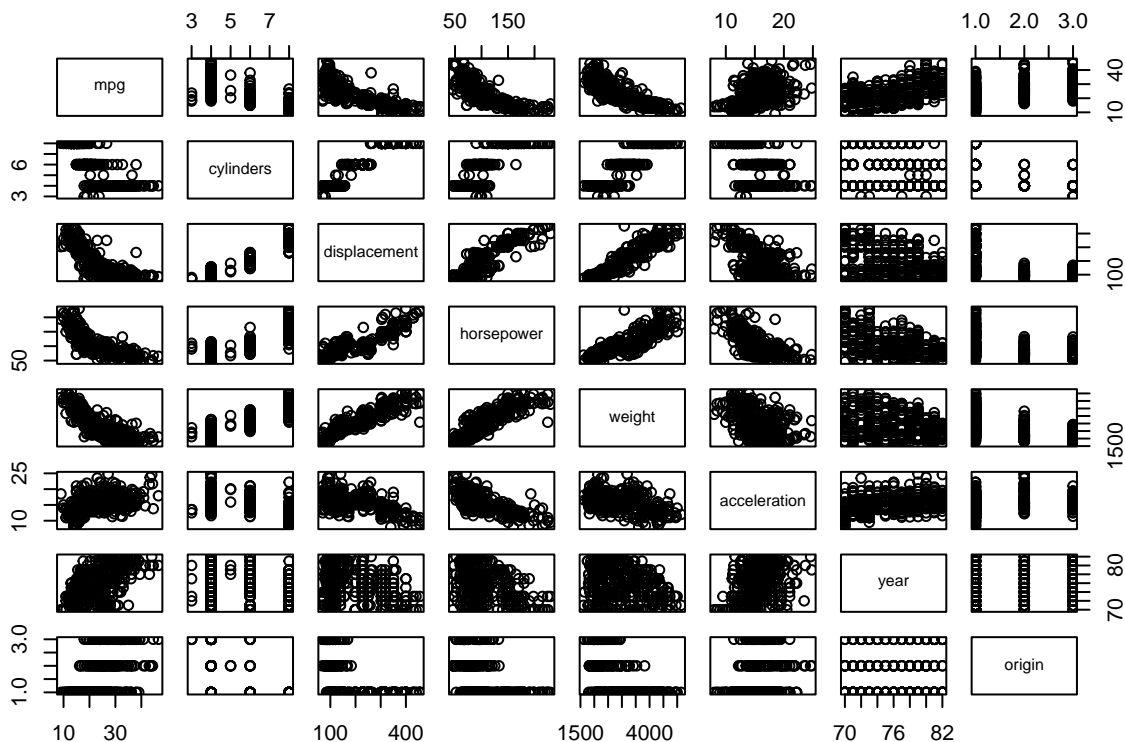


Lab02 Brandon Habschied

```
Auto <- read.csv("C:/Users/brand/OneDrive/Desktop/School/DataDrivenDiscovery/Labs/Lab2/Auto.csv")
View(Auto)
Auto <- na.omit(Auto)
# str(Auto)
# convert horsepower from char to double so it can be in the scatterplot
Auto$horsepower <- as.numeric(Auto$horsepower)
```

```
## Warning: NAs introduced by coercion
```

```
# scatterplot the numerical variables only
Auto_num <- Auto[, -ncol(Auto)]
pairs(Auto_num)
```



```
round(cor(Auto_num), digits = 3)
```

```
##           mpg cylinders displacement horsepower weight acceleration
```

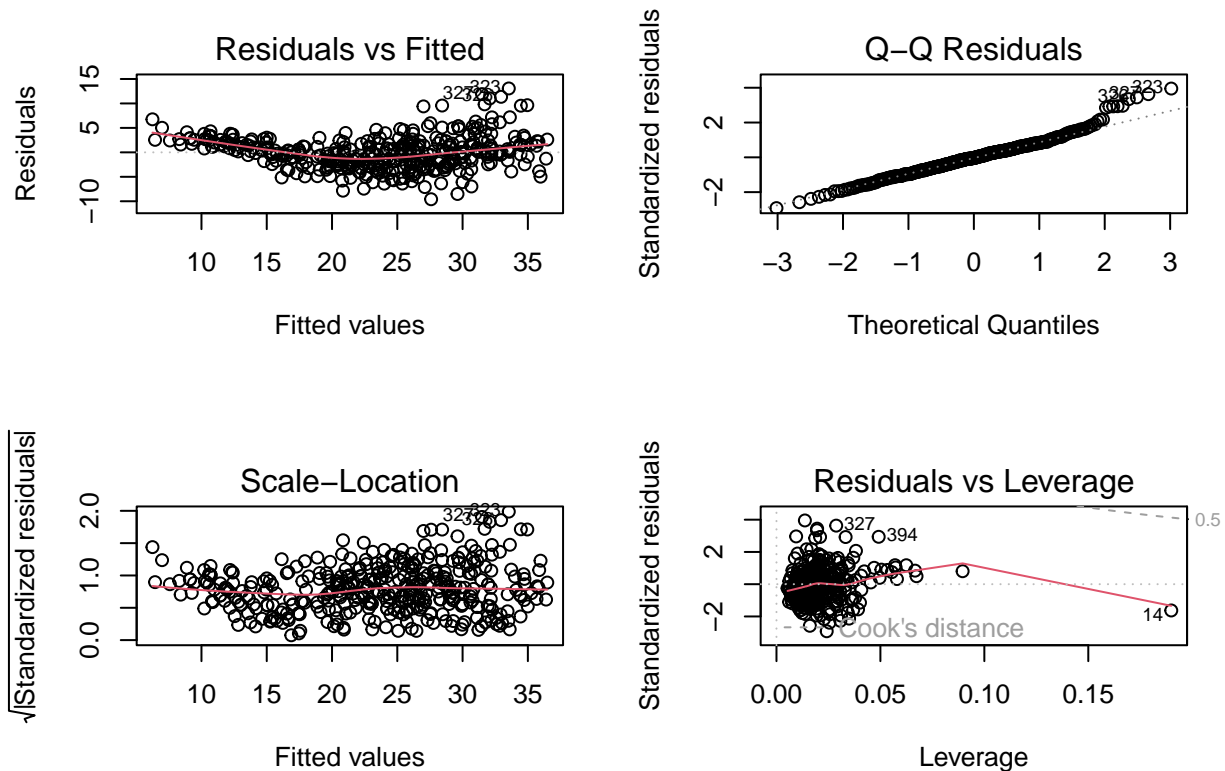
```
## mpg          1.000    -0.776    -0.804      NA -0.832      0.422
## cylinders    -0.776     1.000     0.951      NA  0.897     -0.504
## displacement -0.804     0.951     1.000      NA  0.933     -0.544
## horsepower      NA        NA        NA        1     NA        NA
## weight       -0.832     0.897     0.933      NA  1.000     -0.420
## acceleration  0.422    -0.504    -0.544      NA -0.420      1.000
## year         0.581    -0.347    -0.370      NA -0.308      0.283
## origin       0.564    -0.565    -0.611      NA -0.581      0.210
##              year origin
## mpg          0.581  0.564
## cylinders    -0.347 -0.565
## displacement -0.370 -0.611
## horsepower      NA    NA
## weight       -0.308 -0.581
## acceleration  0.283  0.210
## year         1.000  0.184
## origin       0.184  1.000
```

```
linReg <- lm(mpg ~ . , data = Auto_num)
summary(linReg)
```

```
##
## Call:
## lm(formula = mpg ~ . , data = Auto_num)
##
## 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
## (5 observations deleted due to missingness)
## Multiple R-squared:  0.8215, Adjusted R-squared:  0.8182
## F-statistic: 252.4 on 7 and 384 DF, p-value: < 2.2e-16
```

```
#
# 1. There is a relationship between the predictors and the response as noted by
# the large F statistic of 252.4 and the extremely small p-value of 2.2e-16
#
# 2. The predictors that appear to have significantly significant relationships
# are the ones with the extremely small p-values:
```

