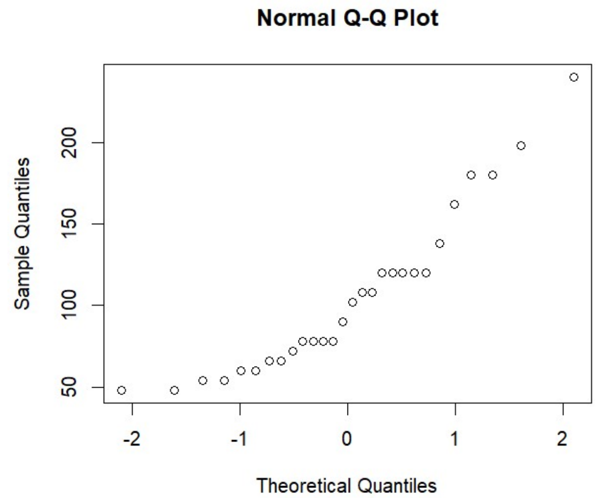
# ANALYSIS FILE

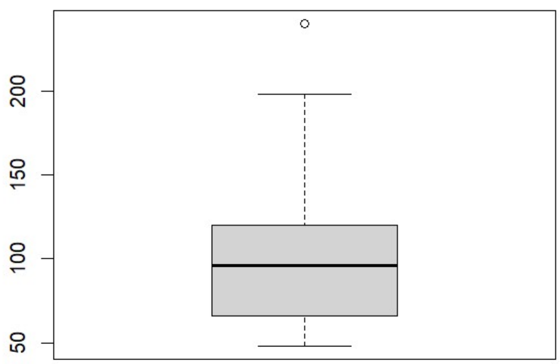
```
> #Part b: Loading the data
> camera <- read.csv('C:/Users/musta/Desktop/Coursework/Statistical Inference/
   R assignment/Nikon.csv')

> #Part c:Data structure
> str(camera)
'data.frame':   28 obs. of  7 variables:
 $ Observation: int  1 2 3 4 5 6 7 8 9 10 ...
 $ Brand      : chr  "Canon" "Canon" "Canon" "Canon" ...
 $ Price_.    : int  198 120 180 120 108 120 120 78 78 66 ...
 $ Megapixels : int  10 12 12 10 12 12 14 10 12 16 ...
 $ Weight_oz  : int  7 5 7 6 5 7 5 7 5 5 ...
 $ Score      : int  73 73 72 69 69 68 67 67 66 62 ...
 $ Brand_code : int  1 1 1 1 1 1 1 1 1 1 ...


> summary(camera)
  Observation       Brand                Price_.         Megapixels       Weight_
oz         Score      
 Min.   : 1.00   Length:28          Min.   : 48.0   Min.   :10.00   Min.   :4
.000   Min.   :49.00  
 1st Qu.: 7.75   Class :character   1st Qu.: 66.0   1st Qu.:12.00   1st Qu.:5
.000   1st Qu.:59.00  
 Median :14.50   Mode  :character   Median : 96.0   Median :12.00   Median :6
.000   Median :63.50  
 Mean   :14.50                      Mean   :105.2   Mean   :12.86   Mean   :5
.821   Mean   :63.36  
 3rd Qu.:21.25                      3rd Qu.:120.0   3rd Qu.:14.00   3rd Qu.:7
.000   3rd Qu.:68.25  
 Max.   :28.00                      Max.   :240.0   Max.   :16.00   Max.   :7
.000   Max.   :73.00  
   Brand_code    
 Min.   :0.0000  
 1st Qu.:0.0000  
 Median :0.0000  
 Mean   :0.4643  
 3rd Qu.:1.0000  
 Max.   :1.0000  
```

The variable “Observation” is a quantitative variable with a discrete scale of measurement and is cardinal since it cannot be ranked. Likewise, “Brand” is qualitative, a categorical variable that is cardinal as it also cannot be ranked. “Price_.” Is quantitative and a scaled variable, discrete in nature. “Megapixels” is also quantitative, a scaled variable, which is also discrete in nature. “Weight_oz” is a quantitative measurement, in this case it is also discrete.

