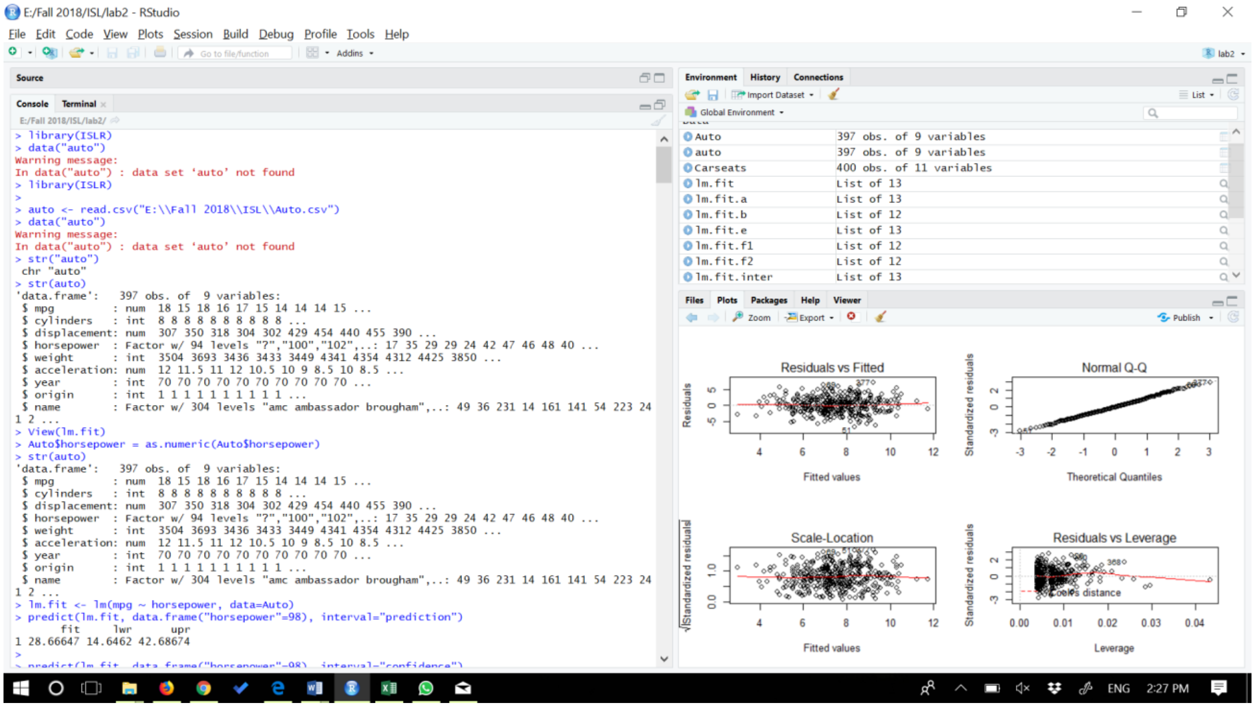
Lab Assignment-2
Harish Chandra Jyoshi

1. Installed R



2.

#2(a)

#Use the lm() function to perform a simple linear regression with mpg as the response and horsepower as the predictor. Use the summary() function to print the results. Comment on the output

```
> library(ISLR)
> data("auto")
Warning message:
In data("auto") : data set 'auto' not found
> library(ISLR)
>
> auto <- read.csv("E:\\Fall 2018\\ISL\\Auto.csv")
> data("auto")
Warning message:
In data("auto") : data set 'auto' not found
> str("auto")
 chr "auto"
> str(auto)
'data.frame':	397 obs. of  9 variables:
 $ mpg         : num  18 15 18 16 17 15 14 14 14 15 ...
 $ cylinders   : int  8 8 8 8 8 8 8 8 8 8 ...
 $ displacement: num  307 350 318 304 302 429 454 440 455 390 ...
 $ horsepower  : Factor w/ 94 levels "?","100","102",..: 17 35 29 29 24 42 47
46 48 40 ...
 $ weight      : int  3504 3693 3436 3433 3449 4341 4354 4312 4425 3850 ...
 $ acceleration: num  12 11.5 11 12 10.5 10 9 8.5 10 8.5 ...
```

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```
 $ year        : int  70 70 70 70 70 70 70 70 70 70 ...
 $ origin      : int  1 1 1 1 1 1 1 1 1 1 ...
 $ name        : Factor w/ 304 levels "amc ambassador brougham",..: 49 36 231
14 161 141 54 223 241 2 ...
> View(lm.fit)
> Auto$horsepower = as.numeric(Auto$horsepower)
> str(auto)
'data.frame':   397 obs. of  9 variables:
 $ mpg         : num  18 15 18 16 17 15 14 14 14 15 ...
 $ cylinders   : int  8 8 8 8 8 8 8 8 8 8 ...
 $ displacement: num  307 350 318 304 302 429 454 440 455 390 ...
 $ horsepower  : Factor w/ 94 levels "?","100","102",..: 17 35 29 29 24 42 47
46 48 40 ...
 $ weight      : int  3504 3693 3436 3433 3449 4341 4354 4312 4425 3850 ...
 $ acceleration: num  12 11.5 11 12 10.5 10 9 8.5 10 8.5 ...
 $ year        : int  70 70 70 70 70 70 70 70 70 70 ...
 $ origin      : int  1 1 1 1 1 1 1 1 1 1 ...
 $ name        : Factor w/ 304 levels "amc ambassador brougham",..: 49 36 231
14 161 141 54 223 241 2 ...
> lm.fit <- lm(mpg ~ horsepower, data=Auto)
```

#i. Is there a relationship between the predictor and the response?

Yes, the coefficient p-value has a very low value.

#ii. How strong is the relationship between the predictor and the response?

Good evidence of relationship, R2R2 presents a value of approximately 0.6, that's 60% of the response variance explained by the simple model.

#iii. Is the relationship between the predictor and the response positive or negative?

Negative, since the coefficient has a negative value.

#iv. **What is the predicted `mpg` associated with a `horsepower` of 98? What are the associated 95% confidence and prediction intervals?**