```
# weight, year, origin, displacement
#
# 3.The coefficient for year is 0.75 which suggests that each year, newer
# vehicles' mpg will increase by .75 should all other variables stay the same.
#
par(mfrow=c(2,2))
plot(linReg)
```

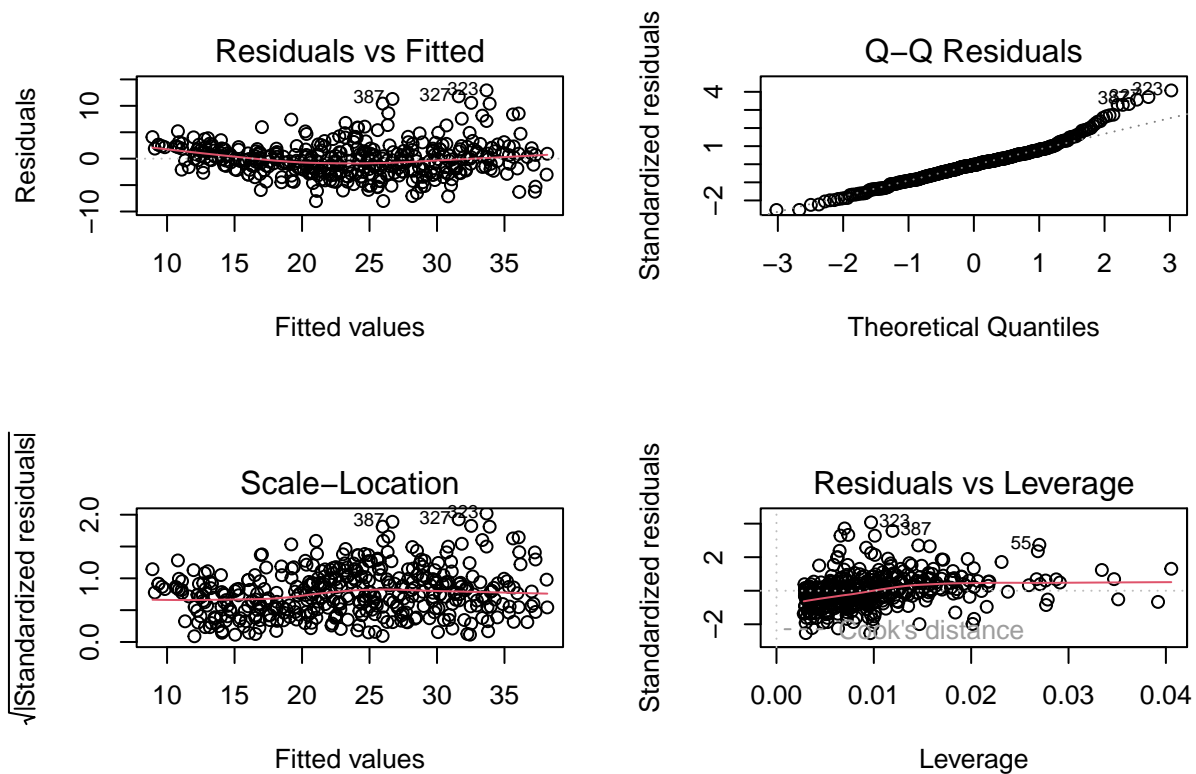


