outliers which will be helpful in determining what variables are best are predicting or explaining the response variable, quality.

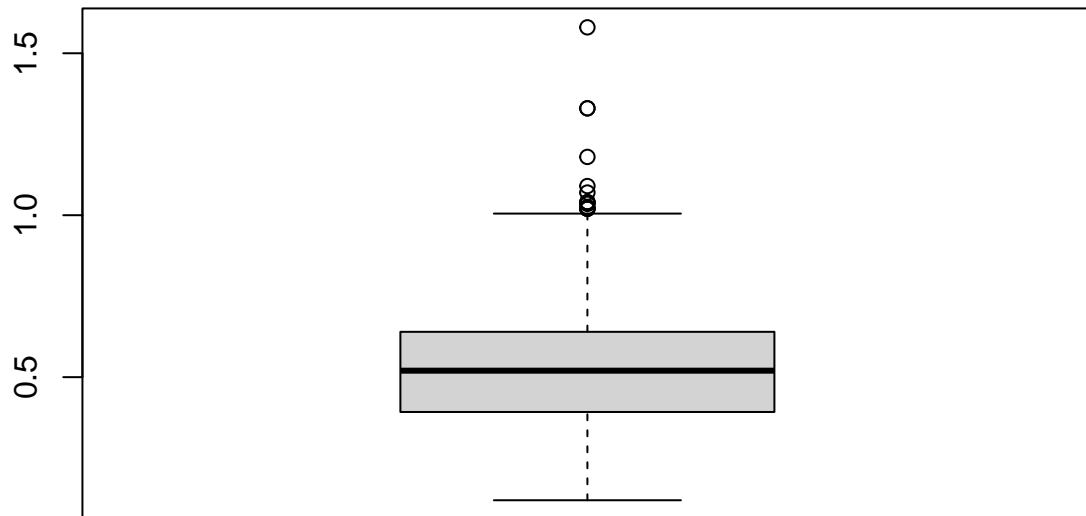
```
# Box Plot
# Uses boxplot() to create a boxplot
boxplot(Wine_Quality$fixed.acidity, main = "Fixed Acidity")
```

## Fixed Acidity



```
boxplot(Wine_Quality$volatile.acidity, main = "Volatile Acidity")
```

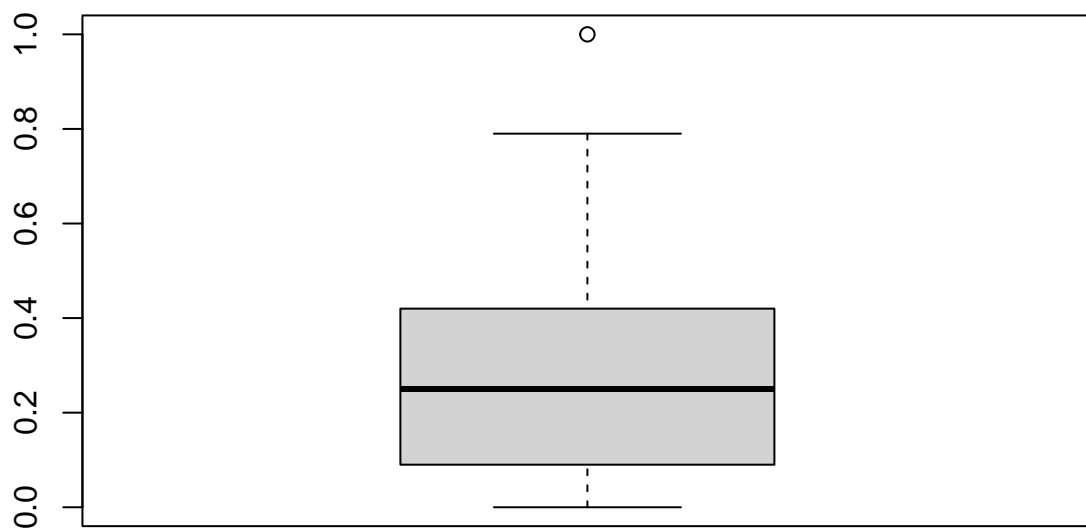
## Volatile Acidity



```
boxplot(Wine_Quality$citric.acid, main = "Citric Acid")
```

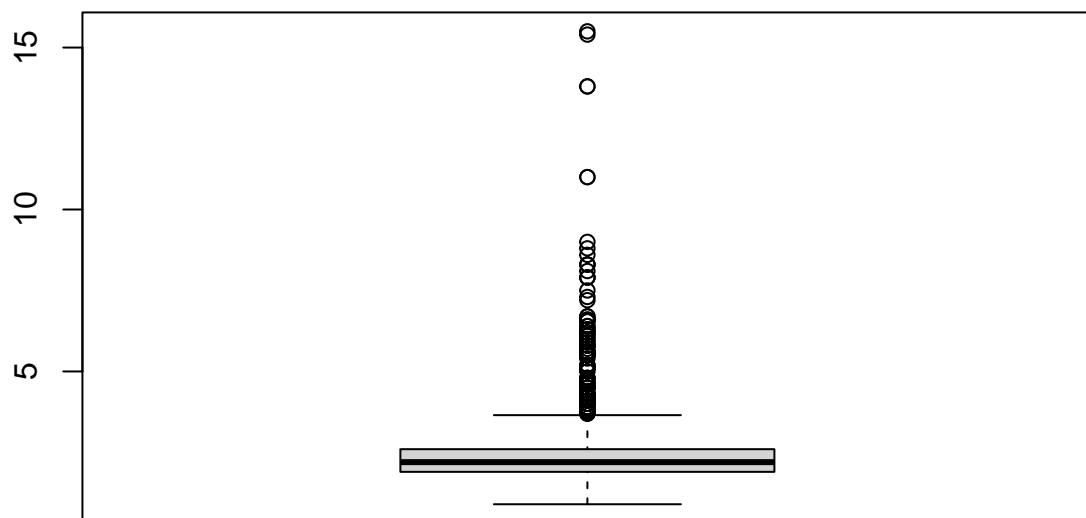


## Citric Acid



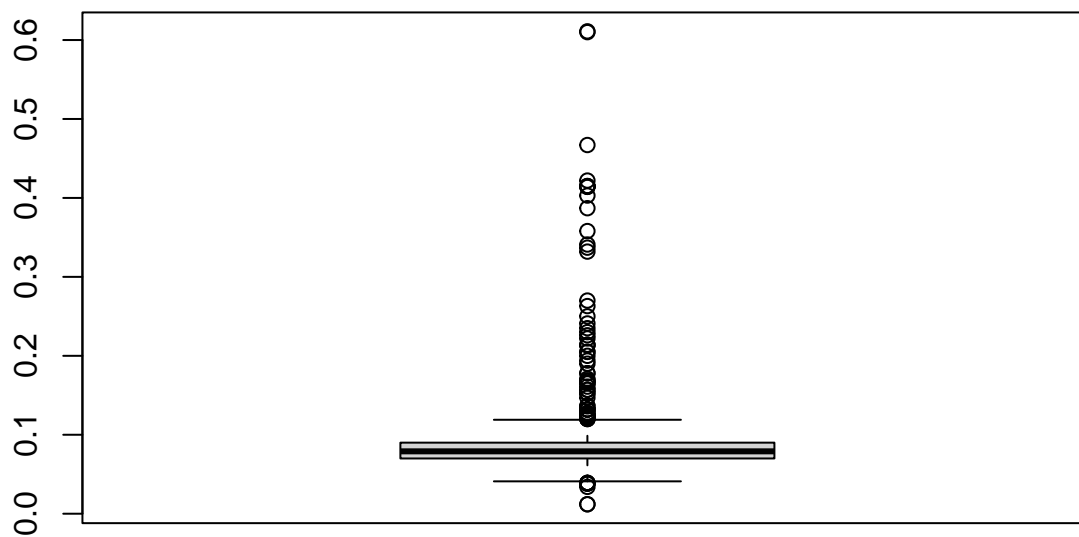
```
boxplot(Wine_Quality$residual.sugar, main = "Residual Sugar")
```

## Residual Sugar



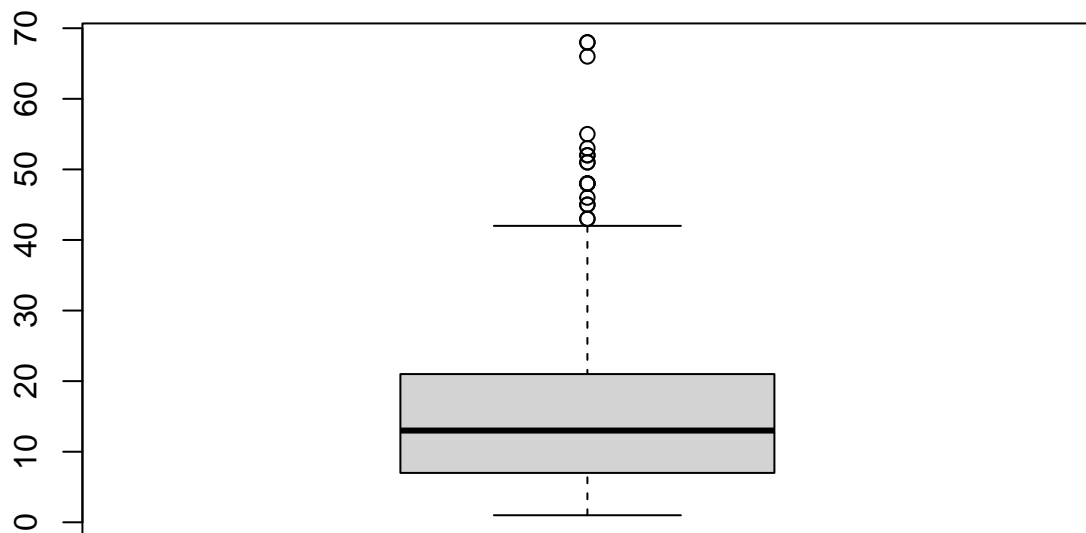
```
boxplot(Wine_Quality$chlorides, main = "Chlorides")
```

## Chlorides

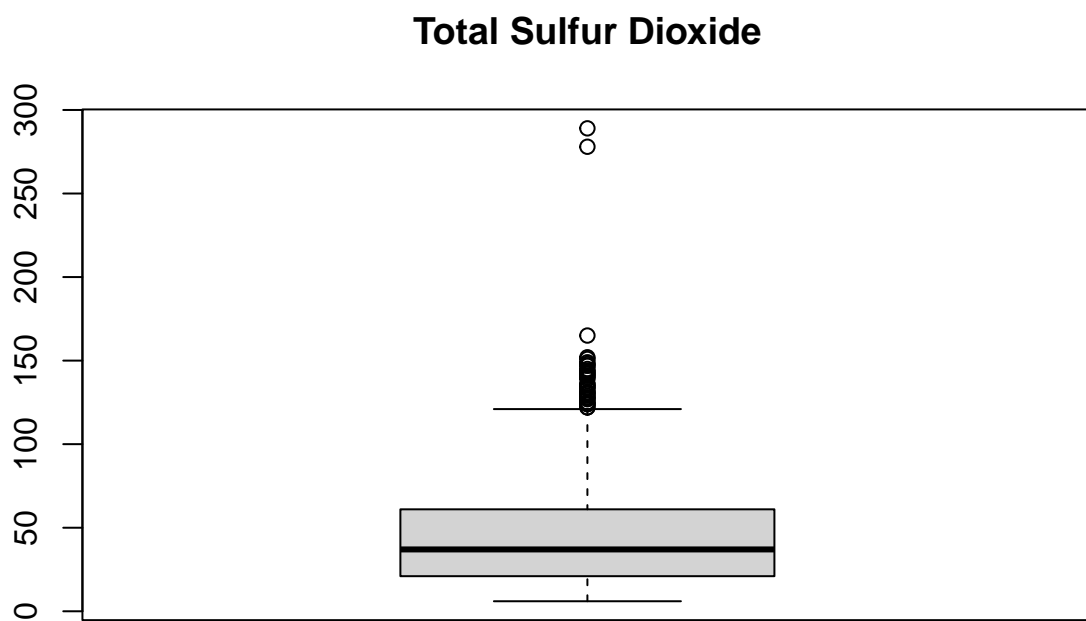


```
boxplot(Wine_Quality$free.sulfur.dioxide, main = "Free Sulfur Dioxide")
```

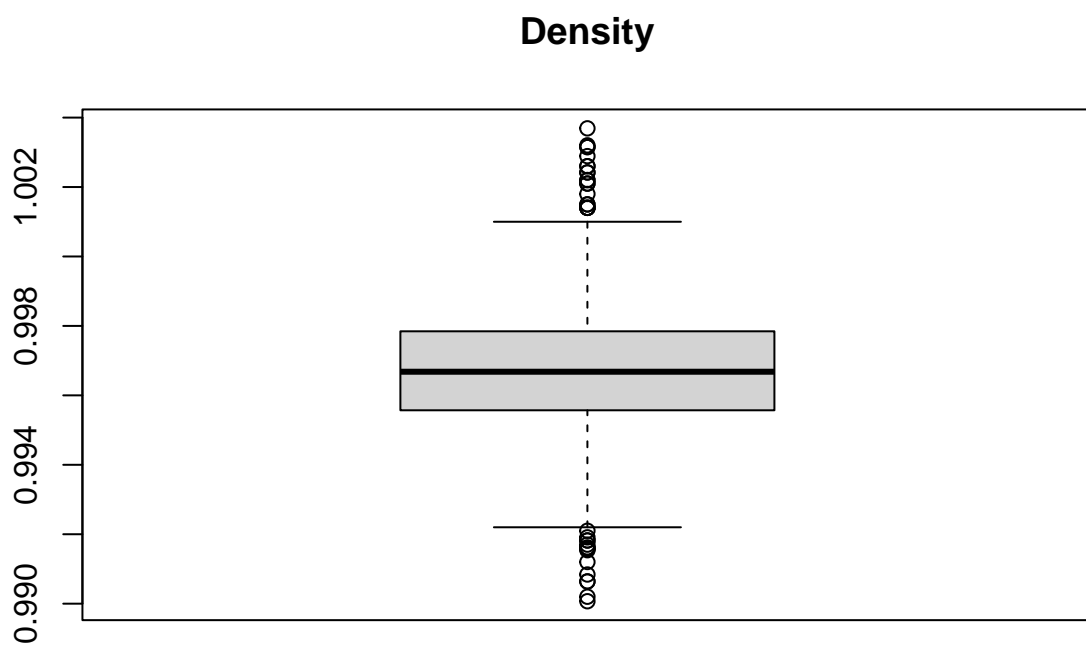
## Free Sulfur Dioxide



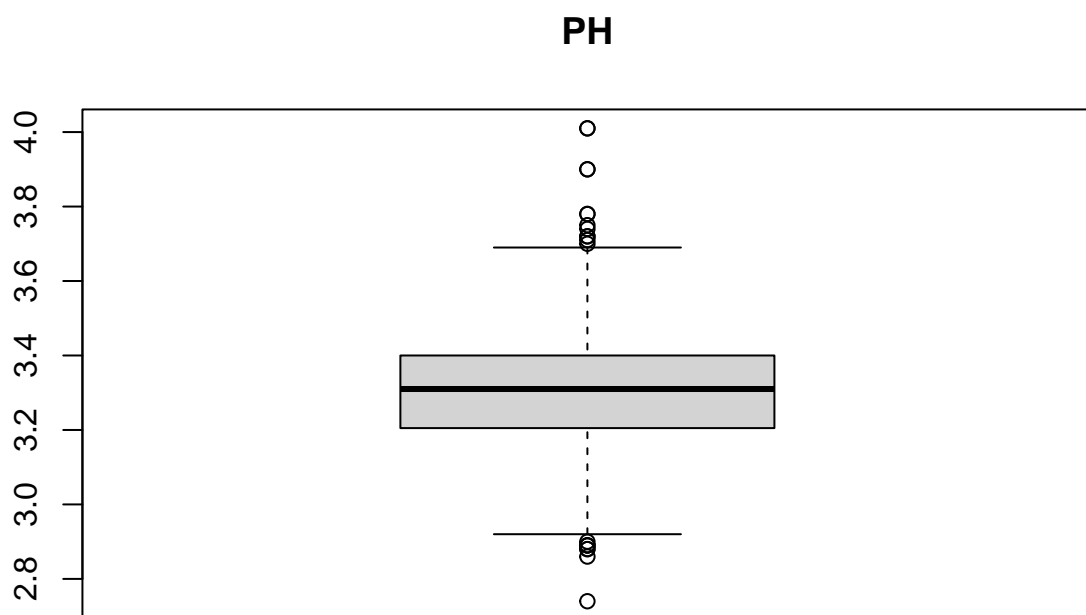
```
boxplot(Wine_Quality$total.sulfur.dioxide, main = "Total Sulfur Dioxide")
```



```
boxplot(Wine_Quality$density, main = "Density")
```