```
> predict(lm.fit, data.frame("horsepower"=98), interval="prediction")
       fit     lwr      upr
1 28.66647 14.6462 42.68674
>
> predict(lm.fit, data.frame("horsepower"=98), interval="confidence")
       fit      lwr      upr
1 28.66647 27.36905 29.96389
```

#2(b) Plot the response and the predictor. Use the `abline()` function to display the least squares regression line.

```
> plot(Auto$horsepower, Auto$mpg)
> abline(lm.fit, lwd=3, col="orange")
```

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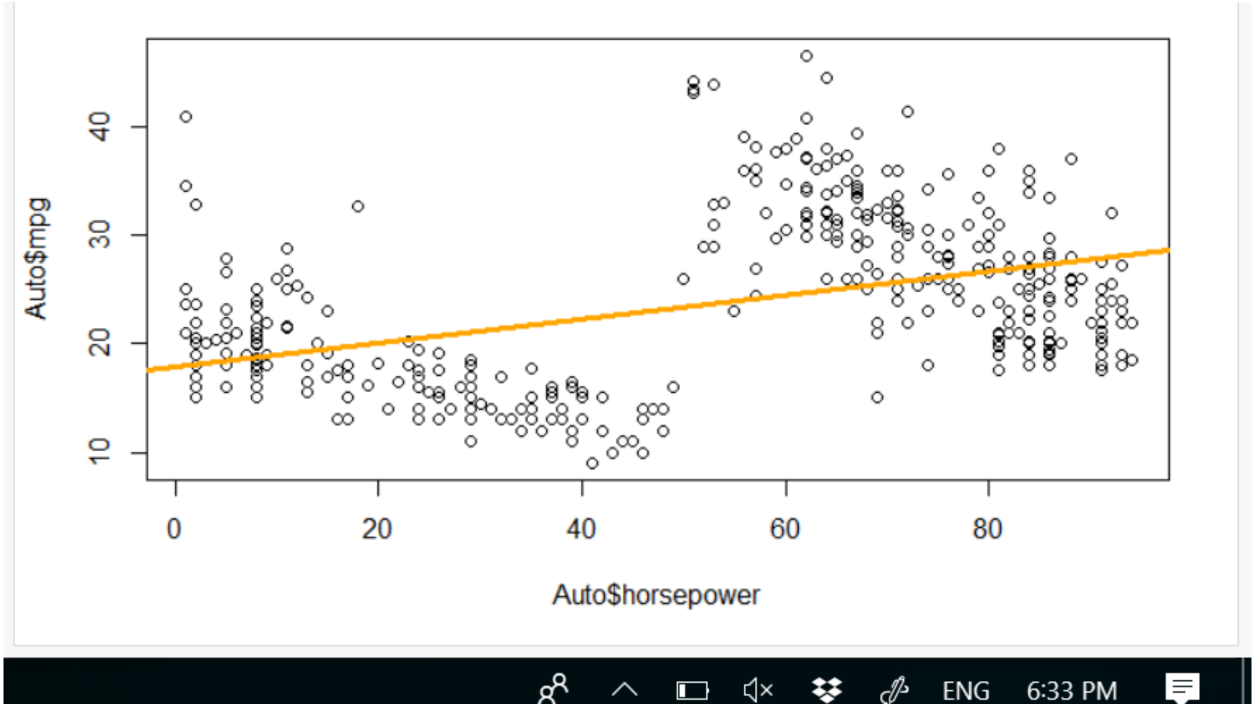
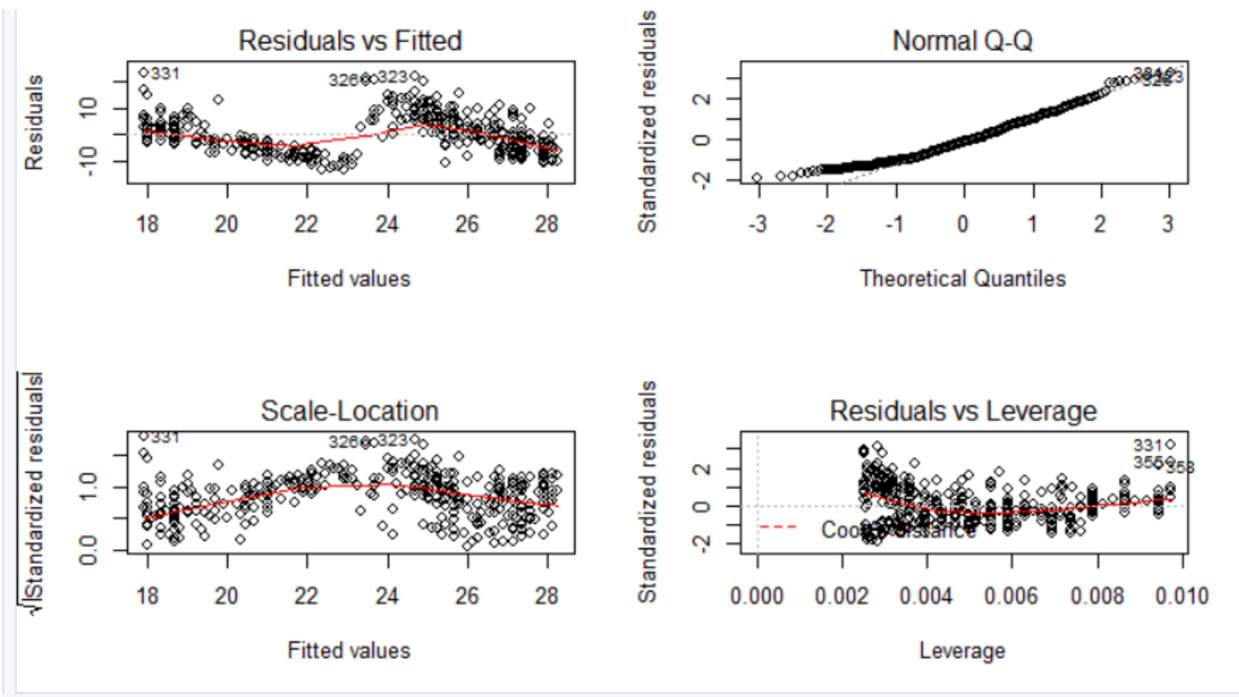


#2(c) Use the `plot()` function to produce diagnostic plots of the least squares regression fit. Comment on any problems you see with the fit.