# ANALYSIS FILE

```
#Part d(1)
Price
```

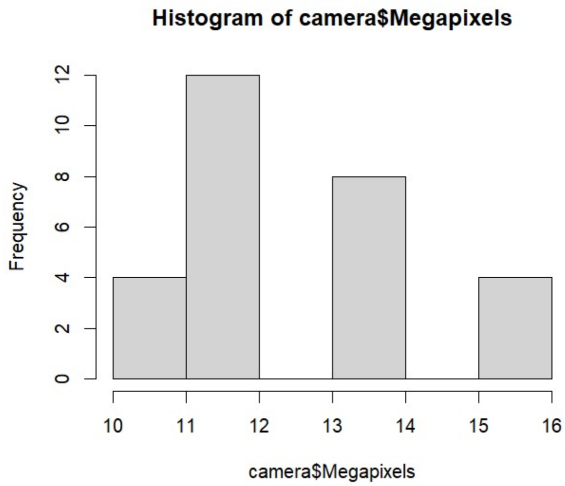



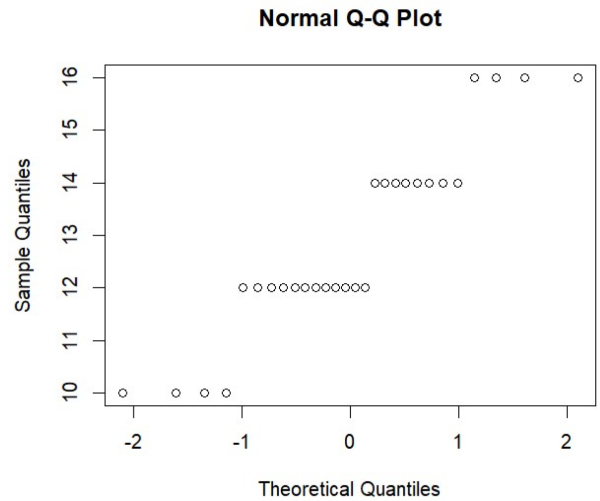

```
        Asymptotic one-sample Kolmogorov-Smirnov test

data:  camera$Price_.
D = 1, p-value < 2.2e-16
alternative hypothesis: two-sided

        Shapiro-Wilk normality test

data:  camera$Price_.
W = 0.89739, p-value = 0.009945
```

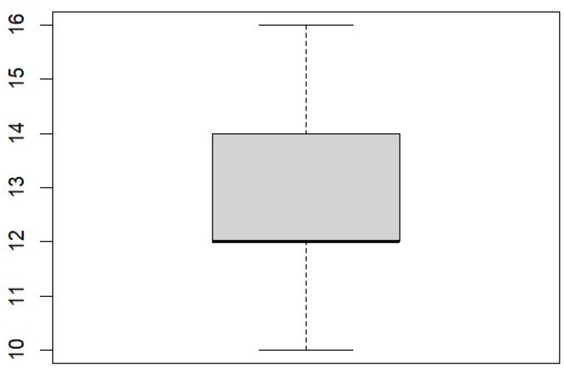
Based on the above graphs and the Kolmogorov-Smirnov as well as the Shapiro test, the Prices are not normally distributed. For instance, the box plot is stretched towards the top and the p-value from the Shapiro test is 0.009945, which is well below the level of significance 0.05 prompting us to reject the null hypothesis of normal distribution. Hence, price does not have a normal distribution.

# ANALYSIS FILE

**Megapixels:**



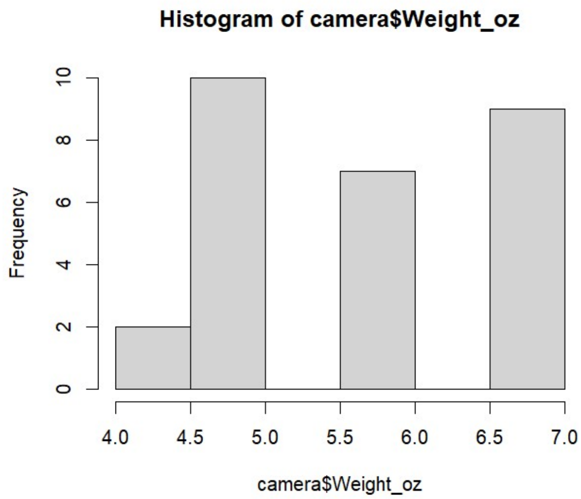
```
        Asymptotic one-sample Kolmogorov-Smirnov test

data:  camera$Megapixels
D = 1, p-value < 2.2e-16
alternative hypothesis: two-sided


        Shapiro-Wilk normality test

data:  camera$Megapixels
W = 0.87756, p-value = 0.003549
```