```
# There are a few unusually large outliers found on the residual plots,
# 327, 323, 336 stand out immediately. The QQ Residuals also has a cluster of
# unusually large outliers. The leverage plot has a specific instance 14 with
# an abnormally large leverage.
linReg2 <- lm(mpg ~ weight * year, data = Auto_num)
summary(linReg2)
```

```
##
## Call:
## lm(formula = mpg ~ weight * year, data = Auto_num)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8.0341 -1.9851 -0.0912  1.6987 12.9292
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) -1.124e+02  1.280e+01 -8.781 < 2e-16 ***
## weight      2.821e-02  4.376e-03  6.447 3.34e-10 ***
## year        2.068e+00  1.699e-01 12.171 < 2e-16 ***
## weight:year -4.672e-04  5.857e-05 -7.977 1.66e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.187 on 393 degrees of freedom
## Multiple R-squared:  0.8354, Adjusted R-squared:  0.8341
## F-statistic: 664.9 on 3 and 393 DF,  p-value: < 2.2e-16
```

```
plot(linReg2)
```

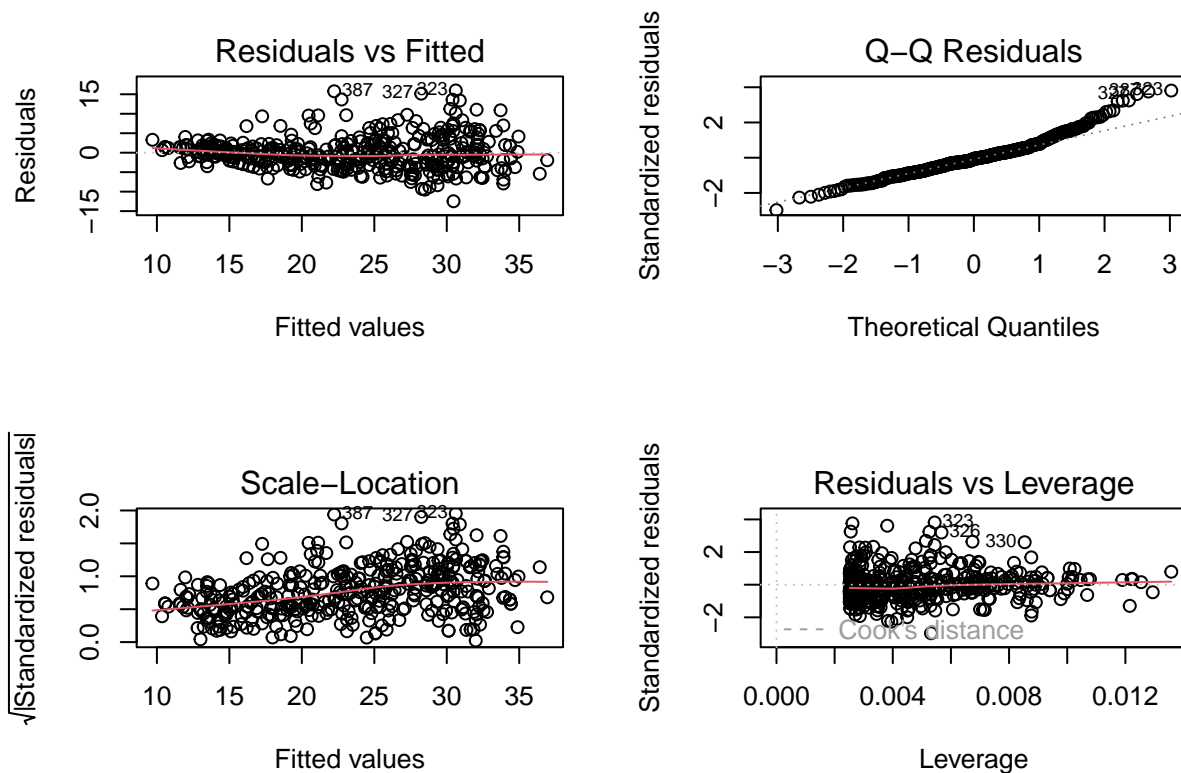


```
linReg3 <- lm(mpg ~ log(weight), data = Auto_num)
summary(linReg3)
```

```
##
## Call:
## lm(formula = mpg ~ log(weight), data = Auto_num)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.4658  -2.6579  -0.2947   1.9395  15.9787
##
## Coefficients:
```

```
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) 210.5391      5.9837   35.19  <2e-16 ***