```
> par(mfrow=c(2,2))
> plot(lm.fit)
```



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```
> #the common problem are:
> #The Residuals vs Fitted graph appears to have a soft U-shape tendency, and
as shown in the plot figure of b, the relationship between predictors and res
ponse is not so linear.
> #Analyzing the Residuals vs Fitted graph, it does NOT shows a great heteros
cedasticity, which the magnitude of the residuals does not tend to increase w
ith the fitted values.
> #Seen the Scale-Location graph, it is pointed some possible outliers, but c
hecking the picture they don’t seem real outliers. I will get the ISLR refere
nce and use the studentized residuals and observe which ones are greater than
3.
> which(rstudent(lm.fit)>3)
323 331
323 331
```

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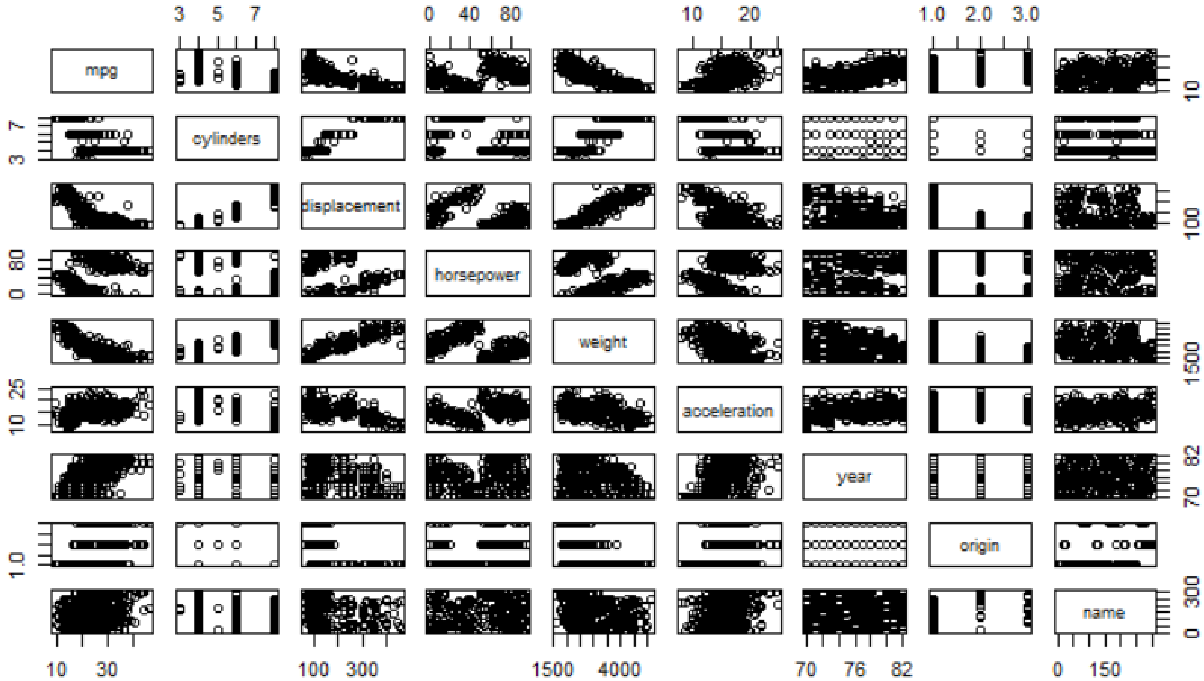
3.

#3(a) Produce a scatterplot matrix which includes all of the variables in the data set.

```
> #3.  Use of multiple regression
> pairs(auto)
```



