Homework 7

Seth Marceno 6/6/2019

Question 1

Here I read in the data and do forwards AIC selection:

```
data(mantel)
X1 <- mantel$X1
X2 <- mantel$X2
X3 <- mantel$X3
Y <- mantel$Y
fullModel \leftarrow ~X1 + X2 + X3
baseModel <- lm(Y \sim X1)
forward <- step(baseModel, fullModel, direction = 'forward')</pre>
## Start: AIC=9.22
## Y ~ X1
##
##
          Df Sum of Sq
                            RSS
                                      AIC
## + X2
           1
                14.189 0.0000 -287.749
## + X3
                 12.141 2.0476
                                    1.536
           1
## <none>
                        14.1888
                                    9.215
##
## Step: AIC=-287.75
## Y ~ X1 + X2
##
##
          Df Sum of Sq
                                 RSS
                                         AIC
## <none>
                         1.5284e-25 -287.75
## + X3
           1 5.7989e-28 1.5225e-25 -285.77
Here we do backwards AIC selection:
m1 <- update(baseModel, fullModel)</pre>
backwards <- step(m1, scope = c(lower = ~ X1) , direction = 'backward')</pre>
## Start: AIC=-285.77
## Y ~ X1 + X2 + X3
##
          Df Sum of Sq
##
                           RSS
                                     AIC
## - X3
              0.0000 0.0000 -287.749
## <none>
                        0.0000 -285.768
## - X2
                2.0476 2.0476
           1
                                   1.536
##
## Step: AIC=-287.75
## Y ~ X1 + X2
##
##
          Df Sum of Sq
                           RSS
                                     AIC
                         0.000 -287.749
## <none>
## - X2
                 14.189 14.189
                                   9.215
Here I do forwards BIC selection:
```

```
forwardBIC <- step(baseModel, fullModel, direction = 'forward', k = log(length(X1)))</pre>
## Start: AIC=8.43
## Y ~ X1
##
##
         Df Sum of Sq
                          RSS
                                    AIC
## + X2
        1
             14.189 0.0000 -288.921
## + X3 1
               12.141 2.0476
                                  0.364
## <none>
                       14.1888
                                  8.434
##
## Step: AIC=-288.92
## Y \sim X1 + X2
##
         Df Sum of Sq
##
                               RSS
                                       AIC
## <none>
                        1.5284e-25 -288.92
## + X3
           1 5.7989e-28 1.5225e-25 -287.33
Here I do backwards BIC selection:
backwardBIC <- step(m1, scope = c(lower = ~ X1), direction = 'backward', k = log(length(X1)))</pre>
## Start: AIC=-287.33
## Y \sim X1 + X2 + X3
##
##
         Df Sum of Sq
                          RSS
                                   AIC
## - X3 1 0.0000 0.0000 -288.921
## <none>
                       0.0000 -287.331
## - X2
        1
               2.0476 2.0476
                                 0.364
##
## Step: AIC=-288.92
## Y ~ X1 + X2
##
##
         Df Sum of Sq
                         RSS
                                   AIC
## <none>
                        0.000 -288.921
## - X2
                14.189 14.189
                                 8.434
```

Based off of both forwards and backwards selection using BIC and AIC, we see that the active regressors are X1 and X2.

Question 2

Case 1:

```
e <- 1
hii <- .9
p <- 4
n <- 54
sigma <- 4

ri_1 <- e/ (sigma*(sqrt(1-hii)))
ri_1</pre>
```

```
## [1] 0.7905694
Di_1 <- (1/p)*(ri_1^2)*(hii/(1-hii))
Di_1
## [1] 1.40625
ti_1 <- ri_1*(((n-p-1)/(n-p-(ri_1^2)))^0.5)
ti_1
## [1] 0.7875615
qt(p = 0.975, df = 49, lower.tail = TRUE)</pre>
```

[1] 2.009575

At level alpha = 0.05, our critical value is 2.01. Since ti_1 is not greater than our critical value, we determine that this point is not influential.

Case 2:

```
e <- 1.732
hii <- 0.75
p <- 4
n <- 54
sigma <- 4

ri_2 <- e/ (sigma*(sqrt(1-hii)))
ri_2

## [1] 0.866
Di_2 <- (1/p)*(ri_2^2)*(hii/(1-hii))
Di_2

## [1] 0.562467
ti_2 <- ri_2*(((n-p-1)/(n-p-(ri_2^2)))^0.5)
ti_2</pre>
```

[1] 0.8637988

Comparing our test statistic to the critical value we found above, again we see our test statistic is smaller, so we conclude that this point is not influential.

Case 3:

```
e <- 9
hii <- 0.25
p <- 4
n <- 54
sigma <- 4
```

```
ri_3 <- e/ (sigma*(sqrt(1-hii)))
ri_3

## [1] 2.598076

Di_3 <- (1/p)*(ri_3^2)*(hii/(1-hii))
Di_3

## [1] 0.5625

ti_3 <- ri_3*(((n-p-1)/(n-p-(ri_3^2)))^0.5)
ti_3
```

[1] 2.765393

Since our test statistic is greater than our critical value (2.01) we determine that this point is influential.