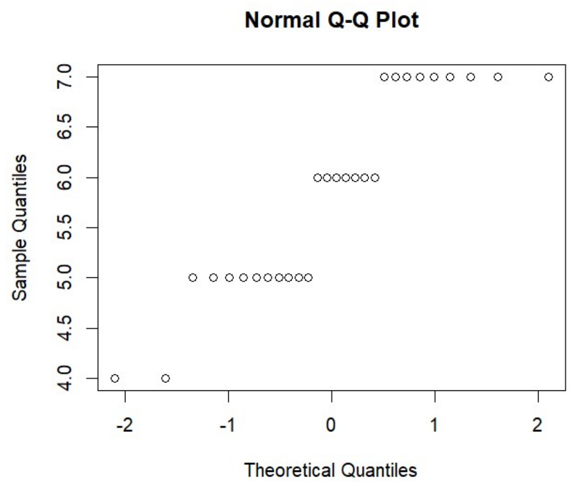
$H_0$: The data is normally distributed
$H_1$: The data is not normally distributed

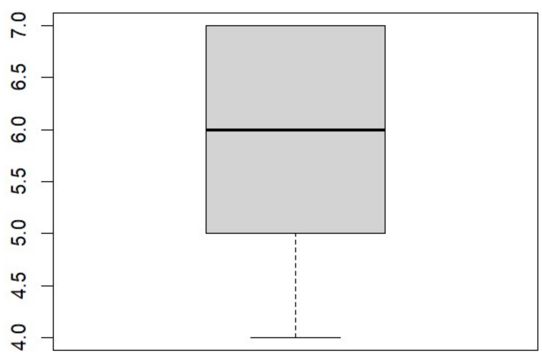
Based on the above graphs and the Kolmogorov-Smirnov as well as the Shapiro test, the 'Megapixels' variable is not normally distributed. The p-value from the Shapiro test is 0.003549, which is well below the level of significance, 0.05 prompting us to reject the null hypothesis of normal distribution. Hence, 'Megapixels' does not have a normal distribution.

# ANALYSIS FILE

**Weight_oz:**



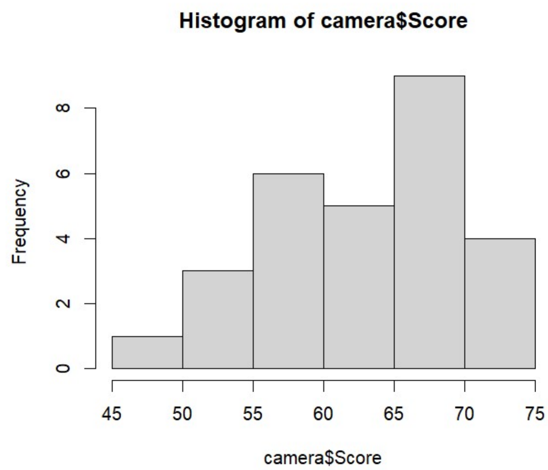
```
Asymptotic one-sample Kolmogorov-Smirnov test

data:  camera$Weight_oz
D = 0.99997, p-value < 2.2e-16
alternative hypothesis: two-sided


        Shapiro-Wilk normality test

data:  camera$Weight_oz
W = 0.84974, p-value = 0.0009235
```

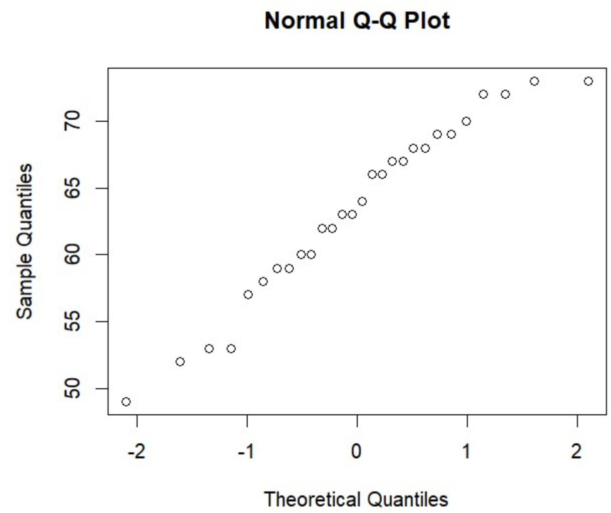
$H_0$: The data is normally distributed
$H_1$: The data is not normally distributed