> #3(b) Compute the matrix of correlations between the variables using the function `cor()`. You will need to exclude the `name` variable which is qualitative.

```
> names(auto)
[1] "mpg"          "cylinders"    "displacement" "horsepower"   "weight"
"acceleration"
[7] "year"         "origin"       "name"
> cor(auto[1:8])
Error in cor(auto[1:8]) : 'x' must be numeric
> cor(Auto[, !(names(Auto)=="name")])
                    mpg  cylinders displacement horsepower     weight acceler
ation       year
mpg           1.0000000 -0.7762599   -0.8044430  0.4228227 -0.8317389    0.42
22974  0.5814695
cylinders    -0.7762599  1.0000000    0.9509199 -0.5466585  0.8970169   -0.50
40606 -0.3467172
displacement -0.8044430  0.9509199    1.0000000 -0.4820705  0.9331044   -0.54
41618 -0.3698041
horsepower    0.4228227 -0.5466585   -0.4820705  1.0000000 -0.4821507    0.26
62877  0.1274167
weight       -0.8317389  0.8970169    0.9331044 -0.4821507  1.0000000   -0.41
95023 -0.3079004
acceleration  0.4222974 -0.5040606   -0.5441618  0.2662877 -0.4195023    1.00
00000  0.2829009
year          0.5814695 -0.3467172   -0.3698041  0.1274167 -0.3079004    0.28
29009  1.0000000
origin        0.5636979 -0.5649716   -0.6106643  0.2973734 -0.5812652    0.21
00836  0.1843141
```

```
                 origin
mpg           0.5636979
cylinders    -0.5649716
displacement -0.6106643
horsepower    0.2973734
weight       -0.5812652
acceleration  0.2100836
year          0.1843141
origin        1.0000000
> cor(auto[, !(names(auto)=="name")])
Error in cor(auto[, !(names(auto) == "name")]) : 'x' must be numeric
> cor(Auto[1:8])
                    mpg  cylinders displacement horsepower     weight acceler
ation       year
mpg           1.0000000 -0.7762599   -0.8044430  0.4228227 -0.8317389    0.42
22974  0.5814695
cylinders    -0.7762599  1.0000000    0.9509199 -0.5466585  0.8970169   -0.50
40606 -0.3467172
displacement -0.8044430  0.9509199    1.0000000 -0.4820705  0.9331044   -0.54
41618 -0.3698041
horsepower    0.4228227 -0.5466585   -0.4820705  1.0000000 -0.4821507    0.26
62877  0.1274167
weight       -0.8317389  0.8970169    0.9331044 -0.4821507  1.0000000   -0.41
95023 -0.3079004
acceleration  0.4222974 -0.5040606   -0.5441618  0.2662877 -0.4195023    1.00
00000  0.2829009
year          0.5814695 -0.3467172   -0.3698041  0.1274167 -0.3079004    0.28
29009  1.0000000
origin        0.5636979 -0.5649716   -0.6106643  0.2973734 -0.5812652    0.21
00836  0.1843141
                 origin
mpg           0.5636979
cylinders    -0.5649716
displacement -0.6106643
horsepower    0.2973734
weight       -0.5812652
acceleration  0.2100836
year          0.1843141
origin        1.0000000


> #3(c) Use the lm() function to perform a multiple linear regression with mp
g as the response and all other variables except name as the predictors. Use
the summary() function to print the results. Comment on the output. For insta
nce:
> lm.fit <- lm(mpg ~ .-name, data=Auto)
> summary(lm.fit)

Call:
lm(formula = mpg ~ . - name, data = Auto)

Residuals:
   Min     1Q Median     3Q    Max 
-9.629 -2.034 -0.046  1.801 13.010 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)  -2.128e+01  4.259e+00  -4.998 8.78e-07 ***
cylinders    -2.927e-01  3.382e-01  -0.865   0.3874    
displacement  1.603e-02  7.284e-03   2.201   0.0283 *  
horsepower    7.942e-03  6.809e-03   1.166   0.2442    
weight       -6.870e-03  5.799e-04 -11.846  < 2e-16 ***
acceleration  1.539e-01  7.750e-02   1.986   0.0477 *  
```

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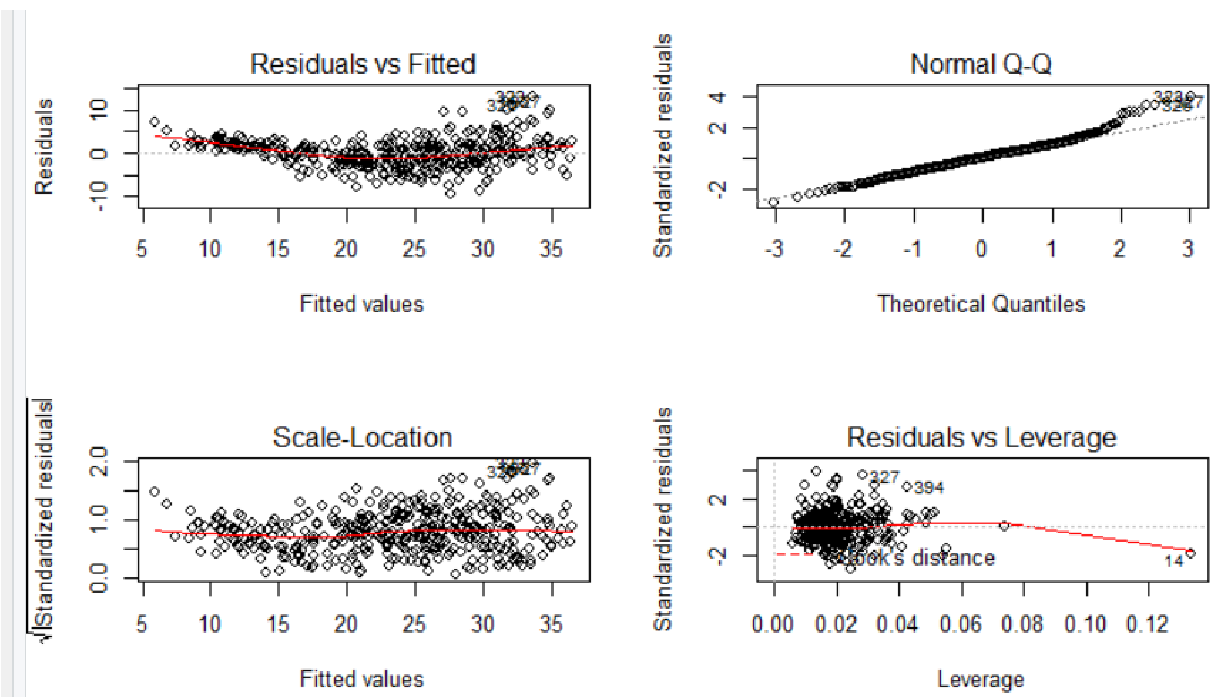
```
year          7.734e-01  4.939e-02  15.661  < 2e-16 ***
origin        1.346e+00  2.691e-01   5.004 8.52e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.331 on 389 degrees of freedom
Multiple R-squared:  0.822,	Adjusted R-squared:  0.8188
F-statistic: 256.7 on 7 and 389 DF,  p-value: < 2.2e-16

> #i. Is there a relationship between the predictors and the response?
> #The p-value corresponding to the F-statistic is 2.037105910^{-139}, this i
ndicates a clear evidence of a relationship between “mpg” and the other predi
ctors
> #ii. Which predictors appear to have a statistically significant relationsh
ip to the response ?
> #The origin, the year and the cylinders.
> #iii. What does the coefficient for the year variable suggest?
> #It suggest that, for each additional year, more 0.75 miles per galon is po
ssible for each car
>
>

> #3(d) Use the plot() function to produce diagnostic plots of the linear reg
ression fit. Comment on any problems you see with the fit. Do the residual plot
s suggest any unusually large outliers? Does the leverage plot identify any o
bservations with unusually high leverage?

> par(mfrow=c(2,2)
+ )
> plot(lm.fit)
```