Case 4

```
e <- 10.295
hii <- 0.185
p <- 4
n <- 54
sigma <- 4

ri_4 <- e/ (sigma*(sqrt(1-hii)))
ri_4

## [1] 2.850937

Di_4 <- (1/p)*(ri_4^2)*(hii/(1-hii))
Di_4

## [1] 0.4612424

ti_4 <- ri_4*(((n-p-1)/(n-p-(ri_4^2)))^0.5)
ti_4</pre>
```

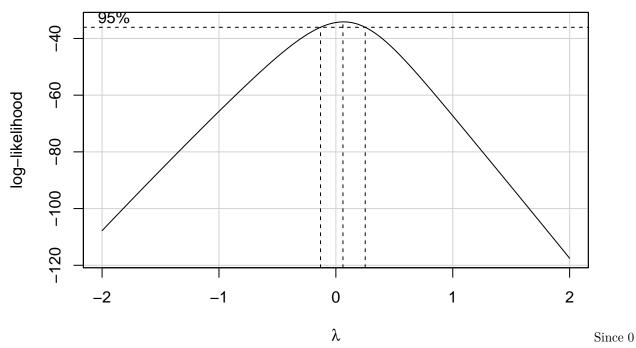
[1] 3.084061

Since our test statistic is greater than our critical value (2.01) we determine that this point is influential.

Question 3

Part(a)

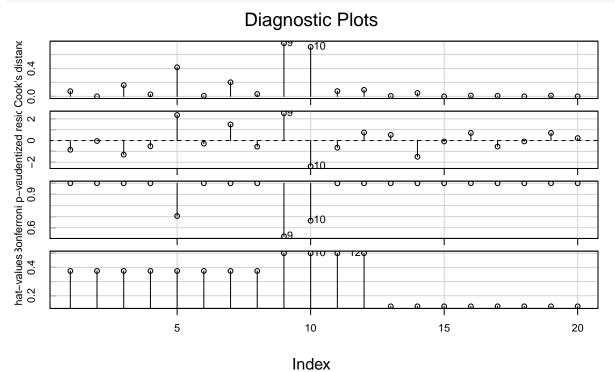
```
data(lathe1)
Speed <- lathe1$Speed
Feed <- lathe1$Feed
Life <- lathe1$Life
fit1 <- lm(Life ~ Speed + Feed + I(Speed^2) + I(Feed^2) + Speed*Feed)
boxCox(fit1)</pre>
```



is within the interval, we know to log transform our response.

Part(b)

```
fit2 <- lm(log(Life) ~ Speed + Feed + I(Speed^2) + I(Feed^2) + Speed*Feed)
influenceIndexPlot(fit2)</pre>
```



Here we see points 9 and 10 have the highest cooks distance, therefore we will remove them.

```
new.lathe1 <- lathe1[-c(9, 10), ]
new.Speed <- new.lathe1$Speed
new.Feed <- new.lathe1$Feed
new.Life <- new.lathe1$Life
fit3 <- lm(log(new.Life) ~ new.Speed + new.Feed + I(new.Speed^2) + I(new.Feed^2) + new.Speed*new.Feed)
summary(fit2)
##
## Call:
## lm(formula = log(Life) ~ Speed + Feed + I(Speed^2) + I(Feed^2) +
##
      Speed * Feed)
##
## Residuals:
       Min
                  1Q
                       Median
                                    3Q
##
## -0.43349 -0.14576 -0.02494 0.16748 0.47992
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
                          0.10508 11.307 2.00e-08 ***
## (Intercept) 1.18809
## Speed
              -1.58902
                           0.08580 -18.520 3.04e-11 ***
                           0.08580 -9.210 2.56e-07 ***
## Feed
               -0.79023
## I(Speed^2)
               0.28808
                           0.10063
                                     2.863 0.012529 *
                                   4.159 0.000964 ***
## I(Feed^2)
               0.41851
                           0.10063
## Speed:Feed -0.07286
                           0.10508 -0.693 0.499426
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.2972 on 14 degrees of freedom
## Multiple R-squared: 0.9702, Adjusted R-squared: 0.9596
## F-statistic: 91.24 on 5 and 14 DF, p-value: 3.551e-10
summary(fit3)
##
## Call:
## lm(formula = log(new.Life) ~ new.Speed + new.Feed + I(new.Speed^2) +
       I(new.Feed^2) + new.Speed * new.Feed)
##
##
## Residuals:
##
       Min
                  1Q
                      Median
                                    3Q
                                            Max
## -0.39963 -0.14660 0.00387 0.14917
##
## Coefficients:
##
                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                      1.18809
                                 0.08241 14.417 6.11e-09 ***
                                  0.08241 -17.388 7.10e-10 ***
## new.Speed
                      -1.43300
## new.Feed
                      -0.79023
                                 0.06729 -11.743 6.15e-08 ***
## I(new.Speed^2)
                       0.28022
                                  0.12363
                                          2.267 0.042700 *
## I(new.Feed^2)
                                           4.583 0.000629 ***
                       0.42244
                                  0.09217
## new.Speed:new.Feed -0.07286
                                  0.08241 -0.884 0.394025
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.2331 on 12 degrees of freedom
```

```
## Multiple R-squared: 0.9759, Adjusted R-squared: 0.9658
## F-statistic: 97.07 on 5 and 12 DF, p-value: 2.804e-09
```

Based off of our summary function we see that before removing the influencial points, our R squared value is 0.9702, and after we get an R squared of 0.9759. Therefore we can see the non-influential data has a slightly better fit than with the influential points.