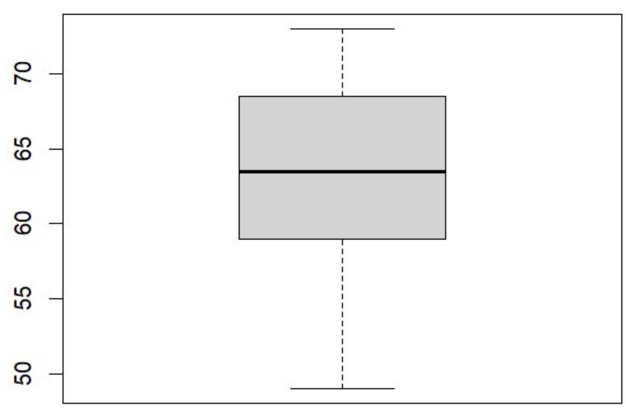
Based on the above graphs and the Kolmogorov-Smirnov as well as the Shapiro test, the 'Weight_oz' are not normally distributed. As observable from the box plot visually, empirically the p-value from the Shapiro test is 0.0009235. As both are well below the level of significance, 0.05, we reject the null hypothesis of normal distribution. Hence, 'Weight_oz' does not have a normal distribution.

# ANALYSIS FILE

**Score:**



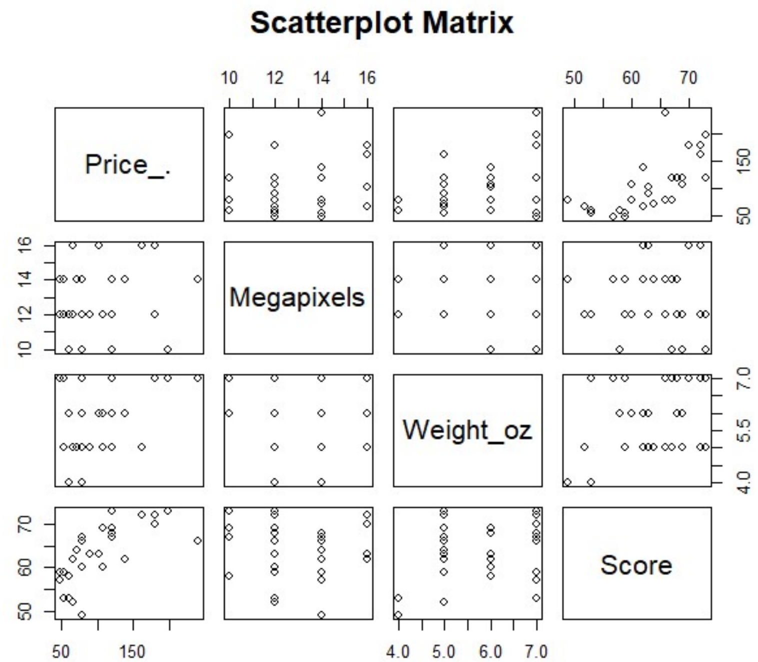

```
        Asymptotic one-sample Kolmogorov-Smirnov test

data:  camera$Score
D = 1, p-value < 2.2e-16
alternative hypothesis: two-sided


        Shapiro-Wilk normality test

data:  camera$Score
W = 0.95719, p-value = 0.2985
<
```

$H_0$: The data is normally distributed
$H_1$: The data is not normally distributed

Based on the above graphs and the Kolmogorov-Smirnov as well as the Shapiro test, the ‘Score’ variable is not normally distributed. As observable from the box plot visually, empirically the p-value from the Shapiro test is 0.2985. As it is above the level of significance, 0.05, we accept the null hypothesis of normal distribution. Hence, ‘Score’ does have a normal distribution.