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```
> #the plot of residuals versus fitted values indicates the presence of mild
non linearity in the data. The plot of standardized residuals versus leverage
indicates the presence of a few outliers (higher than 2 or lower than -2) and
one high leverage point (point 14).
>
>
> #3(e) Use the * and : symbols to fit linear regression models with interacti
on effects. Do any interactions appear to be statistically significant?

> lm.fit.inter = lm(mpg ~ (.-name)*(.-name), data=Auto)
>
> summary(lm.fit.inter)

Call:
lm(formula = mpg ~ (. - name) * (. - name), data = Auto)

Residuals:
   Min     1Q Median     3Q    Max
-8.262 -1.554  0.073  1.306 12.360

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                7.563e+01  4.421e+01   1.710 0.088019 .
cylinders                  9.271e+00  7.736e+00   1.198 0.231526
displacement              -3.392e-01  1.710e-01  -1.983 0.048061 *
horsepower                 2.066e-01  1.433e-01   1.442 0.150225
weight                     1.692e-03  1.476e-02   0.115 0.908770
acceleration              -8.338e+00  1.655e+00  -5.039 7.37e-07 ***
year                       1.425e-01  5.413e-01   0.263 0.792474
origin                    -2.024e+01  6.798e+00  -2.978 0.003095 **
cylinders:displacement    -4.582e-03  5.500e-03  -0.833 0.405308
cylinders:horsepower       8.186e-03  1.136e-02   0.721 0.471490
cylinders:weight           5.995e-04  7.383e-04   0.812 0.417263
cylinders:acceleration     1.790e-01  1.315e-01   1.361 0.174199
cylinders:year            -1.764e-01  1.025e-01  -1.721 0.086094 .
cylinders:origin           1.506e-01  5.935e-01   0.254 0.799826
displacement:horsepower   -2.255e-04  2.970e-04  -0.759 0.448209
displacement:weight        1.939e-05  7.875e-06   2.463 0.014235 *
displacement:acceleration -3.368e-03  2.698e-03  -1.248 0.212707
displacement:year          4.403e-03  2.312e-03   1.905 0.057614 .
displacement:origin        2.733e-02  2.100e-02   1.302 0.193852
horsepower:weight          5.615e-06  2.322e-05   0.242 0.809080
horsepower:acceleration   -3.203e-03  3.483e-03  -0.919 0.358479
horsepower:year           -2.275e-03  1.785e-03  -1.275 0.203111
horsepower:origin         -3.181e-03  1.333e-02  -0.239 0.811472
weight:acceleration        2.419e-04  1.957e-04   1.236 0.217252
weight:year               -2.607e-04  1.734e-04  -1.504 0.133495
weight:origin             -2.628e-04  1.314e-03  -0.200 0.841549
acceleration:year          9.102e-02  1.955e-02   4.655 4.53e-06 ***
acceleration:origin        4.806e-01  1.223e-01   3.930 0.000102 ***
year:origin                1.295e-01  7.043e-02   1.839 0.066721 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.754 on 368 degrees of freedom
Multiple R-squared:  0.8849,	Adjusted R-squared:  0.8762
F-statistic: 101.1 on 28 and 368 DF,  p-value: < 2.2e-16