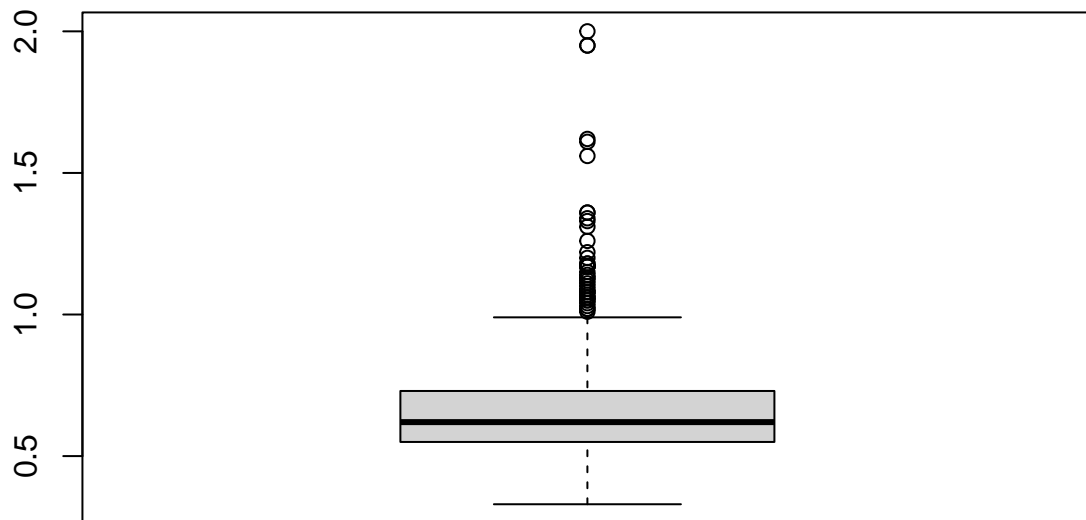


```
boxplot(Wine_Quality$pH, main = "PH")
```



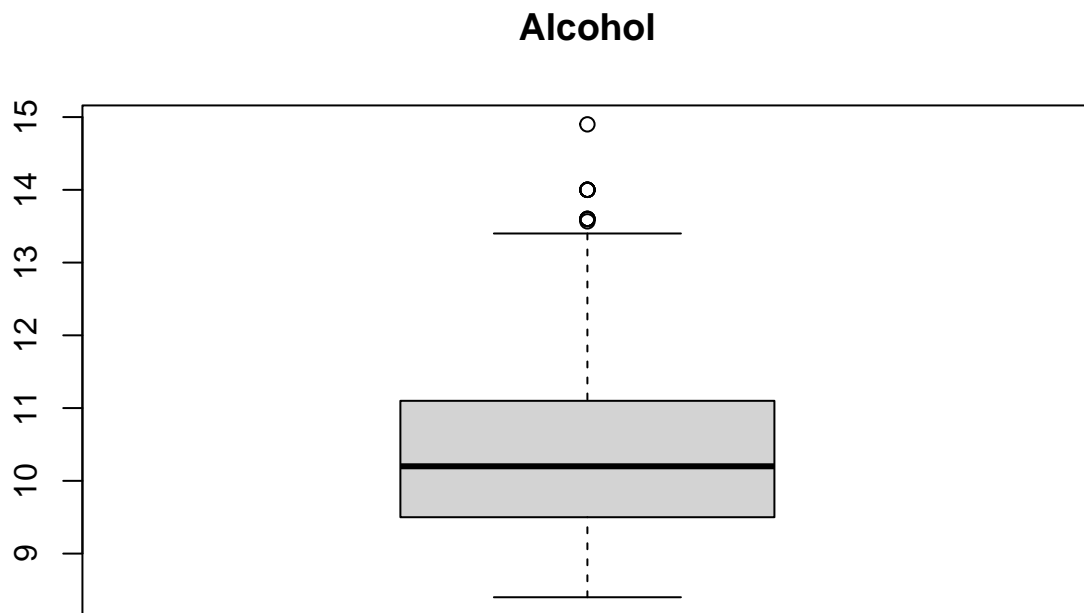
```
boxplot(Wine_Quality$sulphates, main = "Sulphates")
```

## Sulphates



```
boxplot(Wine_Quality$alcohol, main = "Alcohol")
```



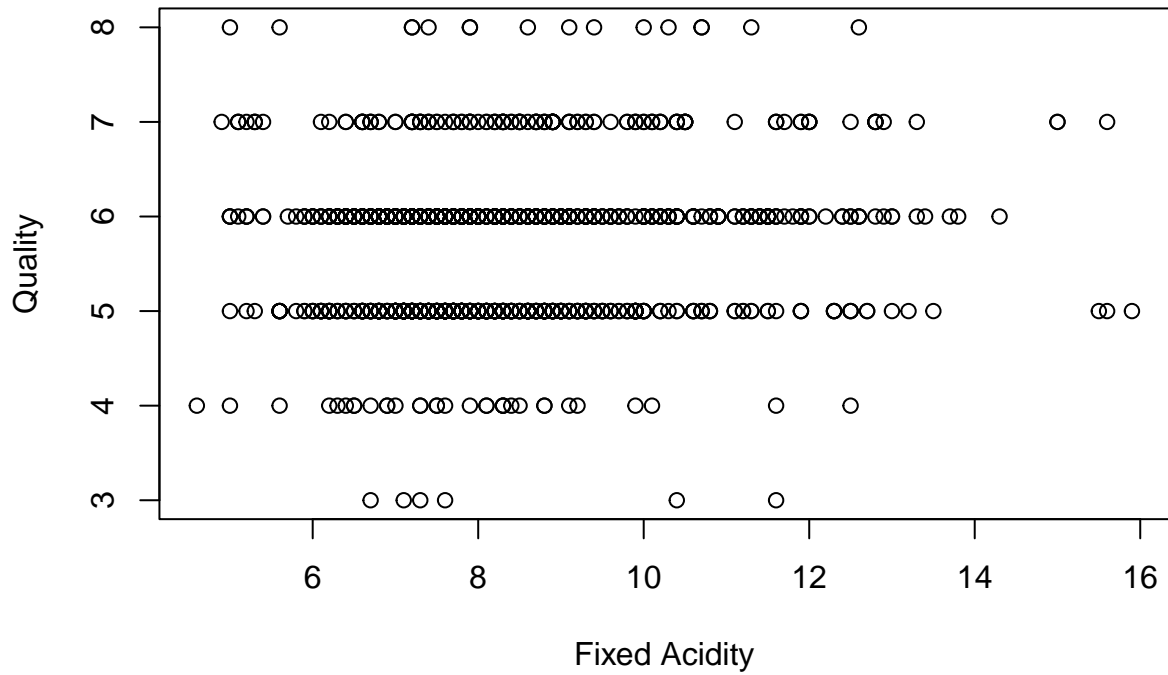


## Scatter Plot

A scatterplot shows the relationship between two variables. In this data set, it's a visual of the relationship between the quality of wine and fixed acidity, pH, alcohol, etc... Variables with a strong relationship will have clusters of data points while variables with weak relationships will have data points that are spread out. From the scatter plots above, we can conclude that there is a strong relationship between wine quality and the other variables as of now.

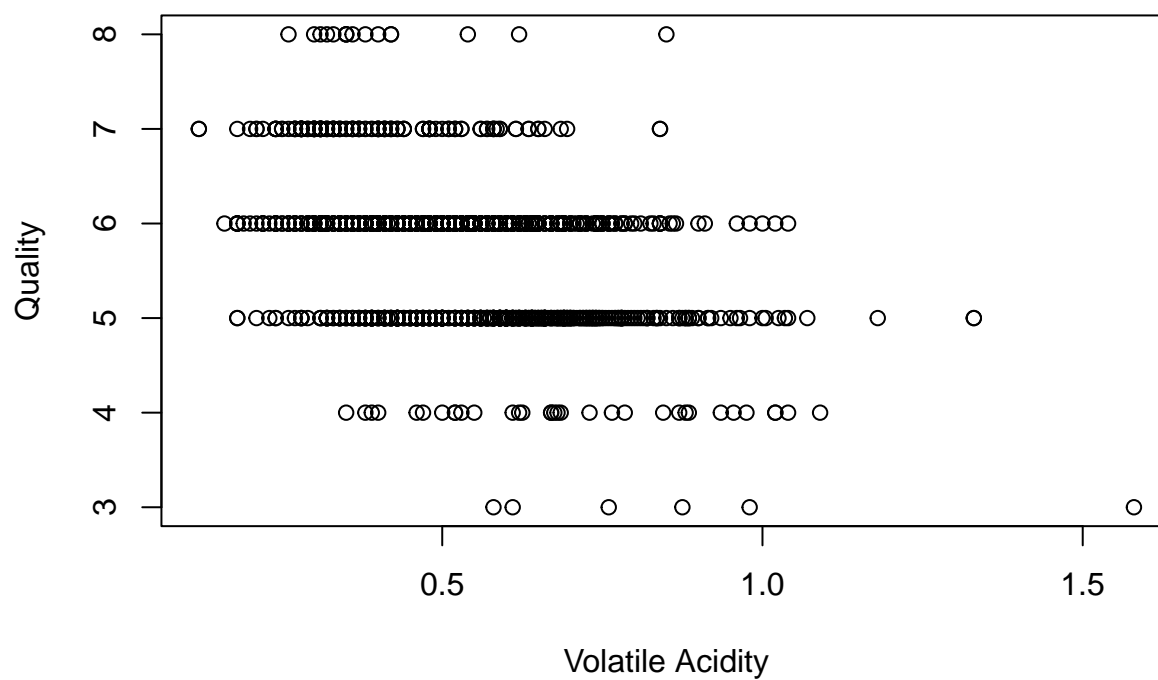
```
# Scatter Plot  
# uses plot() to create the graph with type = "p" for scatter plot  
plot(Wine_Quality$fixed.acidity, Wine_Quality$quality, xlab="Fixed Acidity", ylab="Quality", main = "Scatter Plot of Fixed Acidity vs Quality")
```

**Scatterplot of Fixed Acidity and Quality**



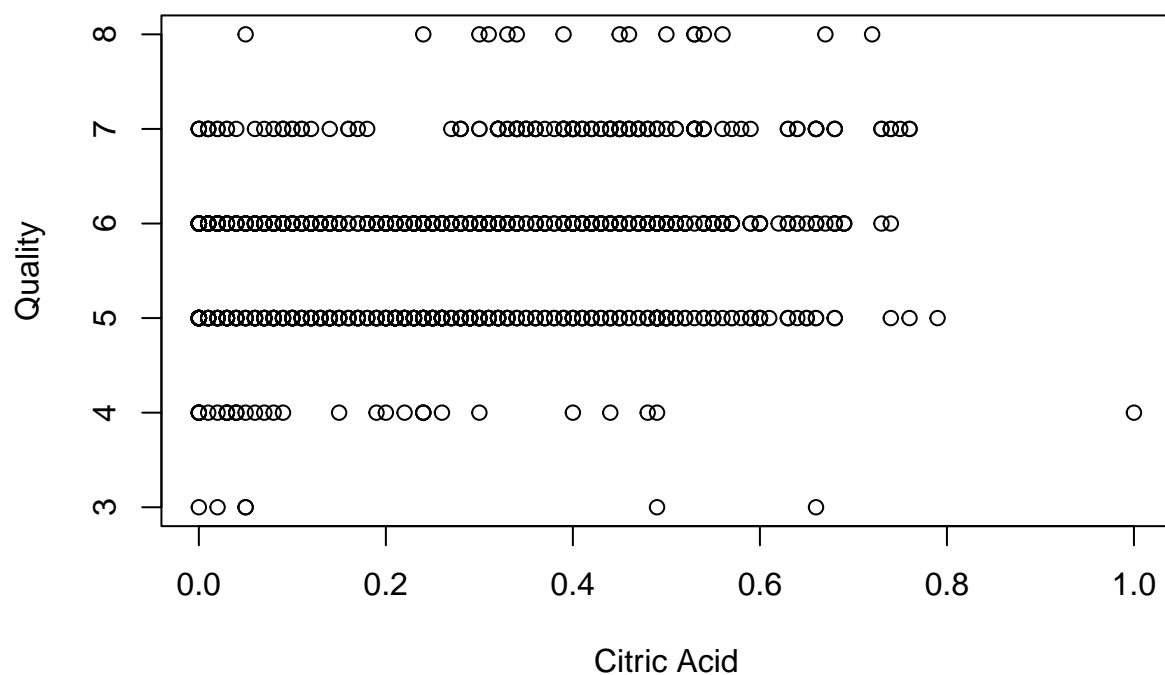
```
plot(Wine_Quality$volatile.acidity, Wine_Quality$quality, xlab="Volatile Acidity", ylab="Quality", main
```

**Scatterplot of Volatile Acidity and Quality**



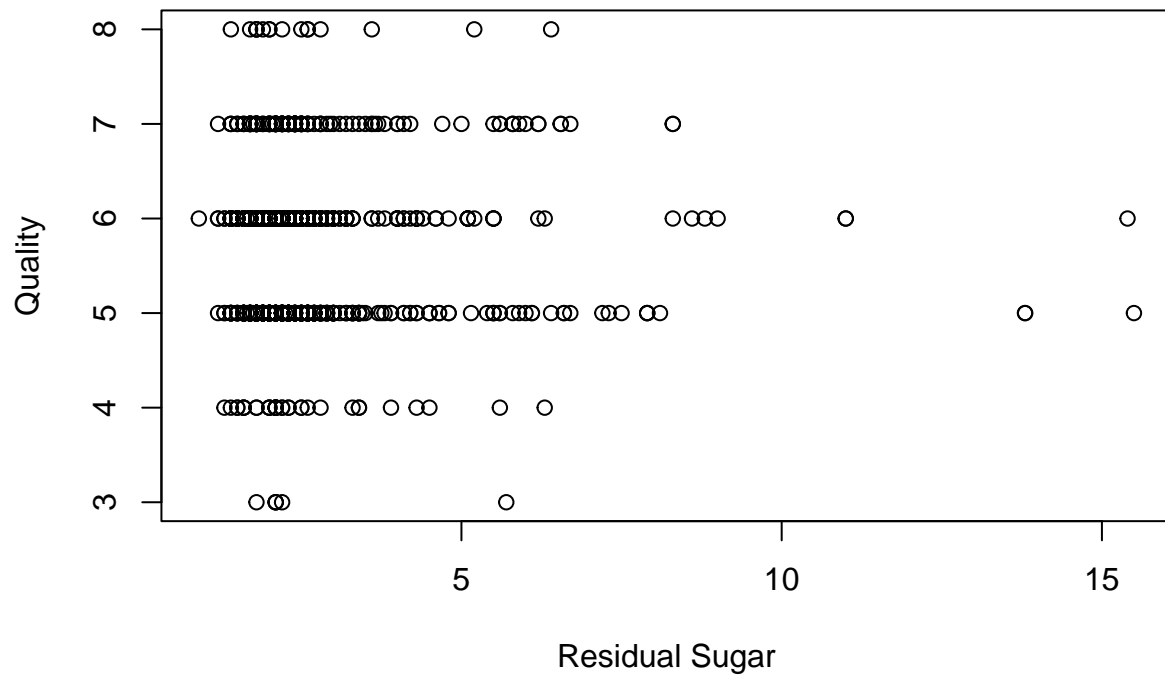
```
plot(Wine_Quality$citric.acid, Wine_Quality$quality, xlab="Citric Acid", ylab="Quality", main = "Scatterplot of Volatile Acidity and Quality")
```