# ANALYSIS FILE

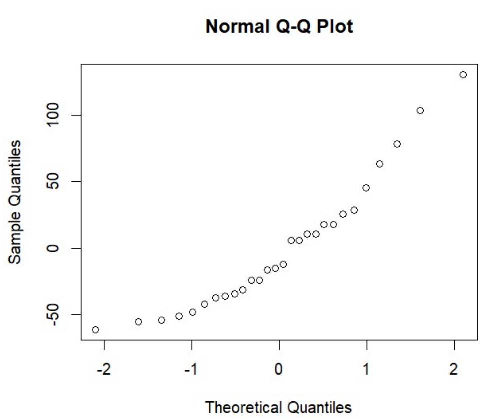
```
#Part d - 2)
> camera1 <- camera[ ,-c(1,2,7)] #removing non-numeric variables
> pairs(camera1, main = 'Scatterplot Matrix')
```

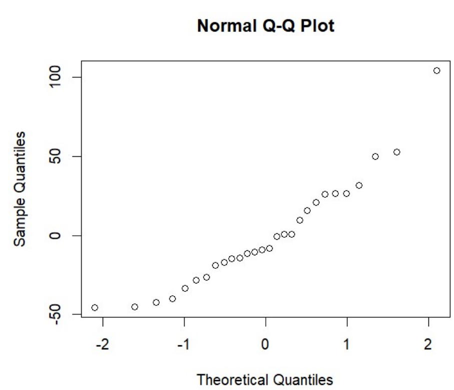



```
#Part d - 3)
> cor_matrix <- cor(camera1)
> cor_matrix
             Price_.   Megapixels  Weight_oz        Score
Price_.    1.0000000  0.138906307  0.3488151  0.683211844
Megapixels 0.1389063  1.000000000 -0.1988338 -0.007729723
Weight_oz  0.3488151 -0.198833809  1.0000000  0.285688204
Score      0.6832118 -0.007729723  0.2856882  1.000000000
>
> install.packages("psych")
> library("psych")
>
> cor_test_mat <- corr.test(camera1)$p
> cor_test_mat
                Price_. Megapixels Weight_oz        Score
Price_.    0.000000e+00  0.9616942 0.3443848 0.0003693039
Megapixels 4.808471e-01  0.0000000 0.9312695 0.9688604750
Weight_oz  6.887697e-02  0.3104232 0.0000000 0.5622358653
Score      6.155065e-05  0.9688605 0.1405590 0.0000000000

#Part d - 4)
> m1 <- lm(Price_. ~ Megapixels, data=camera1)

#Part d - 5)
> m2 <- lm(Price_. ~ Megapixels + Weight_oz, data=camera1)

#Part d - 6)
> m3 <- lm(Price_. ~ Megapixels + Weight_oz + Score, data=camera1)
```

# ANALYSIS FILE

```
#Part d - 7)
> summary(m1)

Call:
lm(formula = Price_. ~ Megapixels, data = camera1)

Residuals:
   Min     1Q Median     3Q    Max 
-61.50 -36.38 -13.50  19.88 130.50 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   57.000     68.074   0.837    0.410
Megapixels     3.750      5.243   0.715    0.481

Residual standard error: 50.13 on 26 degrees of freedom
Multiple R-squared:  0.01929,	Adjusted R-squared:  -0.01842 
F-statistic: 0.5115 on 1 and 26 DF,  p-value: 0.4808

> summary(m3)

Call:
lm(formula = Price_. ~ Megapixels + Weight_oz + Score, data = camera1)

Residuals:
    Min      1Q  Median      3Q     Max 
-45.730 -20.986  -8.589  22.127 104.498 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -313.852     89.606  -3.503 0.001831 ** 
Megapixels     4.991      3.880   1.286 0.210573    
Weight_oz     10.451      7.576   1.379 0.180467    
Score          4.641      1.090   4.256 0.000275 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 36.31 on 24 degrees of freedom
Multiple R-squared:  0.5252,	Adjusted R-squared:  0.4659 
F-statistic:  8.85 on 3 and 24 DF,  p-value: 0.0003961
```