> #The model at all had an improvement in R2 from 0.82 to almost 0.89, maybe
it can be overfitting, though the interactive term most significant was accel
eration:origin with a good coefficient in comparison with the main terms and
a small p-value, validating the coefficient.
>
```

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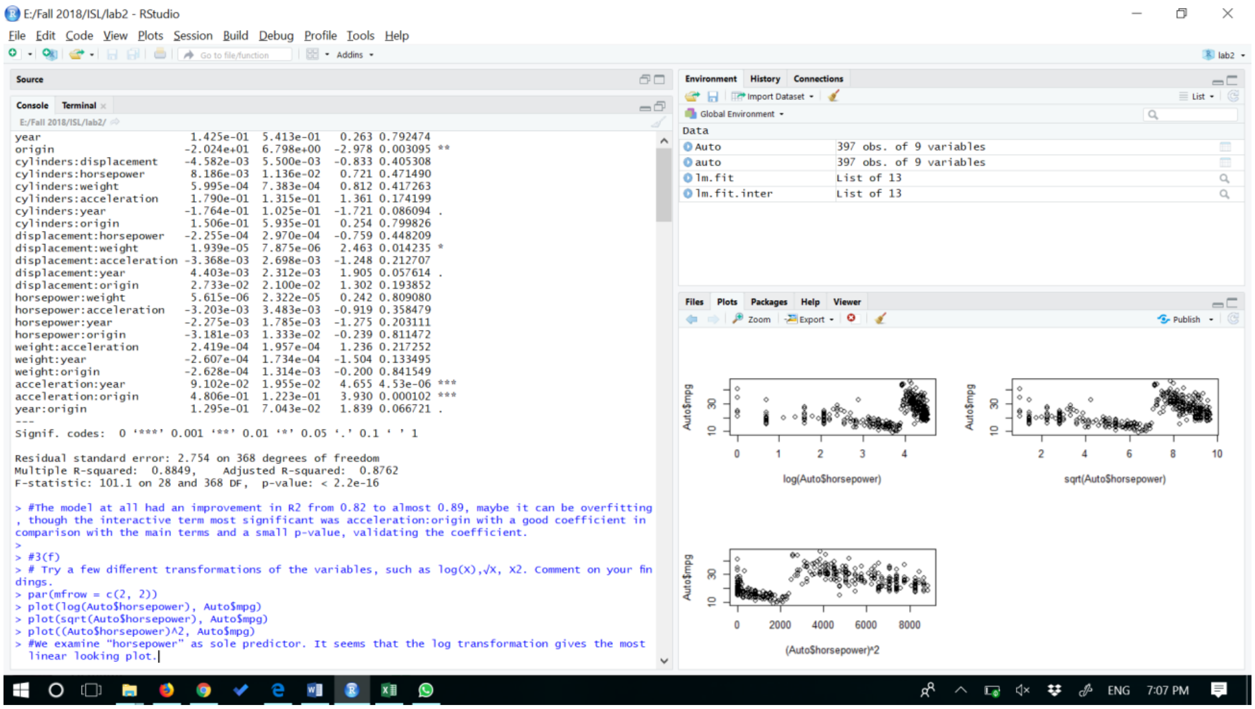
> #3(f) Try a few different transformations of the variables, such as log(X),√X, X2. Comment on your findings.

```
> par(mfrow = c(2, 2))
> plot(log(Auto$horsepower), Auto$mpg)
> plot(sqrt(Auto$horsepower), Auto$mpg)
> plot((Auto$horsepower)^2, Auto$mpg)
```



> #We examine “horsepower” as sole predictor. It seems that the log transformation gives the most linear looking plot.

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4.

> #4(a) Fit a multiple regression model to predict `Sales` using `Price`, `Urban`, and `US`.

```
> data("Carseats")
> > lm.fit.a <- lm(Sales ~ Price + Urban + US, data=Carseats)
Error: unexpected '>' in ">"
> > summary(lm.fit.a)
Error: unexpected '>' in ">"
>
> data("Carseats")
> > lm.fit.a <- lm(Sales ~ Price + Urban + US, data=Carseats)
Error: unexpected '>' in ">"
> > summary(lm.fit.a)
Error: unexpected '>' in ">"
>
> data("Carseats")
> lm.fit.a <- lm(Sales ~ Price + Urban + US, data=Carseats)
> summary(lm.fit.a)

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

>
> #4(b) Provide an interpretation of each coefficient in the model. Be carefu
l - some of the variables in the model are qualitative!

> #checking qualitative and quantitative variables
> attach(Carseats)
> str(data.frame(Price, Urban, US))
'data.frame':   400 obs. of  3 variables:
 $ Price: num  120 83 80 97 128 72 108 120 124 124 ...
 $ 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 ...
> #The Urband and US are qualitative
> attach(Carseats)
The following objects are masked from Carseats (pos = 3):

    Advertising, Age, CompPrice, Education, Income, Population, Price, Sales,
    ShelveLoc, Urban, US

> contrasts(Urban)
    Yes
No    0
Yes   1
```

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```
> contrasts(US)
    Yes
No    0
Yes   1
> #By analyzing the coefficients, the Urban has a very high p-value, so it do
esn't prove any evidence of relevance for Sales. The US indicates a strong in
fluence in the model and assigns more 1.2 thousands sales units for each US l
ocation. The Price coefficient has a negative relationship with Sales
>
> #4(c) Write out the model in the equation form, being careful to handle the
qualitative variables properly.
>
> #Sales=13.0434689+(−0.0544588)×Price+(−0.0219162)×Urban+(1.2005727)×US+ϵ
> If store I sin urban, then urban=1 else 0
Error: unexpected symbol in "If store"
> If stire is in US , then us=1 else 0
Error: unexpected symbol in "If stire"
>
> #If store I sin urban, then urban=1 else 0
> #
> #V
> #If stire is in US , then us=1 else 0
>

>
> #4(d) For which of the predictors can you reject the null hypothesis H0:βj=
0?
> #We can reject the null hypothesis for price and Us variable
>
>
> #4(e) On the basis of your response to the previous question, fit a smaller
model that only uses the predictors for which there is evidence of associatio
n with the outcome.
>
> lm.fit.e <- lm(Sales ~ Price + US, data=Carseats)
> summary(lm.fit.e)

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

>
> #4(f) How well do the models in (a) and (e) fit the data?
> anova(lm.fit.a, lm.fit.e)
Analysis of Variance Table

Model 1: Sales ~ Price + Urban + US
Model 2: Sales ~ Price + US
  Res.Df    RSS Df Sum of Sq      F Pr(>F)
```