# Scatterplot of Citric Acid and Quality



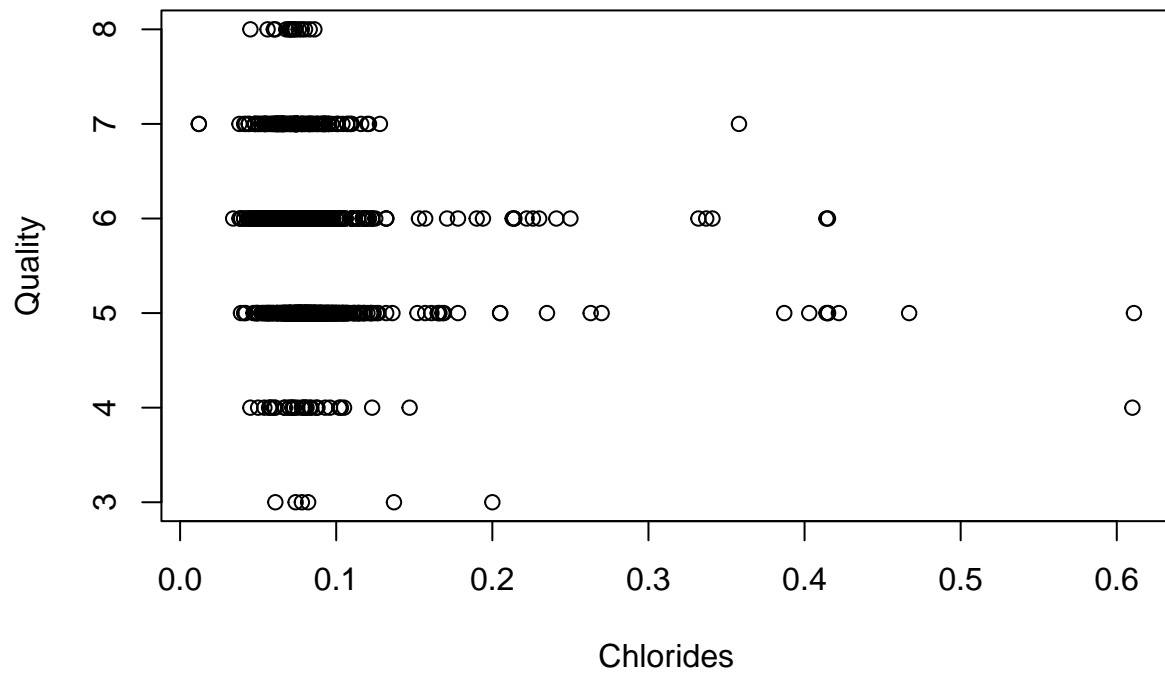
```
plot(Wine_Quality$residual.sugar, Wine_Quality$quality, xlab="Residual Sugar", ylab="Quality", main = "Residual Sugar vs Quality")
```

### Scatterplot of Residual Sugar and Quality



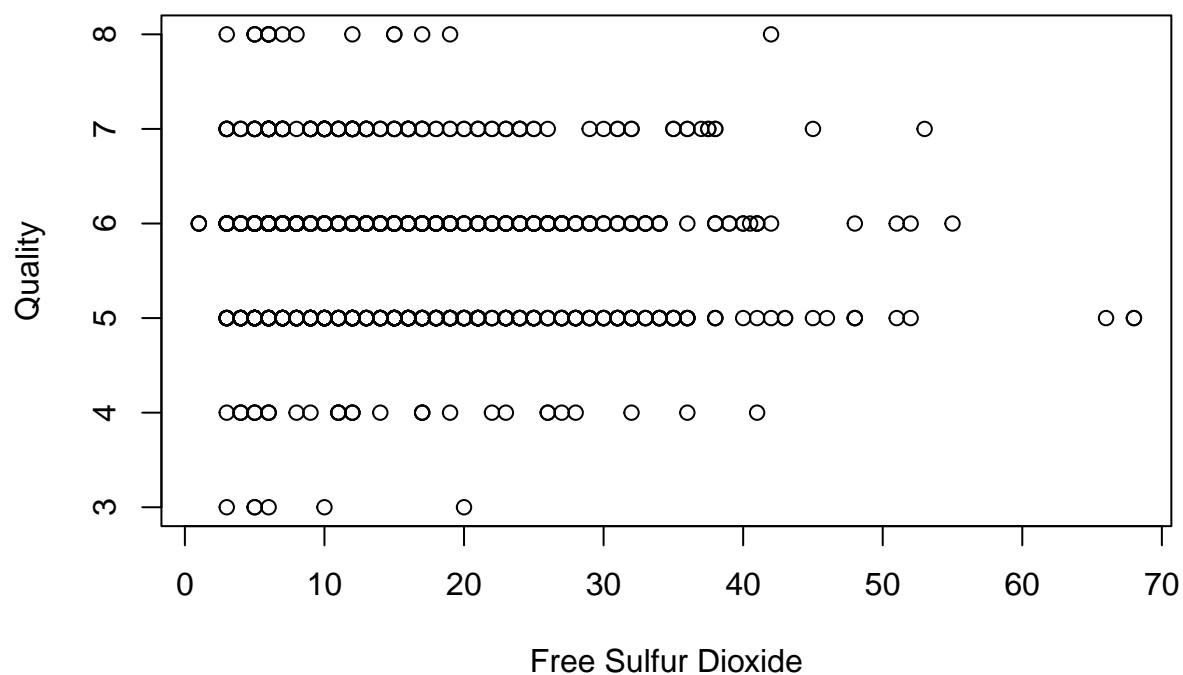
```
plot(Wine_Quality$chlorides, Wine_Quality$quality, xlab="Chlorides", ylab="Quality", main = "Scatterplot of Chlorides and Quality")
```

**Scatterplot of Chlorides and Quality**



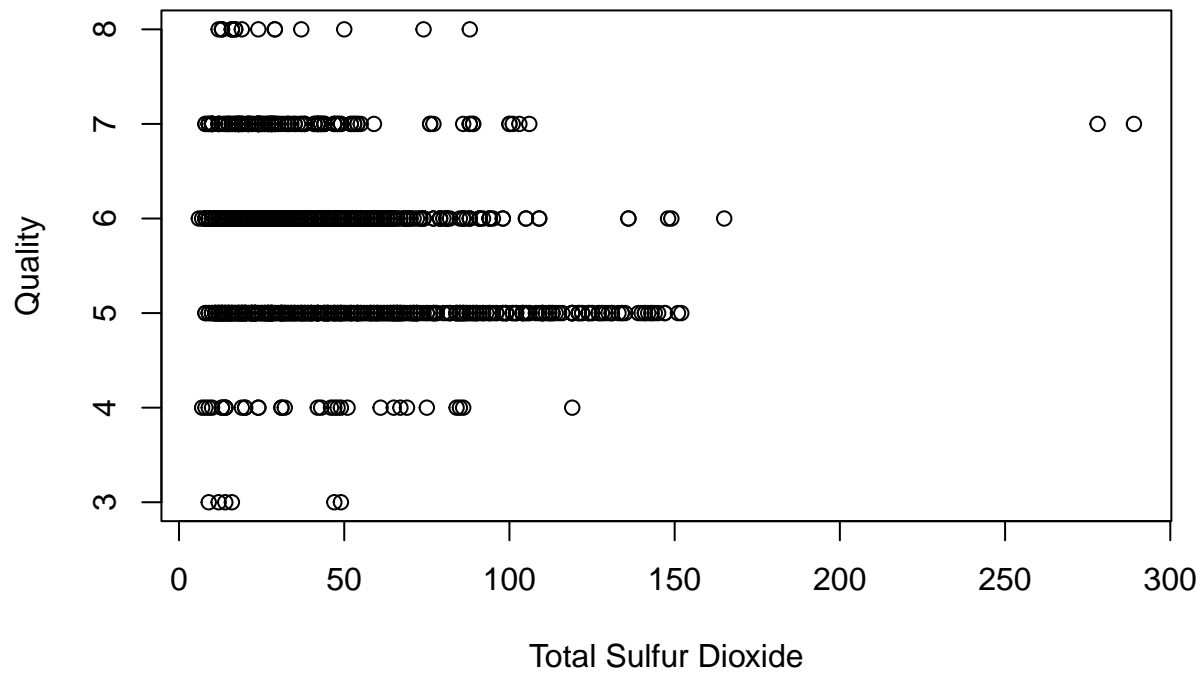
```
plot(Wine_Quality$free.sulfur.dioxide, Wine_Quality$quality, xlab="Free Sulfur Dioxide", ylab="Quality")
```

### Scatterplot of Free Sulfur Dioxide and Quality



```
plot(Wine_Quality$total.sulfur.dioxide, Wine_Quality$quality, xlab="Total Sulfur Dioxide", ylab="Quality")
```

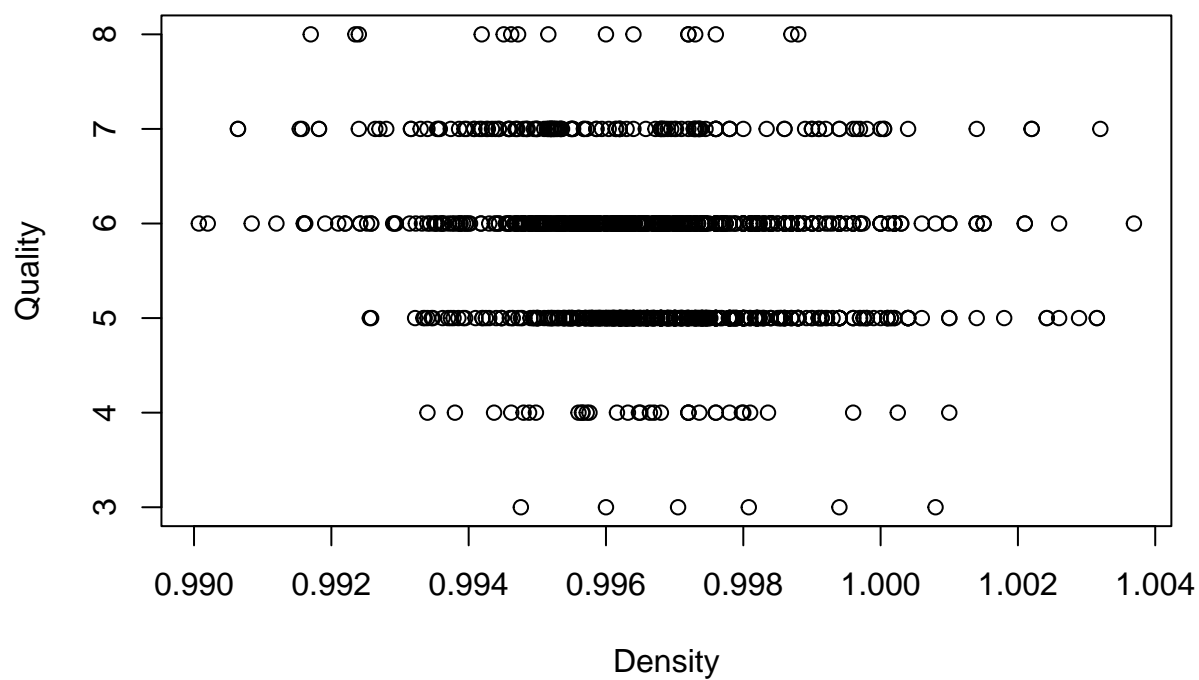
**Scatterplot of Total Sulfur Dioxide and Quality**



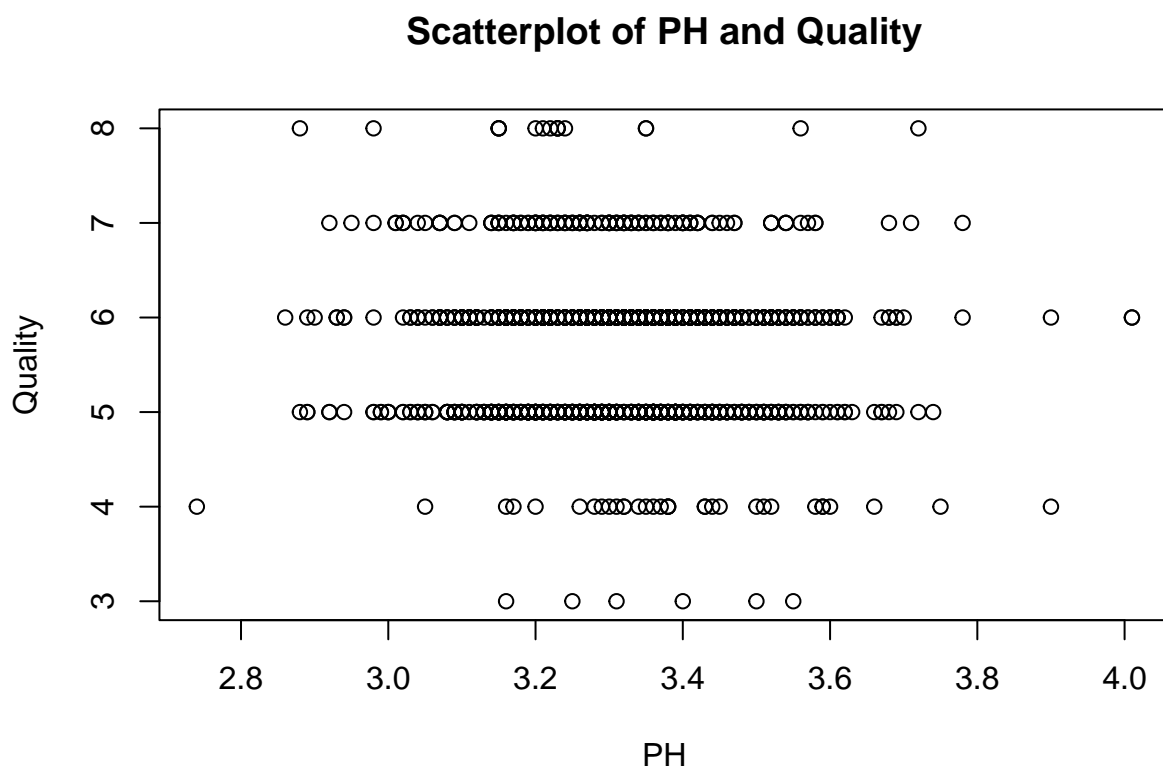
```
plot(Wine_Quality$density, Wine_Quality$quality, xlab="Density", ylab="Quality", main = "Scatterplot of
```



### Scatterplot of Density and Quality

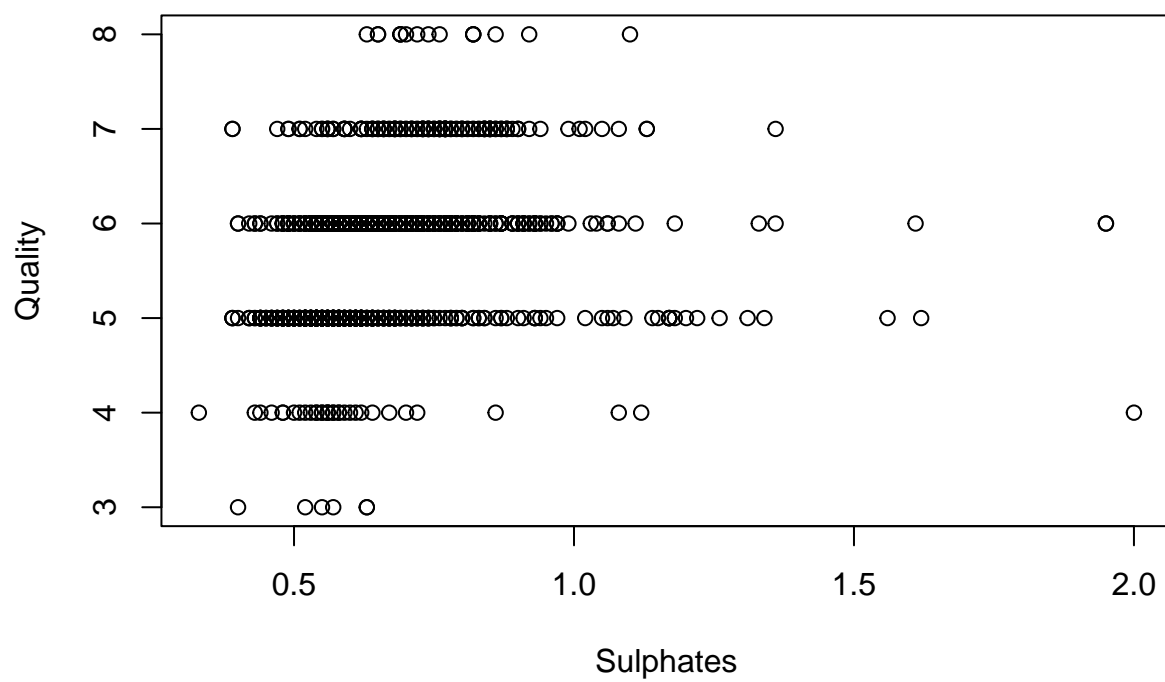


```
plot(Wine_Quality$pH, Wine_Quality$quality, xlab="PH", ylab="Quality", main = "Scatterplot of PH and Quality")
```