## log(weight) -23.5050      0.7516  -31.27  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.203 on 395 degrees of freedom
## Multiple R-squared:  0.7123, Adjusted R-squared:  0.7116
## F-statistic: 978.1 on 1 and 395 DF,  p-value: < 2.2e-16
```

```
plot(linReg3)
```

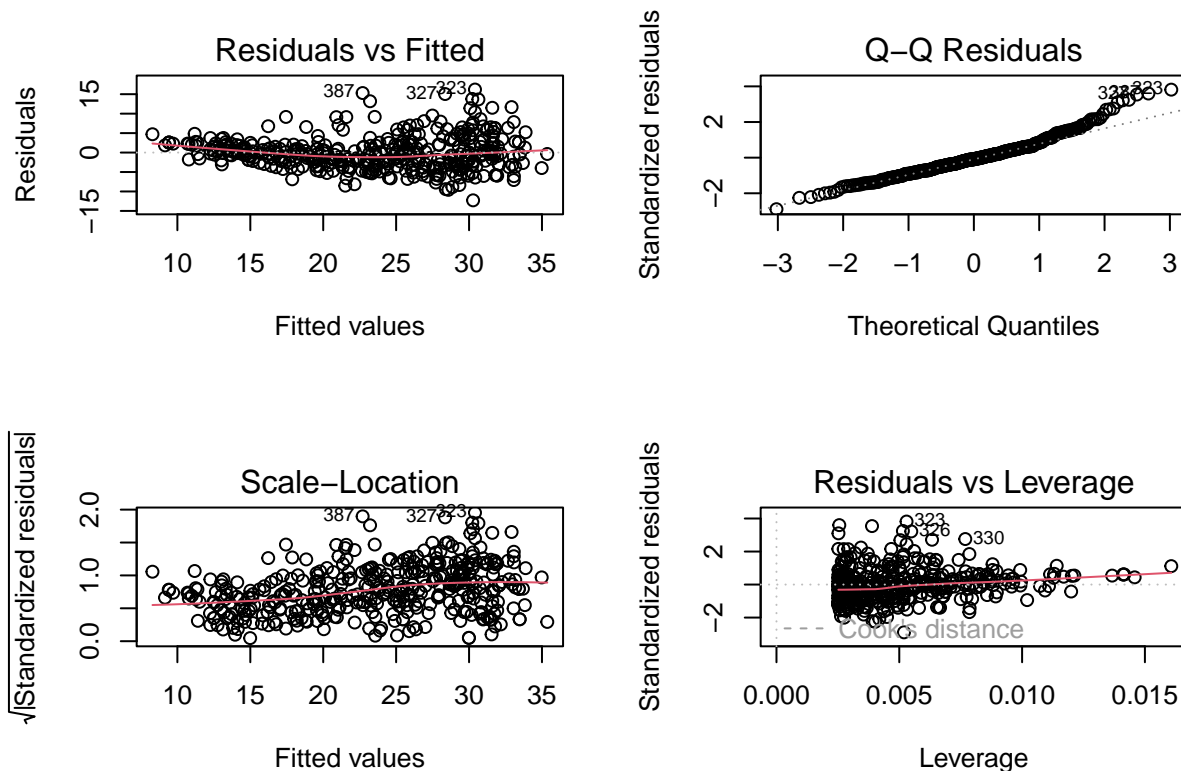


```
linReg4 <- lm(mpg ~ sqrt(weight), data = Auto_num)
summary(linReg4)
```

```
##
## Call:
## lm(formula = mpg ~ sqrt(weight), data = Auto_num)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.2769  -2.8948  -0.3705   2.0839  16.1925
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) 69.84709    1.52239    45.88    <2e-16 ***
## sqrt(weight) -0.85860    0.02793   -30.74    <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.255 on 395 degrees of freedom
## Multiple R-squared:  0.7052, Adjusted R-squared:  0.7044
## F-statistic: 944.8 on 1 and 395 DF,  p-value: < 2.2e-16
```

```
plot(linReg4)
```



```
par(mfrow=c(1,1))
# The interactions I tested above all seem to be statistically significant as
# they all have very small p-values and large F statistics of
# 650, 967, and 935. Using the different interactions caused the leverage
# line of best fit to be more aligned with cook's distance.
```

```
# PART 2
library(ISLR)
```

```
##
## Attaching package: 'ISLR'

## The following object is masked _by_ '.GlobalEnv':
##
## Auto
```

```
data("Carseats")
str(Carseats)
```