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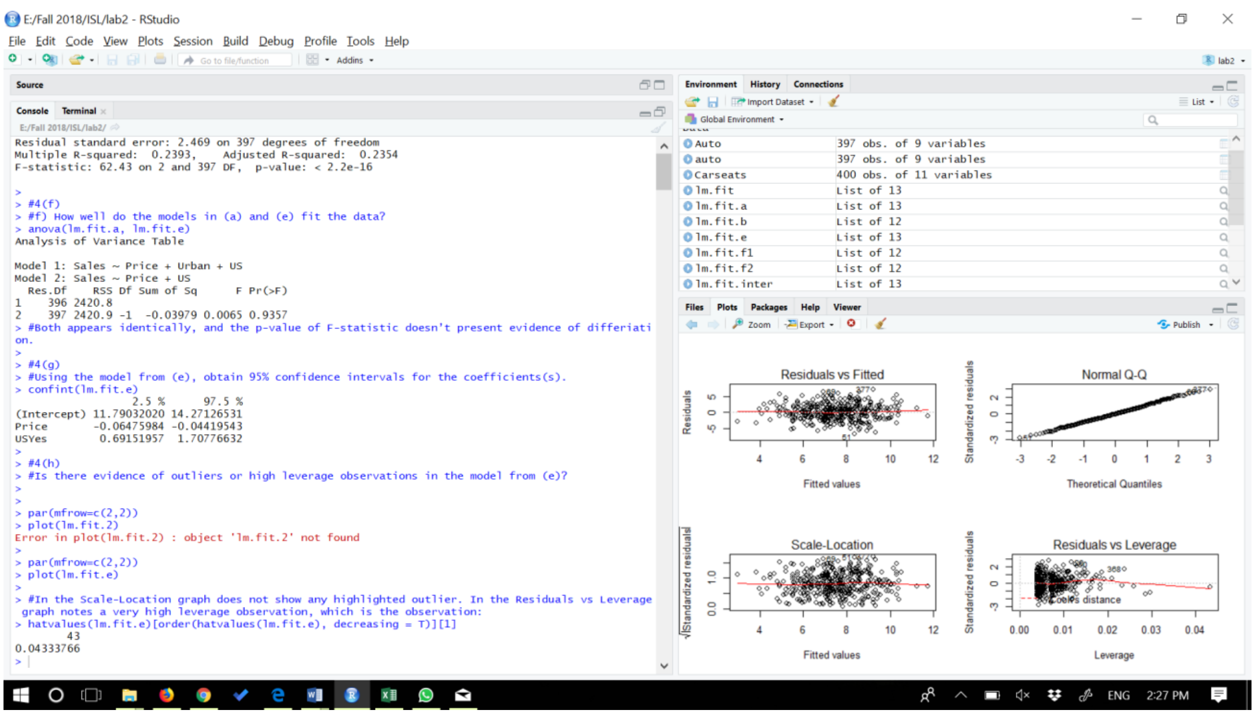
```
1     396 2420.8
2     397 2420.9 -1   -0.03979 0.0065 0.9357
> #Both appears identically, and the p-value of F-statistic doesn't present e
vidence of differiation.
>
> #4(g) Using the model from (e), obtain 95% confidence intervals for the coe
fficients(s).
> confint(lm.fit.e)
                  2.5 %      97.5 %
(Intercept) 11.79032020 14.27126531
Price       -0.06475984 -0.04419543
USYes        0.69151957  1.70776632
>
> #4(h) Is there evidence of outliers or high leverage observations in the mo
del from (e)?
>
>
> par(mfrow=c(2,2))
> plot(lm.fit.2)
Error in plot(lm.fit.2) : object 'lm.fit.2' not found
>
> par(mfrow=c(2,2))
> plot(lm.fit.e)
```




```
>
> #In the Scale-Location graph does not show any highlighted outlier. In the
Residuals vs Leverage graph notes a very high leverage observation, which is
the observation:
> hatvalues(lm.fit.e)[order(hatvalues(lm.fit.e), decreasing = T)][1]
        43
0.04333766
```

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5.

```
>
> #5 In this problem we will investigate the t-statistic for the null hypothesis H0:β=0 i
ar regression without an intercept. To begin, we generate a predictor x and a response y
> set.seed(1)
> x=rnorm(100)
> y=2*x+rnorm(100)
>
> #5(a) Perform a simple linear regression of y onto x, without an intercept. Report the
imate ˆ β, the standard error of this coefficient estimate, and the tstatistic and p-value
th the null hypothesis H0 : β = 0. Comment on these results. (You can perform regression
tercept using the command lm(y ∼ x + 0).)
> lm.fit.a <- lm(y ~ x+0)
> summary(lm.fit.a)$coefficients
  Estimate Std. Error  t value     Pr(>|t|)
x 1.993876  0.1064767 18.72593 2.642197e-34
> lm.fit.a <- lm(y ~ x+0)
> summary(lm.fit.a)

Call:
lm(formula = y ~ x + 0)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.9154 -0.6472 -0.1771  0.5056  2.3109 

Coefficients:
  Estimate Std. Error t value Pr(>|t|)    
x   1.9939     0.1065   18.73   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9586 on 99 degrees of freedom
Multiple R-squared:  0.7798,	Adjusted R-squared:  0.7776 
F-statistic: 350.7 on 1 and 99 DF,  p-value: < 2.2e-16

> #According to the summary above, we have a value of 1.9939 for β^, a value of 0.1065 fo
d error, a value of 18.73 for the t-statistic and a value of 2.642196910^{-34} for the p-
all p-value allows us to reject H0.
>
> #5(b) Now perform a simple linear regression of x onto y without an intercept, and repo
ent estimate, its standard error, and the corresponding t-statistic and p-values associat
ull hypothesis H0 : β = 0. Comment on these results.
> lm.fit.b <- lm(x ~ y+0)
> summary(lm.fit.b)$coefficients
   Estimate Std. Error  t value     Pr(>|t|)
y 0.3911145 0.02088625 18.72593 2.642197e-34
> #According to the summary above, we have a value of 0.3911145 for β^, a value of 0.0208
standard error, a value of 18.72593 for the t-statistic and a value of 2.642196910^{-34}
ue. The small p-value allows us to reject H0.
>
> #5(c) What is the relationship between the results obtained in (a) and (b)?
> #We obtain the same value for the t-statistic and consequently the same value for the c
p-value. Both results in (a) and (b) reflect the same line created in (a)
>

> #5(d)
```