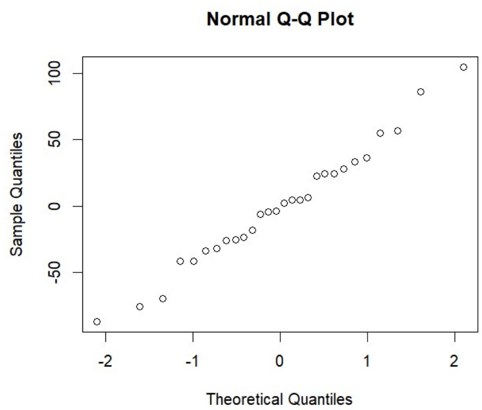


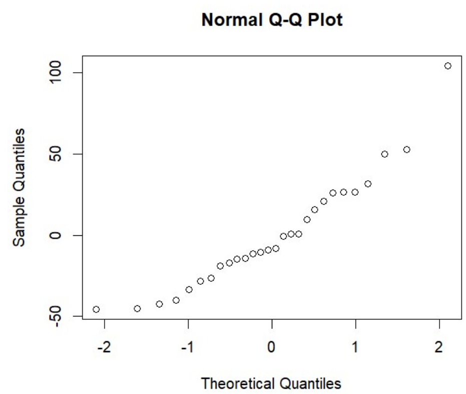




The adjusted R-squared value for m3 is 0.4659, which is higher than that of m1. This indicates that m3 explains a larger proportion of the variability in the data compared to m1. This is also evident by the residual standard errors. Another noteworthy point is that the variables in m3 are more significant predictors of price compared to those in m1 based off the p-values. In conclusion, m3 is a better fit than m1.

# ANALYSIS FILE

```
#Part d - 8)
> summary(m2)

Call:
lm(formula = Price_. ~ Megapixels + Weight_oz, data = camera1)

Residuals:
    Min      1Q  Median      3Q     Max 
-87.241 -27.306  -0.686  25.264 104.759 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept)  -85.317     93.111  -0.916   0.3683  
Megapixels     5.854      5.029   1.164   0.2554  
Weight_oz     19.801      9.411   2.104   0.0456 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 47.12 on 25 degrees of freedom
Multiple R-squared:  0.1668,	Adjusted R-squared:  0.1002 
F-statistic: 2.503 on 2 and 25 DF,  p-value: 0.1021

> summary(m3)

Call:
lm(formula = Price_. ~ Megapixels + Weight_oz + Score, data = camera1)

Residuals:
    Min      1Q  Median      3Q     Max 
-45.730 -20.986  -8.589  22.127 104.498 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -313.852     89.606  -3.503 0.001831 ** 
Megapixels     4.991      3.880   1.286 0.210573    
Weight_oz     10.451      7.576   1.379 0.180467    
Score          4.641      1.090   4.256 0.000275 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 36.31 on 24 degrees of freedom
Multiple R-squared:  0.5252,	Adjusted R-squared:  0.4659 
F-statistic:  8.85 on 3 and 24 DF,  p-value: 0.0003961
```




The adjusted R-squared value for m3 is 0.4659, which is higher than that of m2 (0.1002). This indicates that m3 explains a larger proportion of the variability in the data compared to m2. This is also evident by the residual standard errors. Another noteworthy point is that the variables in m3 are more significant predictors of price compared to those in m2 based off the p-values. In conclusion, m3 is a better fit than m2.