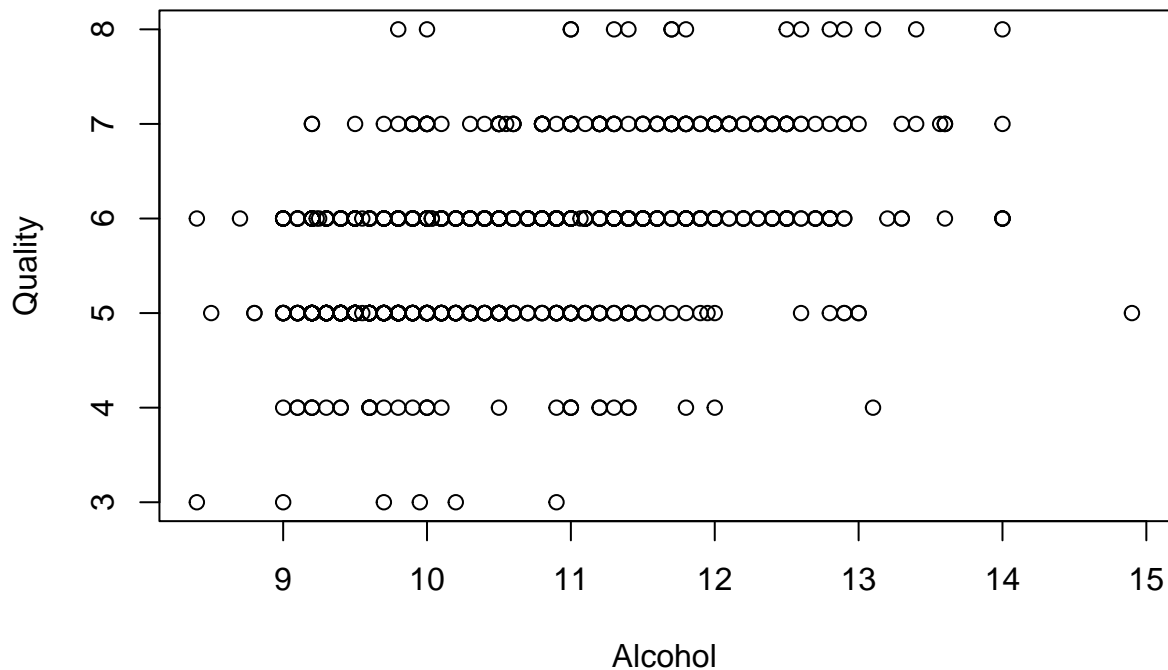
```
plot(Wine_Quality$sulphates, Wine_Quality$quality, xlab="Sulphates", ylab="Quality", main = "Scatterplot of Sulphates and Quality")
```

**Scatterplot of Sulphates and Quality**



```
plot(Wine_Quality$alcohol, Wine_Quality$quality, xlab="Alcohol", ylab="Quality", main = "Scatterplot of
```

## Scatterplot of Alcohol and Quality



## Statistical Summary

Summarizing the data set provides us information about the minimum, 1st quartile, mean, 3rd quartile, and maximum of each variable. Having the average value of each variable, the mean, helps us compare variables and identify outliers.

```
# Statistical Summary (Five-Number Summary)
# Uses summary() for statistical summary
summary(Wine_Quality)
```

```
## fixed.acidity    volatile.acidity    citric.acid    residual.sugar
## Min.   : 4.600    Min.   :0.1200    Min.   :0.0000    Min.   : 0.900
## 1st Qu.: 7.100    1st Qu.:0.3925    1st Qu.:0.0900    1st Qu.: 1.900
## Median : 7.900    Median :0.5200    Median :0.2500    Median : 2.200
## Mean   : 8.311    Mean   :0.5313    Mean   :0.2684    Mean   : 2.532
## 3rd Qu.: 9.100    3rd Qu.:0.6400    3rd Qu.:0.4200    3rd Qu.: 2.600
## Max.   :15.900    Max.   :1.5800    Max.   :1.0000    Max.   :15.500
## chlorides       free.sulfur.dioxide    total.sulfur.dioxide    density
## Min.   :0.01200    Min.   : 1.00      Min.   : 6.00      Min.   :0.9901
## 1st Qu.:0.07000    1st Qu.: 7.00      1st Qu.: 21.00     1st Qu.:0.9956
## Median :0.07900    Median :13.00     Median : 37.00     Median :0.9967
## Mean   :0.08693    Mean   :15.62     Mean   : 45.91     Mean   :0.9967
## 3rd Qu.:0.09000    3rd Qu.:21.00     3rd Qu.: 61.00     3rd Qu.:0.9978
## Max.   :0.61100    Max.   :68.00     Max.   :289.00     Max.   :1.0037
## pH              sulphates              alcohol              quality
```

```
## Min.      :2.740    Min.      :0.3300    Min.      : 8.40    Min.      :3.000
## 1st Qu.:3.205    1st Qu.:0.5500    1st Qu.: 9.50    1st Qu.:5.000
## Median :3.310    Median :0.6200    Median :10.20    Median :6.000
## Mean      :3.311    Mean      :0.6577    Mean      :10.44    Mean      :5.657
## 3rd Qu.:3.400    3rd Qu.:0.7300    3rd Qu.:11.10    3rd Qu.:6.000
## Max.      :4.010    Max.      :2.0000    Max.      :14.90    Max.      :8.000
##          Id
## Min.      : 0
## 1st Qu.: 411
## Median : 794
## Mean      : 805
## 3rd Qu.:1210
## Max.      :1597
```

## Question 2

### Multiple Linear Regression Model

```
# Estimating The Multiple Linear Regression Model
# uses lm() to create linear model
# uses summary() to display regression details
wineq <- lm(quality ~ fixed.acidity + volatile.acidity + citric.acid + residual.sugar + chlorides + free.sulfur.dioxide + total.sulfur.dioxide + density + pH + sulphates + alcohol, data = Wine_Quality)
summary(wineq)

##
## Call:
## lm(formula = quality ~ fixed.acidity + volatile.acidity + citric.acid +
##      residual.sugar + chlorides + free.sulfur.dioxide + total.sulfur.dioxide +
##      density + pH + sulphates + alcohol, data = Wine_Quality)
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-2.49977	-0.36903	-0.04658	0.43956	2.00117

```
##
## Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	2.155e+01	2.477e+01	0.870	0.384551
fixed.acidity	2.297e-02	3.025e-02	0.759	0.447770
volatile.acidity	-1.129e+00	1.407e-01	-8.023	2.56e-15 ***
citric.acid	-1.319e-01	1.730e-01	-0.762	0.446105
residual.sugar	1.351e-02	1.846e-02	0.732	0.464278
chlorides	-1.708e+00	4.974e-01	-3.434	0.000616 ***
free.sulfur.dioxide	2.369e-03	2.553e-03	0.928	0.353547
total.sulfur.dioxide	-2.785e-03	8.386e-04	-3.321	0.000926 ***
density	-1.745e+01	2.529e+01	-0.690	0.490284
pH	-4.082e-01	2.229e-01	-1.832	0.067280 .
sulphates	8.752e-01	1.335e-01	6.555	8.44e-11 ***
alcohol	2.801e-01	3.126e-02	8.963	< 2e-16 ***

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6405 on 1131 degrees of freedom
```

```
## Multiple R-squared:  0.3742, Adjusted R-squared:  0.3682
## F-statistic: 61.49 on 11 and 1131 DF,  p-value: < 2.2e-16
```

### Question 3

#### Outlier, High Leverage, and New Model

It is evident that there are outliers and high leverage observations by the values outputted by the boxplot.stats() and hats() codes. The values derived by performing these tests corroborate the outcomes of the histogram, boxplot, scatterplot, and summary functions. These values are important because they are capable of altering the model's best-fit line.

```
# Outlier
# uses boxplot.stats() with $out to capture outliers
boxplot.stats(Wine_Quality$fixed.acidity)$out
```

```
## [1] 12.8 12.8 15.0 15.0 12.5 13.3 13.4 12.5 13.8 13.5 12.6 12.5 12.8 12.8 13.7
## [16] 12.2 12.5 12.8 12.3 12.3 12.6 15.6 12.5 13.0 12.5 13.3 12.5 12.9 14.3 12.4
## [31] 15.5 15.6 13.0 12.7 13.0 12.7 12.3 12.3 12.4 13.2 15.9 12.9 12.6 12.6
```

```
boxplot.stats(Wine_Quality$volatile.acidity)$out
```

```
## [1] 1.020 1.070 1.330 1.330 1.040 1.090 1.040 1.020 1.035 1.025 1.020 1.580
## [13] 1.180 1.040
```

```
boxplot.stats(Wine_Quality$citric.acid)$out
```

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

```
boxplot.stats(Wine_Quality$residual.sugar)$out
```

```
## [1] 5.50 5.90 4.65 4.65 5.50 5.50 5.50 7.30 7.20 5.60 4.00 4.00
## [13] 4.00 4.00 6.40 5.60 5.60 11.00 11.00 4.50 4.80 5.80 5.80 6.20
## [25] 4.20 7.90 7.90 4.50 6.70 6.60 3.70 5.20 15.50 8.30 6.55 6.55
## [37] 6.10 4.30 5.80 5.15 6.30 4.20 4.60 4.20 4.30 4.30 7.90 5.10
## [49] 5.60 8.60 7.50 6.00 3.90 4.20 4.00 6.60 6.00 3.80 9.00 8.80
## [61] 5.00 3.80 4.10 5.90 4.10 6.20 4.00 3.90 4.00 8.10 6.40 8.30
## [73] 8.30 4.70 5.50 5.50 4.30 5.50 3.70 6.20 5.60 4.60 5.80 4.10
## [85] 4.30 4.80 6.30 4.50 4.50 4.30 3.80 5.40 6.10 5.10 5.10 3.90
## [97] 15.40 4.80 5.20 3.75 13.80 13.80 5.70 4.30 4.10 4.10 4.40 3.70
## [109] 6.70 5.10
```

```
boxplot.stats(Wine_Quality$chlorides)$out
```

```
## [1] 0.341 0.332 0.467 0.178 0.610 0.270 0.039 0.337 0.263 0.611 0.358 0.213
## [13] 0.214 0.121 0.128 0.120 0.122 0.122 0.121 0.127 0.152 0.125 0.122 0.200
## [25] 0.226 0.250 0.124 0.222 0.039 0.157 0.422 0.034 0.387 0.415 0.157 0.241
## [37] 0.190 0.132 0.126 0.038 0.165 0.147 0.012 0.012 0.194 0.132 0.161 0.120
## [49] 0.120 0.123 0.123 0.414 0.171 0.178 0.166 0.136 0.132 0.132 0.123 0.123
## [61] 0.403 0.137 0.414 0.166 0.168 0.415 0.153 0.415 0.123 0.214 0.169 0.205
## [73] 0.205 0.039 0.235 0.230 0.038
```

```
boxplot.stats(Wine_Quality$free.sulfur.dioxide)$out
```

```
## [1] 68 68 43 46 45 53 52 51 45 48 48 43 51 52 55 48 48 66
```

```
boxplot.stats(Wine_Quality$total.sulfur.dioxide)$out
```

```
## [1] 136 125 140 136 134 141 128 129 128 143 127 135 165 124 124 122 134 124 151
## [20] 142 149 147 145 148 152 122 125 127 139 143 144 130 278 289 141 133 147 131
## [39] 131 131
```

```
boxplot.stats(Wine_Quality$density)$out
```

```
## [1] 0.99160 0.99160 1.00140 1.00150 1.00150 1.00180 0.99120 1.00220 1.00220
## [10] 1.00140 1.00140 1.00320 1.00260 1.00140 1.00315 1.00315 1.00210 1.00210
## [19] 0.99170 1.00260 0.99210 0.99154 0.99064 0.99064 1.00289 0.99162 0.99007
## [28] 0.99020 0.99157 0.99084 0.99191 1.00369 1.00242 0.99182 1.00242 0.99182
```

```
boxplot.stats(Wine_Quality$pH)$out
```

```
## [1] 3.90 3.75 2.74 2.88 2.86 3.74 3.72 2.89 2.89 3.90 3.71 2.89 3.78 3.70 3.78
## [16] 4.01 2.90 4.01 2.88 3.72
```

```
boxplot.stats(Wine_Quality$sulphates)$out
```

```
## [1] 1.56 1.08 1.20 1.12 1.95 1.22 1.95 1.31 2.00 1.08 1.02 1.61 1.09 1.26 1.08
## [16] 1.36 1.13 1.04 1.11 1.13 1.07 1.06 1.06 1.05 1.02 1.14 1.36 1.05 1.17 1.62
## [31] 1.06 1.18 1.34 1.15 1.17 1.17 1.33 1.18 1.17 1.03 1.17 1.10 1.01
```

```
boxplot.stats(Wine_Quality$alcohol)$out
```

```
## [1] 14.00000 14.00000 14.00000 14.00000 14.90000 14.00000 13.60000 13.60000
## [9] 13.60000 14.00000 13.56667 13.60000
```

```
# High Leverage
# creates a dataframe named hats
# uses hatvalues to be able to see high leverage
hats <- as.data.frame(hatvalues(wineq))
hats
```