```
## 'data.frame': 400 obs. of 11 variables:
## $ Sales : num 9.5 11.22 10.06 7.4 4.15 ...
## $ CompPrice : num 138 111 113 117 141 124 115 136 132 132 ...
## $ Income : num 73 48 35 100 64 113 105 81 110 113 ...
## $ Advertising: num 11 16 10 4 3 13 0 15 0 0 ...
## $ Population : num 276 260 269 466 340 501 45 425 108 131 ...
## $ Price : num 120 83 80 97 128 72 108 120 124 124 ...
## $ ShelveLoc : Factor w/ 3 levels "Bad","Good","Medium": 1 2 3 3 1 1 3 2 3 3 ...
## $ Age : num 42 65 59 55 38 78 71 67 76 76 ...
## $ Education : num 17 10 12 14 13 16 15 10 10 17 ...
## $ Urban : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 1 2 2 1 1 ...
## $ US : Factor w/ 2 levels "No","Yes": 2 2 2 2 1 2 1 2 1 2 ...
```

```
head(Carseats)
```

```
## Sales CompPrice Income Advertising Population Price ShelveLoc Age Education
## 1 9.50 138 73 11 276 120 Bad 42 17
## 2 11.22 111 48 16 260 83 Good 65 10
## 3 10.06 113 35 10 269 80 Medium 59 12
## 4 7.40 117 100 4 466 97 Medium 55 14
## 5 4.15 141 64 3 340 128 Bad 38 13
## 6 10.81 124 113 13 501 72 Bad 78 16
## Urban US
## 1 Yes Yes
## 2 Yes Yes
## 3 Yes Yes
## 4 Yes Yes
## 5 Yes No
## 6 No Yes
```

```
mReg <- lm(Sales ~ Price + Urban + US, data = Carseats)
summary(mReg)
```

```
##
## Call:
## lm(formula = Sales ~ Price + Urban + US, data = Carseats)
##
## Residuals:
## Min 1Q Median 3Q Max
## -6.9206 -1.6220 -0.0564 1.5786 7.0581
##
## Coefficients:
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 13.043469 0.651012 20.036 < 2e-16 ***
## Price -0.054459 0.005242 -10.389 < 2e-16 ***
## UrbanYes -0.021916 0.271650 -0.081 0.936
## USYes 1.200573 0.259042 4.635 4.86e-06 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 2.472 on 396 degrees of freedom
## Multiple R-squared:  0.2393, Adjusted R-squared:  0.2335
## F-statistic: 41.52 on 3 and 396 DF,  p-value: < 2.2e-16

# The coefficient for price being -0.054 suggests that for every increase in
# in price by 1, sales will drop by 0.054. The coefficient for Urban of
# -0.0219 suggests that a carseat in an urban setting (1) will have 0.0219 less
# sales than one in a non-urban setting (0). The coefficient for US suggests that a
# carseat made in the US (1) is likely to have 1.2 more sale units than one not
# made in the US (0).
#
# C) Sales = 13.043 + (-0.054 * Price) + (-0.219 * Urban) + (1.2 * US) + error
#
# D) We can reject the null hypothesis for the predictors Price and US due to
# their extremely low p-values
# e)
mReg2 <- lm(Sales ~ Price + US, data = Carseats)
summary(mReg2)

##
## Call:
## lm(formula = Sales ~ Price + US, data = Carseats)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6.9269 -1.6286 -0.0574  1.5766  7.0515
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 13.03079    0.63098  20.652 < 2e-16 ***
## Price       -0.05448    0.00523 -10.416 < 2e-16 ***
## USYes        1.19964    0.25846   4.641 4.71e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.469 on 397 degrees of freedom
## Multiple R-squared:  0.2393, Adjusted R-squared:  0.2354
## F-statistic: 62.43 on 2 and 397 DF,  p-value: < 2.2e-16

# f) The models above have RSE values that are close to 0, which indicates a
# good fit for the data. Additionally, they both have relatively low F stats
# which indicates that the model is statistically significant.
#
# g) using mReg2 from e) we can determine a 95% confidence interval using 1.96
# as our critical value.

cat("Sales 95% CI: [", 13.03079 - 1.96 * 0.63098, ",", 13.03079 + 1.96 * 0.63098, "]")

## Sales 95% CI: [ 11.79407 , 14.26751 ]
```



```
cat("Price 95% CI: [", -0.05448 - 1.96 * 0.00523, ",", -0.05448 + 1.96 * 0.00523, "]")
```

```
## Price 95% CI: [ -0.0647308 , -0.0442292 ]
```

```
cat("US 95% CI: [", 1.19964 - 1.96 * 0.25846, ",", 1.19964 + 1.96 * 0.25846, "]")
```

```
## US 95% CI: [ 0.6930584 , 1.706222 ]
```