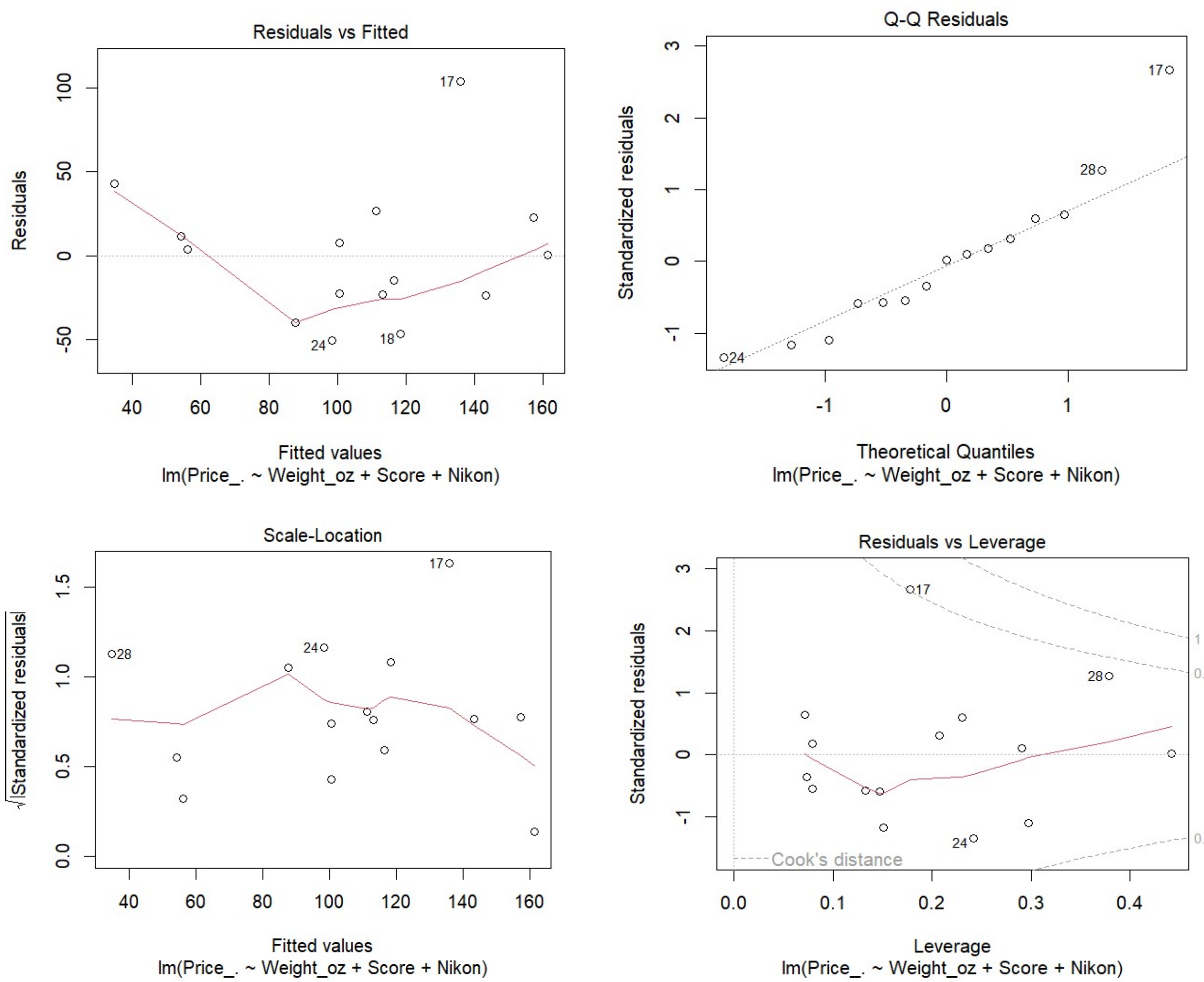
# ANALYSIS FILE

```
#Part d - 9)
> camera$Nikon <- ifelse(camera$Brand_code == 0,0,1)
```

```
#Part d - 10)
> m4 <- lm(Price_. ~ Weight_oz + Score + Nikon, data=camera)
```

These predictors were chosen based on their significance determined by P-values. 'Weight_oz' is a significant predictor in m2 while m3 has 'Score' as a significant predictor. Taking the best from the models m1, m2, m3 we have gotten the above model m4.