```
##      hatvalues(wineq)
## 1      0.005079901
## 2      0.008111271
## 3      0.004023940
## 4      0.007623793
## 5      0.005079901
## 6      0.005195357
## 7      0.004376642
## 8      0.006281831
```

## 9	0.004199146
## 10	0.004587509
## 11	0.007865355
## 12	0.039475498
## 13	0.009102351
## 14	0.031016001
## 15	0.007029088
## 16	0.006842187
## 17	0.007758928
## 18	0.004464620
## 19	0.006623544
## 20	0.004968706
## 21	0.003894204
## 22	0.004424527
## 23	0.004086631
## 24	0.010734583
## 25	0.012192743
## 26	0.011429170
## 27	0.005009245
## 28	0.004019111
## 29	0.013214273
## 30	0.003247586
## 31	0.033958794
## 32	0.018021960
## 33	0.023179000
## 34	0.017739270
## 35	0.006858603
## 36	0.005920293
## 37	0.006436876
## 38	0.007741004
## 39	0.006880550
## 40	0.011403010
## 41	0.002198632
## 42	0.006725434
## 43	0.007631385
## 44	0.012291719
## 45	0.002939521
## 46	0.008984319
## 47	0.008984319
## 48	0.005352136
## 49	0.009143397
## 50	0.005917860
## 51	0.003420589
## 52	0.014484615
## 53	0.005104983
## 54	0.005348206
## 55	0.018567518
## 56	0.007867479
## 57	0.008761552
## 58	0.010479424
## 59	0.002094741
## 60	0.081831903
## 61	0.003620478
## 62	0.017934258



## 63	0.005626477
## 64	0.011034703
## 65	0.081831903
## 66	0.003620478
## 67	0.026058577
## 68	0.004965231
## 69	0.006924950
## 70	0.003190962
## 71	0.002627188
## 72	0.003190962
## 73	0.004031028
## 74	0.005401992
## 75	0.004031028
## 76	0.062431247
## 77	0.009445839
## 78	0.006613036
## 79	0.013188200
## 80	0.005808918
## 81	0.006613036
## 82	0.005807121
## 83	0.002636436
## 84	0.017216599
## 85	0.010090365
## 86	0.006487944
## 87	0.009381146
## 88	0.025899899
## 89	0.025814195
## 90	0.008154838
## 91	0.017073414
## 92	0.016196634
## 93	0.011667638
## 94	0.006802741
## 95	0.007359562
## 96	0.006802741
## 97	0.019198679
## 98	0.007868277
## 99	0.019198679
## 100	0.016013518
## 101	0.008720091
## 102	0.002624015
## 103	0.008817519
## 104	0.133177620
## 105	0.009118347
## 106	0.009118347
## 107	0.012727589
## 108	0.012756503
## 109	0.012727589
## 110	0.004855619
## 111	0.009480488
## 112	0.009656767
## 113	0.018813497
## 114	0.003852312
## 115	0.018054168
## 116	0.017540038

## 117	0.010572574
## 118	0.006444366
## 119	0.006811906
## 120	0.003491123
## 121	0.008754605
## 122	0.004811525
## 123	0.006578860
## 124	0.005091483
## 125	0.005738819
## 126	0.009100582
## 127	0.005299619
## 128	0.003903896
## 129	0.003903896
## 130	0.019719613
## 131	0.003667121
## 132	0.006932116
## 133	0.007178859
## 134	0.008580822
## 135	0.008959370
## 136	0.016851147
## 137	0.008874103
## 138	0.008743930
## 139	0.003114941
## 140	0.003114941
## 141	0.003397219
## 142	0.010101226
## 143	0.014083877
## 144	0.005132741
## 145	0.006620674
## 146	0.010819629
## 147	0.010819629
## 148	0.005353649
## 149	0.012565433
## 150	0.003784830
## 151	0.004905335
## 152	0.005009256
## 153	0.015115312
## 154	0.006786415
## 155	0.006552290
## 156	0.004272601
## 157	0.005587752
## 158	0.005362801
## 159	0.006347747
## 160	0.003965990
## 161	0.003260961
## 162	0.047373878
## 163	0.013709180
## 164	0.008068169
## 165	0.004527924
## 166	0.012228389
## 167	0.004337255
## 168	0.020350076
## 169	0.006367275
## 170	0.012445977

## 171	0.038927348
## 172	0.038927348
## 173	0.013354946
## 174	0.002880585
## 175	0.013354946
## 176	0.005447317
## 177	0.004486328
## 178	0.005743384
## 179	0.013168467
## 180	0.009846312
## 181	0.005307292
## 182	0.005441965
## 183	0.118854325
## 184	0.006671231
## 185	0.004892508
## 186	0.009623948
## 187	0.005224927
## 188	0.004748625
## 189	0.010272145
## 190	0.013920363
## 191	0.015867654
## 192	0.016450816
## 193	0.015948092
## 194	0.005741738
## 195	0.005741738
## 196	0.016450816
## 197	0.015948092
## 198	0.014611609
## 199	0.008730115
## 200	0.013429971
## 201	0.039029734
## 202	0.008730115
## 203	0.012499295
## 204	0.012499295
## 205	0.008724965
## 206	0.005379783
## 207	0.006233517
## 208	0.012040431
## 209	0.006233517
## 210	0.006000866
## 211	0.005537018
## 212	0.010874625
## 213	0.008722790
## 214	0.009601031
## 215	0.010585386
## 216	0.013886143
## 217	0.003703577
## 218	0.010377901
## 219	0.007113945
## 220	0.014361988
## 221	0.005800270
## 222	0.013157968
## 223	0.012623822
## 224	0.008455737

## 225	0.006137896
## 226	0.009964636
## 227	0.004332168
## 228	0.007314865
## 229	0.007856334
## 230	0.006368845
## 231	0.045802556
## 232	0.045802556
## 233	0.008834126
## 234	0.006942294
## 235	0.014390546
## 236	0.009720319
## 237	0.007599918
## 238	0.012673264
## 239	0.006153202
## 240	0.005348831
## 241	0.026551003
## 242	0.009479648
## 243	0.009479648
## 244	0.009438034
## 245	0.015746980
## 246	0.005781693
## 247	0.009408379
## 248	0.006095757
## 249	0.028558323
## 250	0.026248601
## 251	0.011641691
## 252	0.010141486
## 253	0.006726683
## 254	0.006654301
## 255	0.008701215
## 256	0.005024658
## 257	0.004753529
## 258	0.009562148
## 259	0.010455555
## 260	0.013921791
## 261	0.013921791
## 262	0.011758921
## 263	0.011547039
## 264	0.013992321
## 265	0.010405945
## 266	0.012926691
## 267	0.011547039
## 268	0.023843261
## 269	0.006974247
## 270	0.004847490
## 271	0.005092769
## 272	0.020007777
## 273	0.010750765
## 274	0.006550467
## 275	0.023650110
## 276	0.039783183
## 277	0.006765622
## 278	0.007956123

## 279	0.039783183
## 280	0.007861485
## 281	0.005216551
## 282	0.005167776
## 283	0.003596048
## 284	0.006890454
## 285	0.021423679
## 286	0.005482052
## 287	0.004727162
## 288	0.013054666
## 289	0.007306184
## 290	0.023402575
## 291	0.007871348
## 292	0.010072335
## 293	0.007953246
## 294	0.011574141
## 295	0.012706800
## 296	0.010430451
## 297	0.006622259
## 298	0.012706800
## 299	0.003944442
## 300	0.008553293
## 301	0.003698456
## 302	0.017075068
## 303	0.006622259
## 304	0.005273926
## 305	0.010108172
## 306	0.007040437
## 307	0.010108172
## 308	0.011261060
## 309	0.009360822
## 310	0.011490732
## 311	0.011537910
## 312	0.025358646
## 313	0.010417620
## 314	0.010046370
## 315	0.004379162
## 316	0.003219880
## 317	0.008076105
## 318	0.008076105
## 319	0.004270310
## 320	0.011048877
## 321	0.007651280
## 322	0.019567842
## 323	0.005388295
## 324	0.004917417
## 325	0.013032216
## 326	0.005976044
## 327	0.004078504
## 328	0.007996837
## 329	0.008754485
## 330	0.012433077
## 331	0.009526742
## 332	0.016791331

## 333	0.008973606
## 334	0.004982638
## 335	0.009640338
## 336	0.007973323
## 337	0.004951452
## 338	0.009118691
## 339	0.006120230
## 340	0.106565971
## 341	0.007306222
## 342	0.009940647
## 343	0.006553434
## 344	0.006943406
## 345	0.003293674
## 346	0.008400204
## 347	0.010253720
## 348	0.020589839
## 349	0.024727263
## 350	0.004409090
## 351	0.004947392
## 352	0.013087617
## 353	0.004409090
## 354	0.020589839
## 355	0.004947392
## 356	0.020551793
## 357	0.020551793
## 358	0.009875256
## 359	0.009846301
## 360	0.008868427
## 361	0.009615620
## 362	0.012181753
## 363	0.008574148
## 364	0.004609210
## 365	0.009893982
## 366	0.009893982
## 367	0.025941965
## 368	0.013859403
## 369	0.011810765
## 370	0.010962999
## 371	0.012043933
## 372	0.007779451
## 373	0.010138358
## 374	0.005522090
## 375	0.013897454
## 376	0.007779723
## 377	0.007779723
## 378	0.014623105
## 379	0.008180976
## 380	0.013897454
## 381	0.005522090
## 382	0.007608308
## 383	0.019157753
## 384	0.012549933
## 385	0.002669846
## 386	0.012289740

## 387	0.005982028
## 388	0.012811628
## 389	0.018746333
## 390	0.011146179
## 391	0.005947660
## 392	0.005432180
## 393	0.009596262
## 394	0.005086123
## 395	0.003389547
## 396	0.004417586
## 397	0.030825023
## 398	0.025866299
## 399	0.019690144
## 400	0.026132260
## 401	0.029248156
## 402	0.010039624
## 403	0.012731858
## 404	0.007694591
## 405	0.029248156
## 406	0.010039624
## 407	0.013477930
## 408	0.017124899
## 409	0.006930447
## 410	0.009566124
## 411	0.004912524
## 412	0.006744248
## 413	0.008704061
## 414	0.008420771
## 415	0.006231876
## 416	0.010115137
## 417	0.010115137
## 418	0.009559295
## 419	0.006806976
## 420	0.015828703
## 421	0.005841226
## 422	0.025544368
## 423	0.005841226
## 424	0.009191441
## 425	0.018638090
## 426	0.008576398
## 427	0.003954989
## 428	0.006229862
## 429	0.006010567
## 430	0.005674210
## 431	0.019888309
## 432	0.013569976
## 433	0.011202074
## 434	0.010302514
## 435	0.003932326
## 436	0.013615173
## 437	0.008909637
## 438	0.007270941
## 439	0.008210024
## 440	0.007443318

## 441	0.004748573
## 442	0.015410233
## 443	0.005628613
## 444	0.005628613
## 445	0.002867840
## 446	0.004271219
## 447	0.002867840
## 448	0.007069472
## 449	0.004140436
## 450	0.023923626
## 451	0.012181585
## 452	0.012794476
## 453	0.016363669
## 454	0.015786810
## 455	0.022727770
## 456	0.007195552
## 457	0.007195552
## 458	0.007195552
## 459	0.006907687
## 460	0.001791692
## 461	0.037970561
## 462	0.013166343
## 463	0.064431145
## 464	0.017399250
## 465	0.013168482
## 466	0.012250051
## 467	0.013166343
## 468	0.012702911
## 469	0.008022115
## 470	0.008022115
## 471	0.006411230
## 472	0.004665163
## 473	0.007553608
## 474	0.014709885
## 475	0.008890054
## 476	0.008890054
## 477	0.006281198
## 478	0.006281198
## 479	0.005332526
## 480	0.004426889
## 481	0.013874626
## 482	0.011200291
## 483	0.004629409
## 484	0.006649564
## 485	0.006866976
## 486	0.021461370
## 487	0.006866976
## 488	0.006273689
## 489	0.010854356
## 490	0.014800555
## 491	0.047290280
## 492	0.009511356
## 493	0.009359931
## 494	0.021617918



## 495	0.004578662
## 496	0.006762835
## 497	0.005876937
## 498	0.018529768
## 499	0.004578662
## 500	0.004729266
## 501	0.007112874
## 502	0.005939253
## 503	0.015524387
## 504	0.004577662
## 505	0.002813320
## 506	0.004385304
## 507	0.018084401
## 508	0.011204375
## 509	0.005966568
## 510	0.006388212
## 511	0.007729637
## 512	0.005196377
## 513	0.007729637
## 514	0.009955767
## 515	0.062110237
## 516	0.003325647
## 517	0.014533859
## 518	0.006651515
## 519	0.006651515
## 520	0.012517657
## 521	0.046096151
## 522	0.014948332
## 523	0.004961432
## 524	0.008680905
## 525	0.005776592
## 526	0.008964746
## 527	0.012297773
## 528	0.006784455
## 529	0.008975675
## 530	0.011444870
## 531	0.010515204
## 532	0.005503159
## 533	0.007021380
## 534	0.005101395
## 535	0.005503159
## 536	0.003212240
## 537	0.003628557
## 538	0.003212240
## 539	0.048494966
## 540	0.011129079
## 541	0.010087377
## 542	0.005922074
## 543	0.005922074
## 544	0.008646773
## 545	0.009862676
## 546	0.005025752
## 547	0.005335595
## 548	0.004264042

## 549	0.004668932
## 550	0.005471347
## 551	0.008754771
## 552	0.004580484
## 553	0.008754771
## 554	0.015048777
## 555	0.015798171
## 556	0.009343257
## 557	0.010665412
## 558	0.016569613
## 559	0.003670652
## 560	0.008044206
## 561	0.012141367
## 562	0.010582744
## 563	0.007808802
## 564	0.005815284
## 565	0.006908585
## 566	0.006908585
## 567	0.011906876
## 568	0.005876660
## 569	0.010342706
## 570	0.006894703
## 571	0.004542554
## 572	0.008739116
## 573	0.024894062
## 574	0.004867659
## 575	0.008150074
## 576	0.005269406
## 577	0.005914954
## 578	0.018010025
## 579	0.004221806
## 580	0.003050112
## 581	0.007545450
## 582	0.008451368
## 583	0.007954023
## 584	0.005222558
## 585	0.008375444
## 586	0.005558538
## 587	0.009957454
## 588	0.007680146
## 589	0.003830349
## 590	0.016560130
## 591	0.005996954
## 592	0.009899322
## 593	0.005945645
## 594	0.004389160
## 595	0.004096525
## 596	0.007534837
## 597	0.027532005
## 598	0.023159059
## 599	0.023159059
## 600	0.005537560
## 601	0.004678989
## 602	0.009460657

## 603	0.010083623
## 604	0.007014766
## 605	0.004399480
## 606	0.007014766
## 607	0.005678085
## 608	0.005678085
## 609	0.015898135
## 610	0.015898135
## 611	0.015898135
## 612	0.004278369
## 613	0.010689713
## 614	0.007361671
## 615	0.007292338
## 616	0.006532395
## 617	0.006710544
## 618	0.009943311
## 619	0.006108955
## 620	0.004470924
## 621	0.011588365
## 622	0.008686844
## 623	0.013956713
## 624	0.005593725
## 625	0.004229023
## 626	0.005172338
## 627	0.006156458
## 628	0.018335219
## 629	0.007604259
## 630	0.006330111
## 631	0.007604259
## 632	0.007962758
## 633	0.004663281
## 634	0.005123541
## 635	0.004663281
## 636	0.005123541
## 637	0.005592100
## 638	0.005072712
## 639	0.005072712
## 640	0.011886791
## 641	0.005127564
## 642	0.006409780
## 643	0.005798826
## 644	0.013979715
## 645	0.029481967
## 646	0.005616815
## 647	0.004899745
## 648	0.015101840
## 649	0.027337598
## 650	0.004858245
## 651	0.014737887
## 652	0.003340743
## 653	0.014737887
## 654	0.005127724
## 655	0.022672262
## 656	0.025034732

## 657	0.004624759
## 658	0.005127724
## 659	0.006174217
## 660	0.004267040
## 661	0.006067928
## 662	0.009680245
## 663	0.006573470
## 664	0.006853510
## 665	0.014892666
## 666	0.002548746
## 667	0.006516621
## 668	0.009393250
## 669	0.007482932
## 670	0.008340855
## 671	0.008340855
## 672	0.007482932
## 673	0.004246215
## 674	0.009124761
## 675	0.006547528
## 676	0.005937867
## 677	0.005151231
## 678	0.006096341
## 679	0.004860436
## 680	0.005465453
## 681	0.006096341
## 682	0.008863624
## 683	0.008471542
## 684	0.008266779
## 685	0.010812274
## 686	0.008678351
## 687	0.008965891
## 688	0.007292361
## 689	0.002747866
## 690	0.007653995
## 691	0.023051842
## 692	0.002747866
## 693	0.004804278
## 694	0.010378502
## 695	0.009155375
## 696	0.006392998
## 697	0.009155375
## 698	0.008920039
## 699	0.008920039
## 700	0.002764909
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## 1143      0.008912159
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hats[order(hats['hatvalues(wineq)']), ]
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## Warning in xtfrm.data.frame(x): cannot xtfrm data frames
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##     [13] 0.002617161 0.002621911 0.002624015 0.002627188 0.002636436 0.002669846
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##    [115] 0.004121891 0.004135039 0.004140436 0.004163175 0.004173496 0.004173496
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 ## [427] 0.006444366 0.006446435 0.006487944 0.006489302 0.006514514 0.006516621  
 ## [433] 0.006532395 0.006547528 0.006550467 0.006552290 0.006553434 0.006573470  
 ## [439] 0.006578860 0.006582772 0.006613036 0.006613036 0.006620674 0.006622259  
 ## [445] 0.006622259 0.006623544 0.006642425 0.006649564 0.006651515 0.006651515  
 ## [451] 0.006654301 0.006671231 0.006697048 0.006697282 0.006709971 0.006710544  
 ## [457] 0.006720748 0.006725434 0.006726683 0.006744248 0.006762835 0.006763227  
 ## [463] 0.006765622 0.006777982 0.006777982 0.006777982 0.006784455 0.006786415  
 ## [469] 0.006796964 0.006802741 0.006802741 0.006806976 0.006811906 0.006830141  
 ## [475] 0.006830291 0.006838611 0.006842187 0.006853510 0.006858603 0.006866976  
 ## [481] 0.006866976 0.006880550 0.006887978 0.006890454 0.006891000 0.006894703  
 ## [487] 0.006907687 0.006908585 0.006908585 0.006913126 0.006913759 0.006914380  
 ## [493] 0.006924950 0.006930447 0.006932116 0.006942294 0.006942330 0.006943406  
 ## [499] 0.006943704 0.006951249 0.006964141 0.006974247 0.006979356 0.006995281  
 ## [505] 0.007014766 0.007014766 0.007021380 0.007029088 0.007033434 0.007040437  
 ## [511] 0.007069472 0.007083670 0.007112874 0.007113945 0.007120236 0.007124679  
 ## [517] 0.007128400 0.007178859 0.007185641 0.007194722 0.007195552 0.007195552  
 ## [523] 0.007195552 0.007216853 0.007231775 0.007236448 0.007243487 0.007267395  
 ## [529] 0.007270451 0.007270941 0.007273566 0.007292338 0.007292361 0.007306184  
 ## [535] 0.007306222 0.007314865 0.007340511 0.007340511 0.007340511 0.007359562  
 ## [541] 0.007360142 0.007361671 0.007382903 0.007392169 0.007443318 0.007450408  
 ## [547] 0.007482932 0.007482932 0.007483683 0.007527427 0.007532963 0.007534837  
 ## [553] 0.007538937 0.007540516 0.007545450 0.007546168 0.007553608 0.007561172  
 ## [559] 0.007573492 0.007575138 0.007584605 0.007599918 0.007600662 0.007604259  
 ## [565] 0.007604259 0.007608308 0.007623793 0.007625080 0.007628939 0.007631385  
 ## [571] 0.007641965 0.007651280 0.007653995 0.007680146 0.007694591 0.007719376  
 ## [577] 0.007729637 0.007729637 0.007741004 0.007758928 0.007769967 0.007779451  
 ## [583] 0.007779723 0.007779723 0.007808802 0.007835479 0.007846673 0.007856334  
 ## [589] 0.007861485 0.007865355 0.007866858 0.007866858 0.007867479 0.007868277  
 ## [595] 0.007871348 0.007875178 0.007933250 0.007953246 0.007954023 0.007956123  
 ## [601] 0.007962758 0.007973323 0.007989529 0.007996837 0.008005156 0.008022115