Lab Assignment-2
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5(d) The $\hat{\beta}$ given in 3.38 is

$$\hat{\beta} = \left(\sum_{i=1}^{n} x_i y_i\right) \Big/ \left(\sum_{i=1}^{n} x_i^2\right) \rightarrow (1)$$

considering all the summations limits equals $[1, n]$, we'll omit to clear equations.

$$t = \frac{\hat{\beta}}{SE(\hat{\beta})}$$

$$t = \frac{\hat{\beta}}{\sqrt{\frac{\sum (y_i - x_i \hat{\beta})^2}{(n-1)\sum x_i^2}}}$$

~~or~~ Squaring on both sides

$$t^2 = \frac{\hat{\beta}^2}{\frac{\sum (y_i - x_i \hat{\beta})^2}{(n-1)\sum x_i^2}}$$

$$t^2 = (n-1)\sum x_i^2 \frac{\hat{\beta}^2}{\sum (y_i - x_i \hat{\beta})^2}$$

Expanding the denominator:-

$$t^2 = (n-1)\sum x_i^2 \frac{\hat{\beta}^2}{\sum (y_i^2 - 2y_i x_i \hat{\beta} + x_i^2 \hat{\beta}^2)}$$

$$t^2 = (n-1)\sum x_i^2 \frac{\hat{\beta}^2}{\sum y_i^2 - 2\hat{\beta}\sum y_i x_i + \hat{\beta}^2 \sum x_i^2}$$

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$$t^2 = (n-1)\sum x_i^2 \frac{\hat{\beta}^2}{\sum y_i^2 + \hat{\beta}\left(\hat{\beta}\sum x_i^2 - 2\sum y_i x_i\right)}$$

Substituting the down right $\hat{\beta}$ by ①

$$t^2 = (n-1)\sum x_i^2 \cdot \frac{\hat{\beta}^2}{\sum y_i^2 + \hat{\beta}\left[\left(\frac{\sum x_i y_i}{\sum x_i^2}\right)\sum x_i^2 - 2\sum y_i x_i\right]}$$

$$t^2 = (n-1)\sum x_i^2 \cdot \frac{\hat{\beta}^2}{\sum y_i^2 + \hat{\beta}\left[\sum x_i y_i - 2\sum y_i x_i\right]}$$

$$t^2 = (n-1)\sum x_i^2 \cdot \frac{\hat{\beta}^2}{\sum y_i^2 - \hat{\beta}\sum x_i y_i}$$

substituting the upper β and below β by ①, we get

$$t^2 = \left(\frac{\sum x_i y_i}{\sum x_i^2}\right)^2 \frac{(n-1)\left(\sum x_i^2\right)^2}{\sum y_i^2 \sum x_i^2 - \left(\sum x_i y_i\right)^2}$$

Simplifying the above term, we get

$$t = \frac{\sqrt{(n-1)}\ \sum x_i y_i}{\sqrt{\sum y_i^2 \sum x_i^2 - \left(\sum x_i y_i\right)^2}}$$

```
> #lets conform by R
> t_value = (sqrt(length(x)-1)*sum(x*y))/sqrt(sum(y^2)*sum(x^2) - (sum(x*y))^2)
> summary(t_value)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  18.73   18.73   18.73   18.73   18.73   18.73 
> n <- length(x)
> t <- sqrt(n - 1)*(x %*% y)/sqrt(sum(x^2) * sum(y^2) - (x %*% y)^2)
> as.numeric(t)
[1] 18.72593
> as.numeric((t_value))
[1] 18.72593
```

Lab Assignment-2

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```
> #We may see that the t above is exactly the t-statistic given in the summary of “fit.b”
>
>
> #5(e) Using the results from (d), argue that the t-statistic for the regression of y on
ame as the t-statistic for the regression of  x onto y.
> #if we take only the formula of β^ and SE(β^), the ratio of them will be the same indep
do regression onto x or y.
>
>
> #5(f) In R, show that when regression is performed with an intercept, the t-statistic f
0. is the same for the regression of y onto x as it is for the regression of x onto y.
>
> lm.fit.f1 <- lm(x ~ y)
> summary(lm.fit.f1)$coefficients[2,3]
[1] 18.5556
> #th above is the regression of x onto y
> #regression y onto x
> lm.fit.f2 <- lm(y ~ x)
> summary(lm.fit.f2)$coefficients[2,3]
[1] 18.5556
> # we can see both t values are equal
```