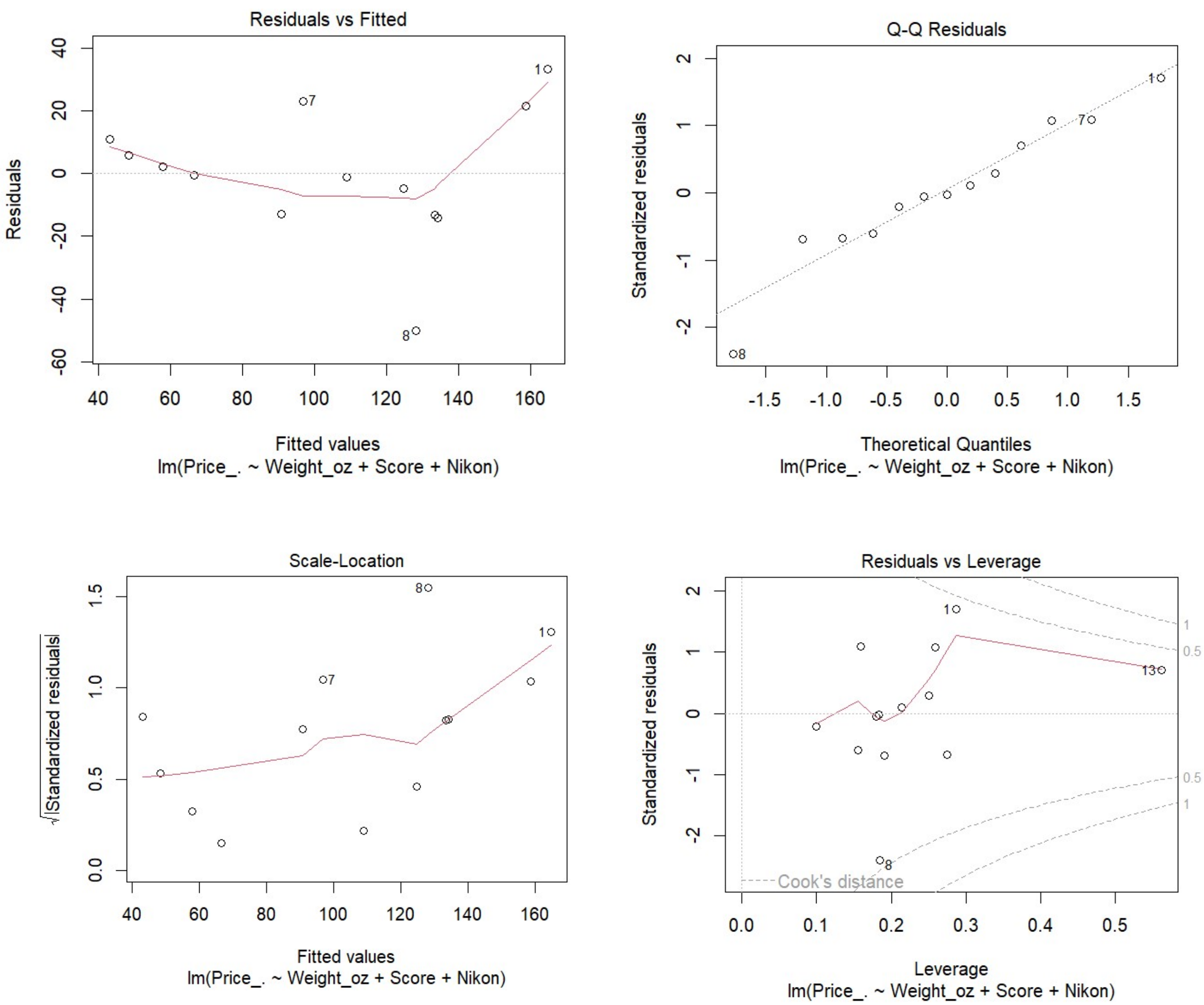
```
#Part d - 11)
> nikon_df <- subset(camera, Brand=='Nikon')
> canon_df <- subset(camera, Brand=='Canon')

> m4_nikon <- lm(Price_. ~ Weight_oz + Score + Nikon, data=nikon_df)
> m4_canon <- lm(Price_. ~ Weight_oz + Score + Nikon, data=cannon_df)

> plot(m4_nikon)
```




Overall, these residual plots above suggest that the linear regression model might not be ideal. There seems to be a curvature in the relationship between the residuals and fitted values, and the residuals are not normally distributed. These issues could lead to biased or unreliable predictions.

# ANALYSIS FILE

```
> plot(m4_canon)
```




Overall, these residual plots suggest that the linear regression model might not be ideal. There seems to be a funnel shape in the residuals vs fitted plot, and the residuals are not normally distributed. These issues could lead to biased or unreliable predictions.

# ANALYSIS FILE

```
#Part d - 12)
> new_data <- data.frame(
+   Brand = c("Canon", "Canon", "Nikon", "Nikon"),
+   Price_ = c(100, 90, 270, 300),
+   Megapixels = c(10, 12, 16, 16),
+   Weight_oz = c(6, 7, 5, 7),
+   Score = c(51, 46, 65, 63),
+   Brand_code = c(1, 1, 0, 0)
+ )

> pred_m1 <- predict(m1, new_data)
> pred_m2 <- predict(m2, new_data)
> pred_m3 <- predict(m3, new_data)

> new_data1 <- new_data
> new_data1$Nikon <- ifelse(new_data1$Brand_code == 0,0,1)
> pred_m4 <- predict(m4, new_data1)



#Error values
> error_m1 <- new_data$Price_ - pred_m1
> error_m1
    1     2     3     4 
  5.5 -12.0 153.0 183.0 
>
> error_m2 <- new_data$Price_ - pred_m2
> error_m2
         1          2          3          4 
  7.975075 -33.533151 162.652792 153.051595 
>
> error_m3 <- new_data$Price_ - pred_m3
> error_m3
        1         2         3         4 
 64.53223  57.30575 150.05963 168.44028 
>
> error_m4 <- new_data1$Price_ - pred_m4
> error_m4
        1         2         3         4 
 76.48554  85.50565 149.32050 173.47598 
```