```

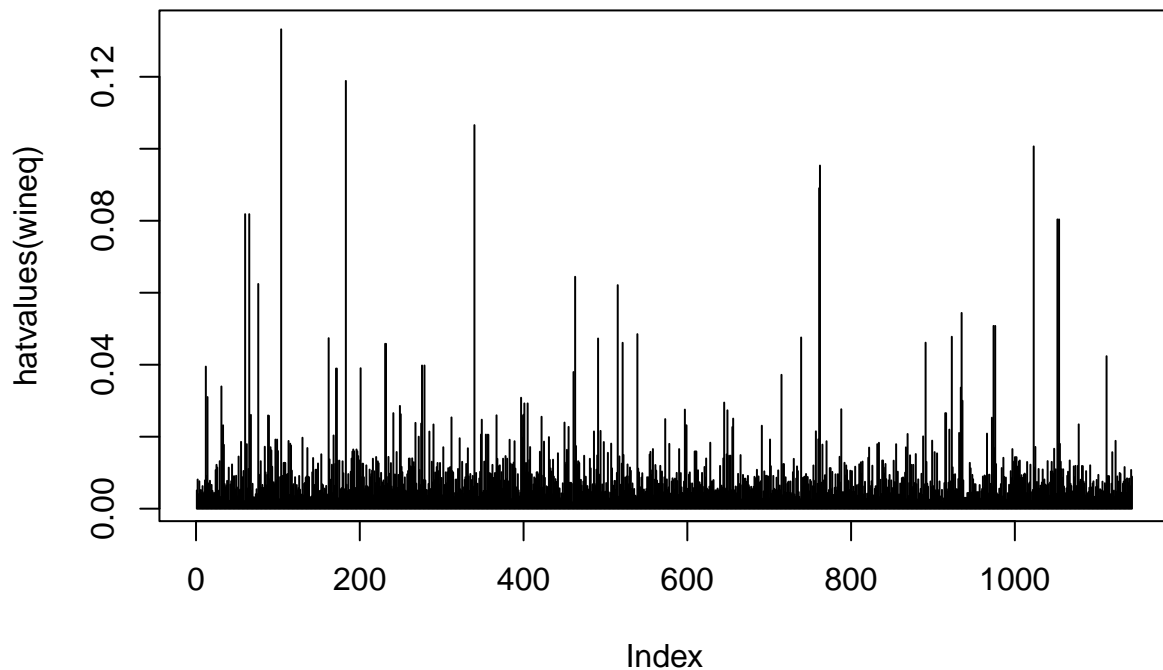
## [607] 0.008022115 0.008037051 0.008044206 0.008050690 0.008068169 0.008076105
## [613] 0.008076105 0.008082932 0.008111271 0.008118296 0.008144575 0.008150074
## [619] 0.008154838 0.008177478 0.008180976 0.008200358 0.008210024 0.008233760
## [625] 0.008242147 0.008266779 0.008319370 0.008340855 0.008340855 0.008351917
## [631] 0.008375444 0.008382766 0.008400204 0.008420771 0.008429891 0.008451368
## [637] 0.008455737 0.008471542 0.008493557 0.008498004 0.008553293 0.008564196
## [643] 0.008564196 0.008572701 0.008574148 0.008576398 0.008580822 0.008599023
## [649] 0.008621481 0.008638927 0.008638927 0.008646773 0.008650269 0.008664132
## [655] 0.008678351 0.008680905 0.008686844 0.008701215 0.008704061 0.008720091
## [661] 0.008722790 0.008724965 0.008728782 0.008730115 0.008730115 0.008739116
## [667] 0.008743930 0.008754485 0.008754605 0.008754771 0.008754771 0.008761552
## [673] 0.008776780 0.008784370 0.008817519 0.008826964 0.008826964 0.008834126
## [679] 0.008846999 0.008863624 0.008868427 0.008874103 0.008890054 0.008890054
## [685] 0.008909637 0.008912159 0.008920039 0.008920039 0.008940215 0.008959370
## [691] 0.008964746 0.008965891 0.008973606 0.008975675 0.008976918 0.008977899
## [697] 0.008984319 0.008984319 0.009022129 0.009048258 0.009048258 0.009048258
## [703] 0.009100582 0.009102351 0.009109378 0.009118347 0.009118347 0.009118691
## [709] 0.009124761 0.009143397 0.009149252 0.009155375 0.009155375 0.009191437
## [715] 0.009191441 0.009227998 0.009289638 0.009289638 0.009311933 0.009343257
## [721] 0.009359931 0.009360822 0.009381146 0.009381935 0.009393250 0.009398812
## [727] 0.009402272 0.009408379 0.009422035 0.009438034 0.009445839 0.009449523
## [733] 0.009449523 0.009460657 0.009466940 0.009466940 0.009479648 0.009479648
## [739] 0.009480488 0.009511356 0.009526742 0.009555612 0.009556038 0.009559295
## [745] 0.009562148 0.009566124 0.009577336 0.009596262 0.009601031 0.009606222
## [751] 0.009615620 0.009623948 0.009640338 0.009641035 0.009656767 0.009669513
## [757] 0.009680245 0.009700822 0.009701620 0.009720319 0.009725129 0.009754534
## [763] 0.009772217 0.009846301 0.009846312 0.009862676 0.009875256 0.009893982
## [769] 0.009893982 0.009899322 0.009940292 0.009940647 0.009943311 0.009955767
## [775] 0.009957454 0.009964636 0.010019829 0.010026880 0.010039624 0.010039624
## [781] 0.010046370 0.010072335 0.010083623 0.010087377 0.010090365 0.010101226
## [787] 0.010108172 0.010108172 0.010115137 0.010115137 0.010138358 0.010138885
## [793] 0.010141486 0.010235618 0.010253720 0.010272145 0.010275511 0.010277925
## [799] 0.010285306 0.010302514 0.010331102 0.010331102 0.010342706 0.010377901
## [805] 0.010378502 0.010405945 0.010417620 0.010430451 0.010434008 0.010434640
## [811] 0.010450933 0.010452715 0.010455555 0.010479424 0.010515204 0.010553850
## [817] 0.010572574 0.010582744 0.010585386 0.010650066 0.010665412 0.010689713
## [823] 0.010704968 0.010734583 0.010750765 0.010764761 0.010812274 0.010819629
## [829] 0.010819629 0.010854356 0.010874625 0.010897408 0.010954447 0.010954447
## [835] 0.010962999 0.010965160 0.011034703 0.011039110 0.011048877 0.011129079
## [841] 0.011146179 0.011200291 0.011202074 0.011204375 0.011224403 0.011261060
## [847] 0.011283793 0.011283793 0.011306016 0.011401571 0.011403010 0.011413265
## [853] 0.011429170 0.011444870 0.011490732 0.011494110 0.011537910 0.011547039
## [859] 0.011547039 0.011571489 0.011574141 0.011588365 0.011641691 0.011667638
## [865] 0.011672394 0.011699119 0.011754239 0.011758921 0.011772503 0.011802889
## [871] 0.011810765 0.011819245 0.011886690 0.011886791 0.011901712 0.011901712
## [877] 0.011906876 0.011957933 0.012010198 0.012024577 0.012040431 0.012043933
## [883] 0.012049071 0.012141367 0.012181585 0.012181753 0.012187564 0.012187564
## [889] 0.012192743 0.012228389 0.012229035 0.012250051 0.012289740 0.012291719
## [895] 0.012297773 0.012330594 0.012388005 0.012398413 0.012398413 0.012428795
## [901] 0.012433077 0.012445977 0.012499295 0.012499295 0.012517657 0.012549933
## [907] 0.012565433 0.012623822 0.012673264 0.012702911 0.012706800 0.012706800
## [913] 0.012727589 0.012727589 0.012731858 0.012743047 0.012756503 0.012757563
## [919] 0.012794476 0.012811628 0.012898719 0.012926691 0.012976820 0.013004286
## [925] 0.013010326 0.013032216 0.013054666 0.013056016 0.013087617 0.013093002

```

```
## [931] 0.013094985 0.013094985 0.013157968 0.013166343 0.013166343 0.013168467
## [937] 0.013168482 0.013188200 0.013214273 0.013228564 0.013347722 0.013354946
## [943] 0.013354946 0.013380879 0.013385955 0.013385955 0.013400156 0.013429971
## [949] 0.013477930 0.013569976 0.013615173 0.013709180 0.013850561 0.013859403
## [955] 0.013874626 0.013886143 0.013897454 0.013897454 0.013920363 0.013921791
## [961] 0.013921791 0.013956713 0.013979715 0.013992321 0.014083877 0.014139366
## [967] 0.014153490 0.014296550 0.014300420 0.014300420 0.014336139 0.014361988
## [973] 0.014390546 0.014417906 0.014484615 0.014533859 0.014611609 0.014623105
## [979] 0.014709885 0.014737887 0.014737887 0.014800555 0.014832368 0.014892666
## [985] 0.014948332 0.015048777 0.015101840 0.015115312 0.015181362 0.015368149
## [991] 0.015410233 0.015524387 0.015697848 0.015716002 0.015746980 0.015786810
## [997] 0.015798171 0.015828703 0.015867654 0.015898135 0.015898135 0.015898135
## [1003] 0.015948092 0.015948092 0.016013518 0.016196634 0.016363669 0.016450816
## [1009] 0.016450816 0.016560130 0.016563469 0.016569613 0.016651301 0.016791331
## [1015] 0.016836973 0.016851147 0.016977571 0.017050344 0.017073414 0.017075068
## [1021] 0.017124899 0.017162004 0.017216599 0.017399250 0.017540038 0.017739270
## [1027] 0.017810722 0.017867082 0.017916361 0.017923817 0.017934258 0.018006516
## [1033] 0.018010025 0.018021960 0.018054168 0.018084401 0.018309636 0.018335219
## [1039] 0.018529768 0.018567518 0.018638090 0.018742820 0.018746333 0.018813497
## [1045] 0.018848437 0.018905110 0.019157753 0.019198679 0.019198679 0.019219638
## [1051] 0.019281406 0.019567842 0.019690144 0.019719613 0.019888309 0.020007777
## [1057] 0.020086082 0.020350076 0.020551793 0.020551793 0.020589839 0.020589839
## [1063] 0.020759346 0.020860507 0.021044316 0.021423679 0.021461370 0.021496085
## [1069] 0.021617918 0.021971806 0.022672262 0.022727770 0.023051842 0.023159059
## [1075] 0.023159059 0.023179000 0.023402575 0.023428407 0.023650110 0.023843261
## [1081] 0.023923626 0.024727263 0.024894062 0.025034732 0.025291476 0.025358646
## [1087] 0.025544368 0.025814195 0.025866299 0.025899899 0.025941965 0.026058577
## [1093] 0.026132260 0.026248601 0.026538314 0.026538314 0.026551003 0.027337598
## [1099] 0.027532005 0.027627730 0.028558323 0.029248156 0.029248156 0.029481967
## [1105] 0.029995529 0.030825023 0.031016001 0.033641770 0.033958794 0.037193878
## [1111] 0.037970561 0.038927348 0.038927348 0.039029734 0.039475498 0.039783183
## [1117] 0.039783183 0.042366306 0.045802556 0.045802556 0.046096151 0.046122909
## [1123] 0.047290280 0.047373878 0.047571012 0.047768638 0.048494966 0.050782777
## [1129] 0.050782777 0.054385943 0.062110237 0.062431247 0.064431145 0.080368069
## [1135] 0.080368069 0.081831903 0.081831903 0.089029480 0.095333756 0.100657718
## [1141] 0.106565971 0.118854325 0.133177620
```

```
plot(hatvalues(wineq), type = 'h')
```





#### # New Regression Model

```
wineq2 <- lm(quality ~ volatile.acidity + chlorides + free.sulfur.dioxide + total.sulfur.dioxide + pH +
summary(wineq2)
```

```
##
## Call:
## lm(formula = quality ~ volatile.acidity + chlorides + free.sulfur.dioxide +
##     total.sulfur.dioxide + pH + sulphates + alcohol, data = Wine_Quality)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.39463 -0.36932 -0.04649  0.44290  2.00640
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    4.466534   0.461804   9.672  < 2e-16 ***
## volatile.acidity -1.082354   0.117570  -9.206  < 2e-16 ***
## chlorides      -1.837430   0.465909  -3.944 8.51e-05 ***
## free.sulfur.dioxide  0.002845   0.002510   1.134 0.257199
## total.sulfur.dioxide -0.002937   0.000796  -3.689 0.000236 ***
## pH              -0.485507   0.135380  -3.586 0.000350 ***
## sulphates       0.845081   0.128332   6.585 6.93e-11 ***
## alcohol         0.293758   0.019382  15.156 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 0.6398 on 1135 degrees of freedom
## Multiple R-squared: 0.3736, Adjusted R-squared: 0.3697
## F-statistic: 96.69 on 7 and 1135 DF, p-value: < 2.2e-16
```

## Question 4

### Boruta Algorithm

We first used the Boruta Algorithm to filter out which response variables were insignificant before also conducting the Mallows CP test. With the Boruta Algorithm we were able to see that alcohol was the best variable, as it had the highest importance. Also, we could eliminate variables that reported “rejected” from this test which meant they had no significance. Next, we took only the results of the significant variables from the Boruta algorithm and ran the Mallows CP test. Here, the smaller the value, the better the model. Evidently, the best model had the predictors volatile acidity, chlorides, total sulfur dioxide, sulphates, and alcohol. The models to the right of the model are higher and therefore, insignificant. These two tests helped us create a better model by determining and eliminating what variables were insignificant.

```
library(Boruta)
# Uses Boruta() for Boruta algorithm process
Bor.res <- Boruta(quality ~ volatile.acidity + chlorides + free.sulfur.dioxide + total.sulfur.dioxide +

## 1. run of importance source...

## 2. run of importance source...

## 3. run of importance source...

## 4. run of importance source...

## 5. run of importance source...

## 6. run of importance source...

## 7. run of importance source...

## 8. run of importance source...

## 9. run of importance source...

## 10. run of importance source...

## After 10 iterations, +4.9 secs:

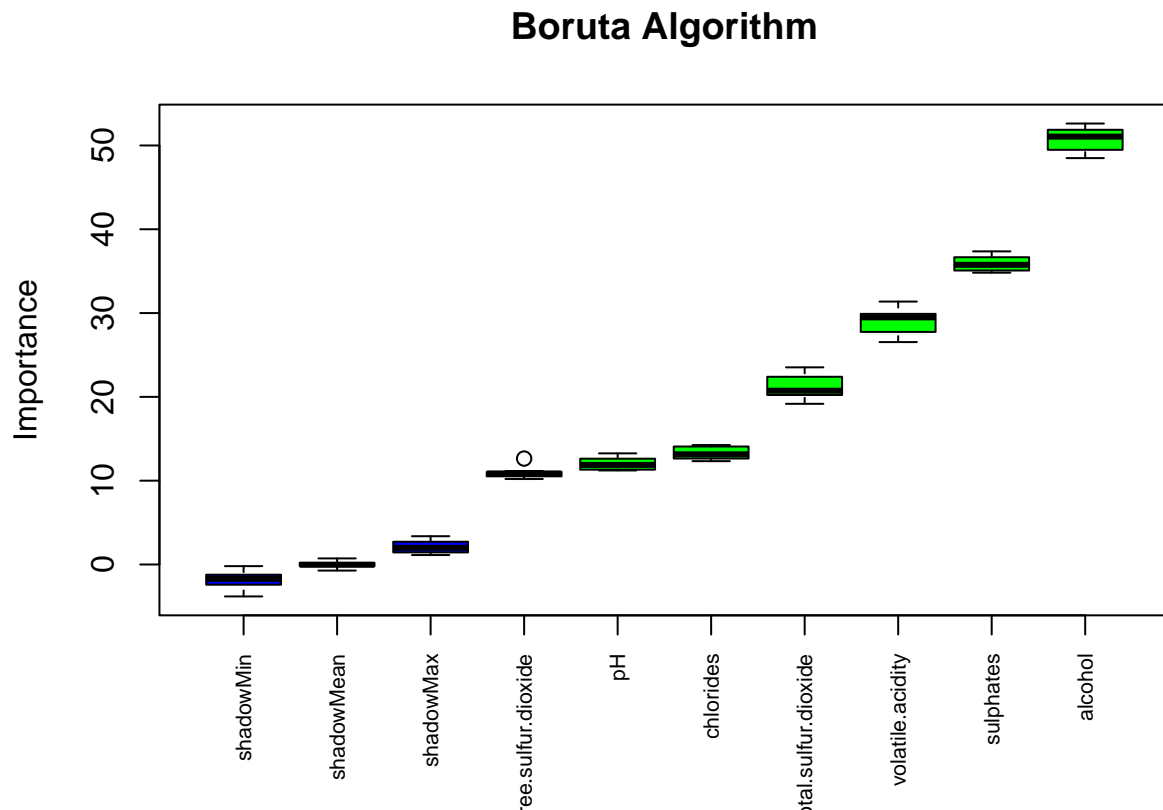
## confirmed 7 attributes: alcohol, chlorides, free.sulfur.dioxide, pH, sulphates and 2 more;

## no more attributes left.
```

```

plot(Bor.res, xlab = "", xaxt = "n", main="Boruta Algorithm")
Lz <- lapply(1:ncol(Bor.res$ImpHistory),function(i) Bor.res$ImpHistory[is.finite(Bor.res$ImpHistory[,i]),i])
names(Lz) <- colnames(Bor.res$ImpHistory)
Labels <- sort(sapply(Lz,median))
axis(side = 1,las=2,labels = names(Labels),
at = 1:ncol(Bor.res$ImpHistory), cex.axis = 0.7)

```



```

boruta_signif <- names(Bor.res$finalDecision[Bor.res$finalDecision %in% c("Confirmed", "Tentative")])
boruta_signif_Conf <- names(Bor.res$finalDecision[Bor.res$finalDecision %in% c("Confirmed")])
boruta_signif_Tent <- names(Bor.res$finalDecision[Bor.res$finalDecision %in% c("Tentative")])
boruta_signif_Reject <- names(Bor.res$finalDecision[Bor.res$finalDecision %in% c("Rejected")])
print(boruta_signif_Conf)

```

```

## [1] "alcohol"          "sulphates"        "pH"
## [4] "total.sulfur.dioxide" "free.sulfur.dioxide" "chlorides"
## [7] "volatile.acidity"

```

```
attStats(Bor.res)
```

```

##           meanImp medianImp  minImp  maxImp normHits  decision
## alcohol      50.75096  51.05660 48.49180 52.61674         1 Confirmed
## sulphates     35.89367  35.75507 34.81560 37.36271         1 Confirmed
## pH            12.03961  11.88174 11.21923 13.25784         1 Confirmed
## total.sulfur.dioxide 21.19278  20.73419 19.17124 23.52463         1 Confirmed

```

```
## free.sulfur.dioxide 10.92329 10.86146 10.19757 12.63947      1 Confirmed
## chlorides          13.25104 13.14339 12.33071 14.25105      1 Confirmed
## volatile.acidity   29.18301 29.48177 26.53715 31.36999      1 Confirmed
```

```
sorted_vars = attStats(Bor.res)[order(-attStats(Bor.res)$meanImp),]
print(sorted_vars)
```

```
##           meanImp medianImp  minImp  maxImp normHits  decision
## alcohol      50.75096  51.05660 48.49180 52.61674      1 Confirmed
## sulphates     35.89367  35.75507 34.81560 37.36271      1 Confirmed
## volatile.acidity 29.18301 29.48177 26.53715 31.36999      1 Confirmed
## total.sulfur.dioxide 21.19278 20.73419 19.17124 23.52463      1 Confirmed
## chlorides     13.25104 13.14339 12.33071 14.25105      1 Confirmed
## pH            12.03961 11.88174 11.21923 13.25784      1 Confirmed
## free.sulfur.dioxide 10.92329 10.86146 10.19757 12.63947      1 Confirmed
```

```
# Mallows CP
library(AER)
```

```
## Loading required package: car
```

```
## Loading required package: carData
```

```
## Loading required package: lmtest
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

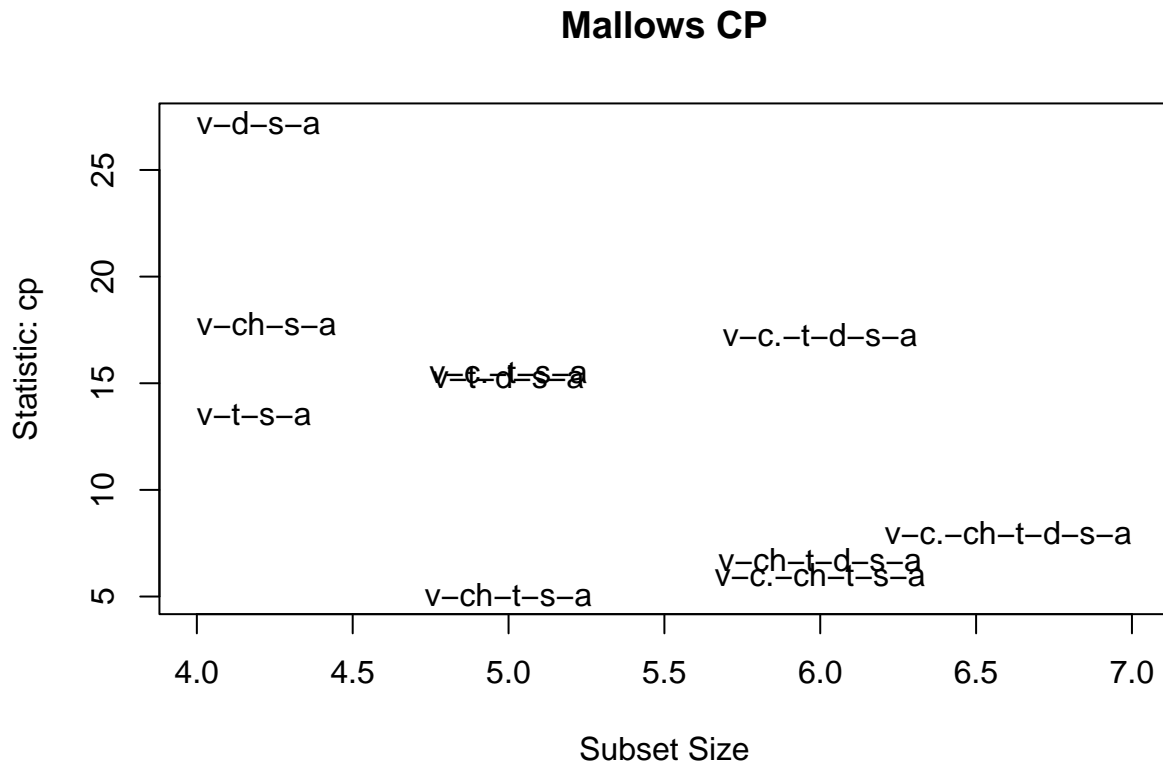
```
## The following objects are masked from 'package:base':
##
##   as.Date, as.Date.numeric
```

```
## Loading required package: sandwich
```

```
library(leaps)
```

```
# Codes use subsets and regsubset to perform the Mallows CP
```

```
mcp <- lm(quality ~ volatile.acidity + citric.acid + chlorides + total.sulfur.dioxide + density + sulphur.dioxide)
ss =regsubsets(quality ~ volatile.acidity + citric.acid + chlorides + total.sulfur.dioxide + density)
subsets(ss, statistic = "cp", legend = F, main = "Mallows CP", col = "green", min.size = 4)
```



```
##                               Abbreviation
## volatile.acidity              v
## citric.acid                   c.
## chlorides                     ch
## total.sulfur.dioxide          t
## density                       d
## sulphates                     s
## alcohol                       a
```

## Question 5

### Multi Collinearity with VIF

With the output for the `vif()`, all of the predictor variables are in the range of  $[1,2]$ . This means there are no variables that are highly correlated with another. Therefore the model with the removed variables won't have significant issues with multicollinearity.

```
# Multi Collinearity
vifFunction<- lm(quality ~ volatile.acidity + chlorides + total.sulfur.dioxide + sulphates + alcohol,
vif(vifFunction))
```

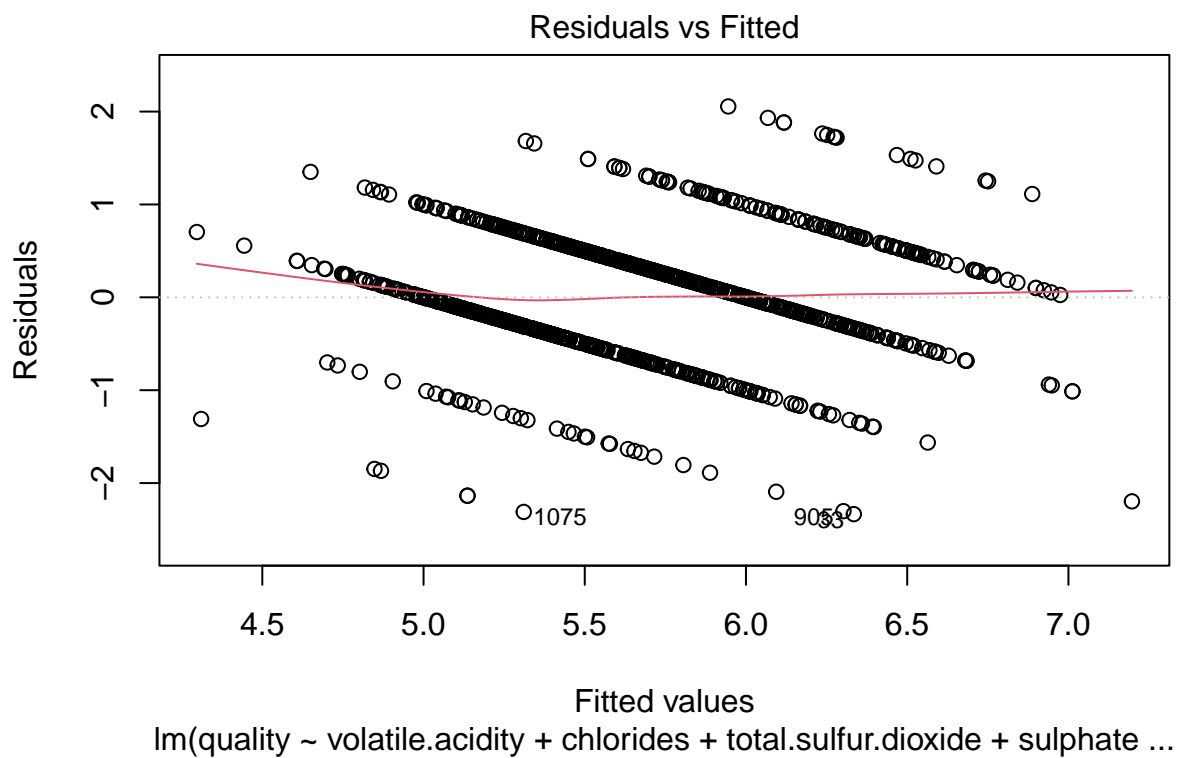
```
##      volatile.acidity      chlorides total.sulfur.dioxide
##           1.145466           1.291971           1.042551
##           sulphates           alcohol
##           1.331226           1.159650
```

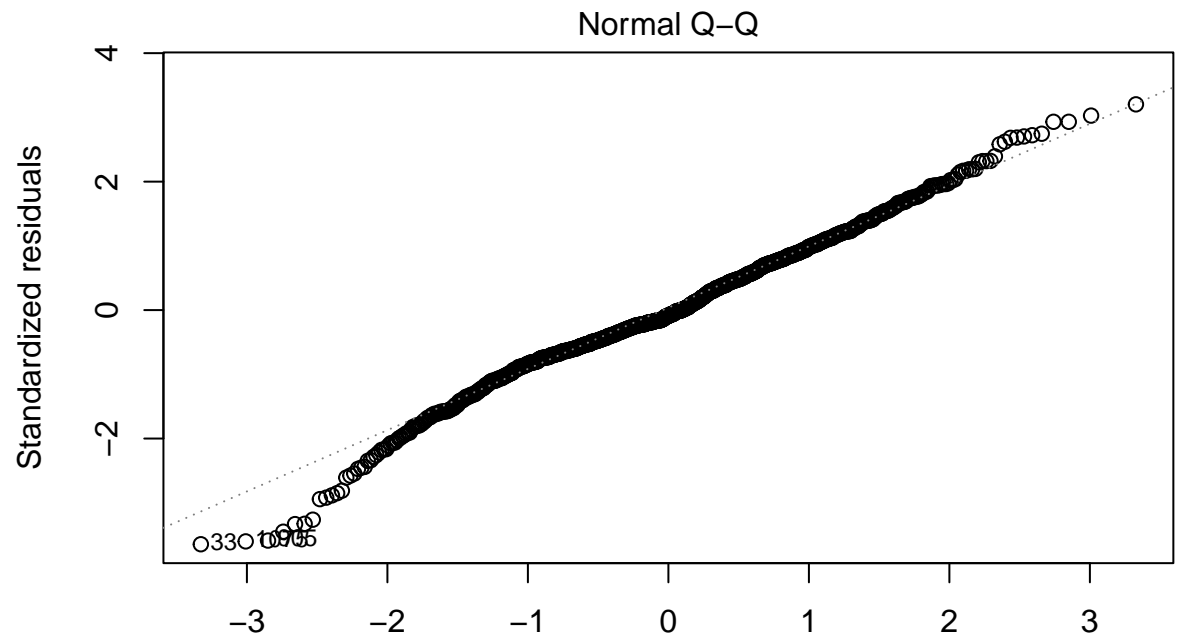
## Question 6

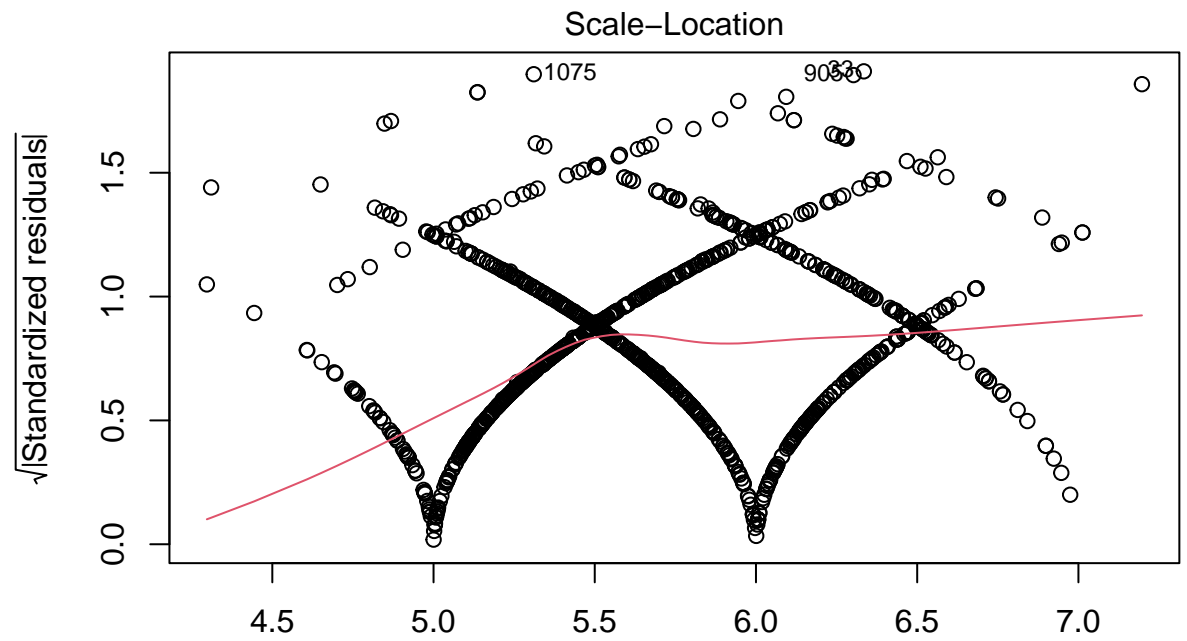
### Plotting The Respective Residuals

The graph with residuals versus fitted shows a red line that tries to capture all of the residuals. There are more values that are above the red line than below the red line. The residuals vs y-hat plot lets us visualize whether heteroskedasticity is present. Our results show that there is a spread in the variance, which allows us to conclude that heteroskedasticity is present in our model.

```
plot(vifFunction)
```

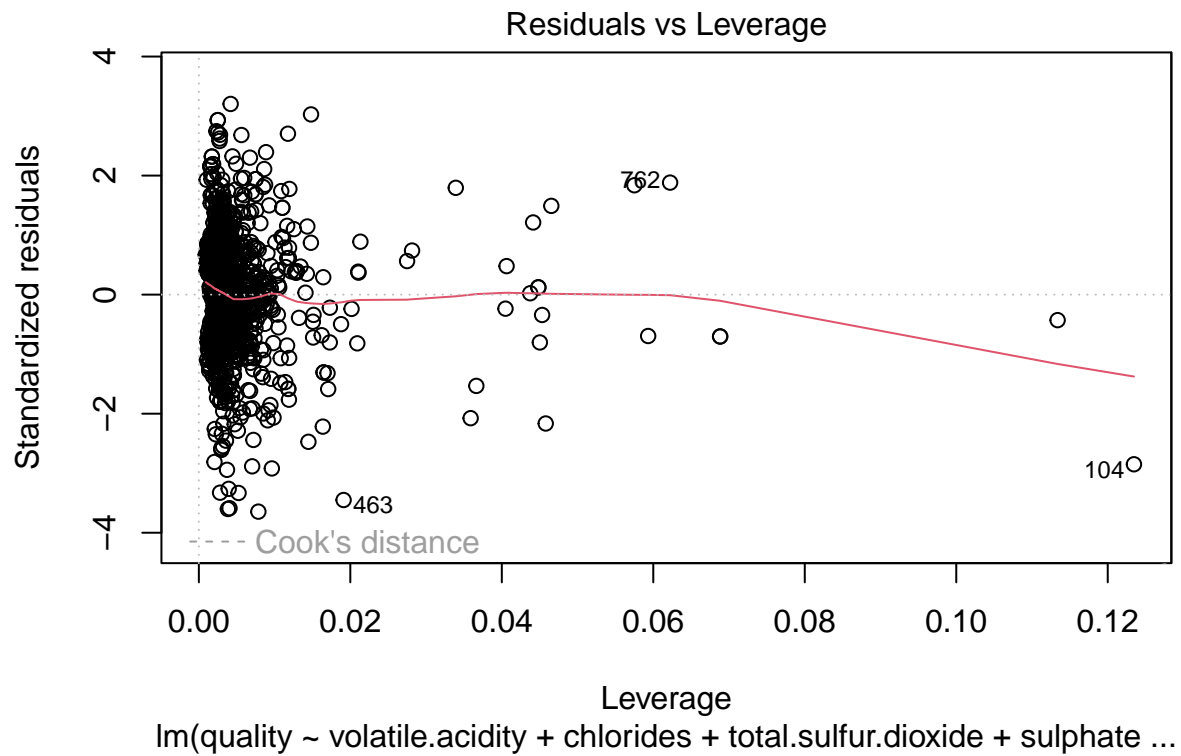




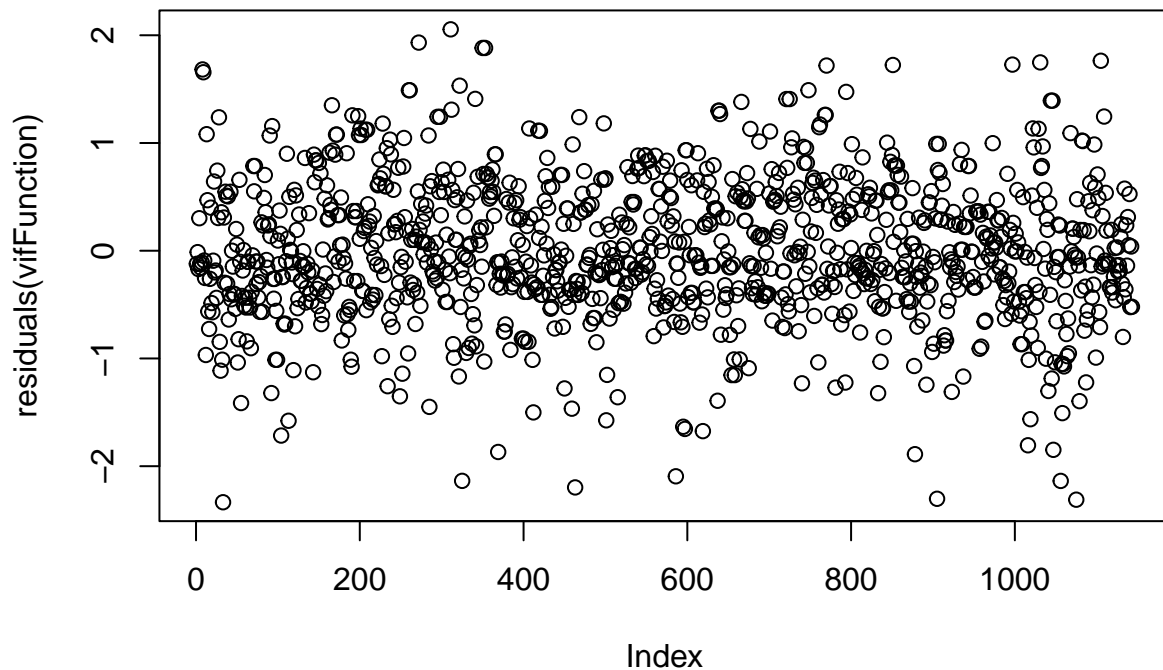


lm(quality ~ volatile.acidity + chlorides + total.sulfur.dioxide + sulphate ...





```
plot(residuals(vifFunction))
```



## Question 7

### Heteroskedasticity

Using the Breusch Pagan test, we reject the null and conclude there is heteroskedasticity present. To fix this, we apply robust standard errors. With this, all of our variables are significant and the standard errors decreased resulting in a better model.

```
reg.mod = lm(quality ~ volatile.acidity + chlorides + total.sulfur.dioxide + sulphates + alcohol, data = wine)
# BP Test Short Way
bptest(reg.mod)
```

```
##
## studentized Breusch-Pagan test
##
## data: reg.mod
## BP = 35.162, df = 5, p-value = 1.397e-06
```

```
# BP Test Long Way
alpha <- 0.05
ressq <- resid(reg.mod)^2
modres <- lm(ressq ~ volatile.acidity + chlorides + total.sulfur.dioxide + sulphates + alcohol, data = wine)
summary(modres)
```

```
##
## Call:
## lm(formula = ressq ~ volatile.acidity + chlorides + total.sulfur.dioxide +
##     sulphates + alcohol, data = Wine_Quality)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.7400 -0.3492 -0.2046  0.0790  4.8907
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -0.6402296  0.2461118  -2.601  0.00941 **
## volatile.acidity  0.1707468  0.1183714   1.442  0.14945
## chlorides      -0.2438618  0.4777576  -0.510  0.60985
## total.sulfur.dioxide -0.0014706  0.0006188  -2.377  0.01764 *
## sulphates       0.3664716  0.1345247   2.724  0.00654 **
## alcohol         0.0774116  0.0197697   3.916 9.55e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6714 on 1137 degrees of freedom
## Multiple R-squared:  0.03076,    Adjusted R-squared:  0.0265
## F-statistic: 7.217 on 5 and 1137 DF,  p-value: 1.156e-06
```

```
#Robust Standard Errors
cov1<-hccm(reg.mod, type="hc1")
coeftest(reg.mod, vcov.=cov1)
```

```
##
## t test of coefficients:
##
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    3.03976345  0.27457600 11.0708 < 2.2e-16 ***
## volatile.acidity -1.20284003  0.12700674  -9.4707 < 2.2e-16 ***
## chlorides      -1.48112808  0.51586067  -2.8712 0.0041653 **
## total.sulfur.dioxide -0.00227580  0.00062456  -3.6439 0.0002807 ***
## sulphates       0.86674198  0.14302592   6.0600 1.848e-09 ***
## alcohol         0.27959699  0.02268052 12.3276 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## Question 8

### AIC/BIC Model

Visualizing the plot of the respective residuals and y-hats in question 6, it seemed that the best fit could be a log linear form. With AIC/BIC we are able to see if our hypothesis is correct. We included different models with varying predictors, the best model we have found previously, and in the best model in terms of log. From the results, the best model is still the best model but better as a log linear with the same predictors obtained from previous tests.

```

#AIC Model
# For the new model, it is in log linear form.
bestMOD<- lm(log(quality) ~ chlorides + total.sulfur.dioxide + sulphates + alcohol + volatile.acidity, data = Wine_Quality)
bestMOD2<- lm(log(quality) ~ chlorides + total.sulfur.dioxide + sulphates + alcohol + volatile.acidity, data = Wine_Quality)
MOD_1 <- lm(log(quality) ~ sulphates + alcohol,data = Wine_Quality)
MOD_2 <- lm(log(quality) ~ pH + sulphates + alcohol,data = Wine_Quality)
MOD_3 <- lm(log(quality) ~ density + pH + sulphates + alcohol,data = Wine_Quality)
MOD_4 <- lm(log(quality) ~ total.sulfur.dioxide + density + pH + sulphates + alcohol,data = Wine_Quality)
MOD_5 <- lm(log(quality) ~ free.sulfur.dioxide + total.sulfur.dioxide + density + pH + sulphates + alcohol,data = Wine_Quality)
MOD_6 <- lm(log(quality) ~ chlorides + free.sulfur.dioxide + total.sulfur.dioxide + density + pH + sulphates + alcohol,data = Wine_Quality)
MOD_7 <-lm(log(quality) ~ residual.sugar + chlorides + free.sulfur.dioxide + total.sulfur.dioxide + density + pH + sulphates + alcohol,data = Wine_Quality)
MOD_8 <-lm(log(quality) ~ citric.acid + residual.sugar + chlorides + free.sulfur.dioxide + total.sulfur.dioxide + density + pH + sulphates + alcohol,data = Wine_Quality)
MOD_9 <- lm(log(quality) ~ volatile.acidity + citric.acid + residual.sugar + chlorides + free.sulfur.dioxide + total.sulfur.dioxide + density + pH + sulphates + alcohol,data = Wine_Quality)
MOD_10<- lm(log(quality) ~ fixed.acidity + volatile.acidity + citric.acid + residual.sugar + chlorides + free.sulfur.dioxide + total.sulfur.dioxide + density + pH + sulphates + alcohol,data = Wine_Quality)
AIC(MOD_1, MOD_2, MOD_3, MOD_4, MOD_5, MOD_6, MOD_7, MOD_8, MOD_9, MOD_10, bestMOD, bestMOD2)

```

```

##          df          AIC
## MOD_1      4 -1526.656
## MOD_2      5 -1547.205
## MOD_3      6 -1545.221
## MOD_4      7 -1558.177
## MOD_5      8 -1559.779
## MOD_6      9 -1586.914
## MOD_7     10 -1584.923
## MOD_8     11 -1599.442
## MOD_9     12 -1670.418
## MOD_10    13 -1668.687
## bestMOD     7 -1667.423
## bestMOD2     7  2241.781

```

```

BIC(MOD_1, MOD_2, MOD_3, MOD_4, MOD_5, MOD_6, MOD_7, MOD_8, MOD_9, MOD_10, bestMOD, bestMOD2)

```

```

##          df          BIC
## MOD_1      4 -1506.491
## MOD_2      5 -1521.998
## MOD_3      6 -1514.973
## MOD_4      7 -1522.887
## MOD_5      8 -1519.448
## MOD_6      9 -1541.541
## MOD_7     10 -1534.509
## MOD_8     11 -1543.987
## MOD_9     12 -1609.921
## MOD_10    13 -1603.149
## bestMOD     7 -1632.133
## bestMOD2     7  2277.070

```

## Question 9

### Cross-Validation

We performed a 5-fold cross validation and obtained an RMSE of .11608. This means that on average the predicted value is off by .11608. We also split the data into testing/training and calculated the RMSE for

both and got small numbers. Overall, we can conclude our model is a good fit for our data and the results are accurate.

```
# train for training sample
# test for testing sample
set.seed(1)
row.number <- sample(1:nrow(Wine_Quality), 0.66*nrow(Wine_Quality))
train = Wine_Quality[row.number,]
test = Wine_Quality[-row.number,]
reg.mod=lm(log(quality) ~ volatile.acidity + chlorides + total.sulfur.dioxide + sulphates + alcohol, data=train)
#RMSE
sqrt(mean(log(test$quality)-predict(reg.mod,test))^2)
```

```
## [1] 0.009056762
```

```
sqrt(mean(log(train$quality)-predict(reg.mod,train))^2)
```

```
## [1] 1.582641e-15
```

```
# Cross Validation
library(lmvar)
fit= lm(log(quality) ~ volatile.acidity + chlorides + total.sulfur.dioxide + sulphates + alcohol, data=train)
cv.lm(fit, k = 5)
```

```
## Mean absolute error      : 0.08922306
## Sample standard deviation : 0.007942391
##
## Mean squared error       : 0.01370225
## Sample standard deviation : 0.003211446
##
## Root mean squared error  : 0.1164704
## Sample standard deviation : 0.01308115
```