CSCI E-106:Assignment 9

Due Date: November 23, 2020 at 7:20 pm EST

Instructions

Students should submit their reports on Canvas. The report needs to clearly state what question is being solved, step-by-step walk-through solutions, and final answers clearly indicated. Please solve by hand where appropriate.

Please submit two files: (1) a R Markdown file (.Rmd extension) and (2) a PDF document, word, or html generated using knitr for the .Rmd file submitted in (1) where appropriate. Please, use RStudio Cloud for your solutions.

Solutions:

Problem 1

Refer to Brand preference data, build a model with all independent variables (45 pts, 5 points each)

a-) Obtain the studentized deleted residuals and identify any outlying Y observations. Use the Bonferroni outlier test procedure with $\alpha = 0.10$. State the decision rule and conclusion.

No outliers based on the bonferoni test.

```
Brand.Preference <- read.csv("/cloud/project/Brand Preference.csv")
pr1<-lm(Y~X1+X2,data=Brand.Preference)
library(olsrr)

##
## Attaching package: 'olsrr'

## The following object is masked from 'package:datasets':
##
## rivers

drst<-rstudent(pr1)
tb<-qt(1-0.1/(2*16),16-3-1)
sum(abs(drst)>abs(tb))
```

[1] 0

b-) Obtain the diagonal elements of the hat matrix, and provide an explanation for the pattern in these elements.

Max hat value is 0.2375 and the min is 0.1375. The average is 0.19. The compact range, no indication of outliers.

```
hii <- hatvalues(pr1)
hii</pre>
```

```
## 1 2 3 4 5 6 7 8 9 10 11
## 0.2375 0.2375 0.2375 0.2375 0.1375 0.1375 0.1375 0.1375 0.1375 0.1375 0.1375
## 12 13 14 15 16
## 0.1375 0.2375 0.2375 0.2375 0.2375
```

summary(hii)

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.1375 0.1375 0.1875 0.1875 0.2375 0.2375
```

c-) Are any of the observations outlying with regard to their X values according?

No outliers in direction of X, hat values are less than 2*p/n.

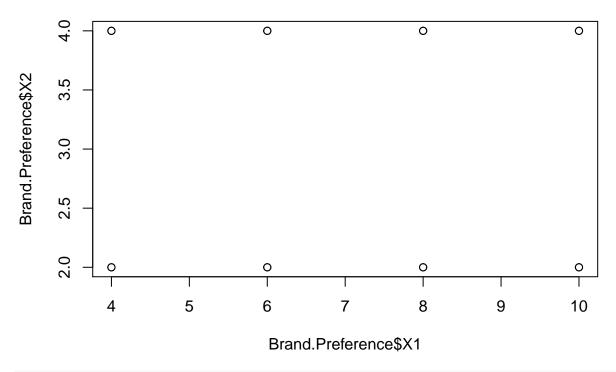
```
sum(hii>(2*3/16))
```

```
## [1] 0
```

d-) Management wishes to estimate the mean degree of brand liking for moisture content $X_1 = 10$ and sweetness $X_2 = 3$. Construct a scatter plot of X_2 against X_1 and determine visually whether this prediction involves an extrapolation beyond the range of the data. Also, determine whether an extrapolation is involved. Do your conclusions from the two methods agree?

The hat value for the prediction is 0.175 which is within the hat values calculated pat c(max = 0.2375 and min = 0.1375). No extrapolation is required.

```
plot(Brand.Preference$X1,Brand.Preference$X2)
```



```
X<-model.matrix(pr1)
XXInv<-solve(t(X)%*%X)
Xhnew<-matrix(c(1,10,3),nrow=1,ncol=3)
Hatnew<-Xhnew%*%XXInv%*%t(Xhnew)
Hatnew</pre>
```

```
## [,1]
## [1,] 0.175
```

e-) The largest absolute studentized deleted residual is for case 14. Obtain the DFFITS, DFBETAS, and Cook's distance values for this case to assess the influence of this case. What do you conclude?

Case 14 has the max DFIITS, DFBETAS, and Cooks distance. Cooks distance is 2000 larger than the smallest cooks distance. Indicating influential point.

```
cd<-influence.measures(pr1)
cd</pre>
```

```
Influence measures of
##
##
   lm(formula = Y ~ X1 + X2, data = Brand.Preference) :
##
##
            dfb.X1
                  dfb.X2
                          dffit cov.r
                                     cook.d
      dfb.1_{-}
    -0.02155 0.0157
                   0.0117 -0.0228 1.667 0.000188 0.238
## 1
     0.00868 -0.0235
##
  2
                   0.0175
                         0.0342 1.666 0.000422 0.237
## 3
    -0.71785 0.5226
                   0.3895 -0.7593 1.084 0.180392 0.237
                         0.7735 1.068 0.186258 0.238
     0.19619 - 0.5324
                   0.3968
    -0.11987
           0.0442
                   0.0988 -0.1465 1.426 0.007666 0.138
##
##
  6
     -0.25062 0.0924 0.2065 -0.3063 1.277 0.032297 0.138
## 8
    -0.01832 -0.0607
                  ## 9
```

```
## 10 0.12431 -0.0728 -0.1627 -0.2413 1.347 0.020406 0.138

## 11 0.28674 0.2195 -0.4907 0.7279 0.708 0.149828 0.138

## 12 -0.20113 0.1177 0.2632 0.3904 1.171 0.050983 0.138

## 13 0.01467 -0.4378 0.3263 -0.6360 1.225 0.131821 0.237

## 14 0.83881 -0.8077 -0.6020 -1.1735 0.651 0.363412 0.237

## 15 -0.01917 0.5722 -0.4265 0.8314 1.002 0.210661 0.237

## 16 -0.09802 0.0944 0.0704 0.1371 1.643 0.006758 0.237
```

cd\$infmat[14,6]/cd\$infmat[,6]

```
3
                                                                                  6
##
                            2
                                                       4
                                                                     5
              1
   1936.000000
                  860.444444
                                 2.014568
                                               1.951121
                                                            47.408648
                                                                         14.804950
##
                            8
                                         9
                                                      10
                                                                                 12
                                                                    11
##
     11.252151
                   25.317340
                                 29.712712
                                              17.809076
                                                             2.425527
                                                                          7.128081
##
             13
                           14
                                        15
                                                      16
      2.756853
                    1.000000
                                 1.725106
##
                                              53.777778
```

f-) Calculate the average absolute percent difference in the fitted values with and without case 14. What does this measure indicate about the influence of case 14?

Predicted values are increased by %0.62.

```
p1<-pr1$fitted.values[-c(14)]
t1<-lm(Y~X1+X2,data=Brand.Preference[-c(14),])
p2<-t1$fitted.values
cbind(Brand.Preference[-c(14),1],p1,p2)</pre>
```

```
##
             p1
                        p2
## 1
       64 64.10
                  63.45082
## 2
       73 72.85
                  72.92213
## 3
       61 64.10
                  63.45082
## 4
       76 72.85
                  72.92213
## 5
       72 72.95
                  72.73361
## 6
       80 81.70
                  82.20492
##
       71 72.95
                  72.73361
## 8
       83 81.70
                  82.20492
## 9
       83 81.80
                  82.01639
## 10
       89 90.55
                  91.48770
## 11
       86 81.80
                  82.01639
## 12
       93 90.55
                  91.48770
       88 90.65
  13
                  91.29918
## 15
       94 90.65
                 91.29918
## 16 100 99.40 100.77049
```

```
mean((abs(p1-p2)/p2)*100)
```

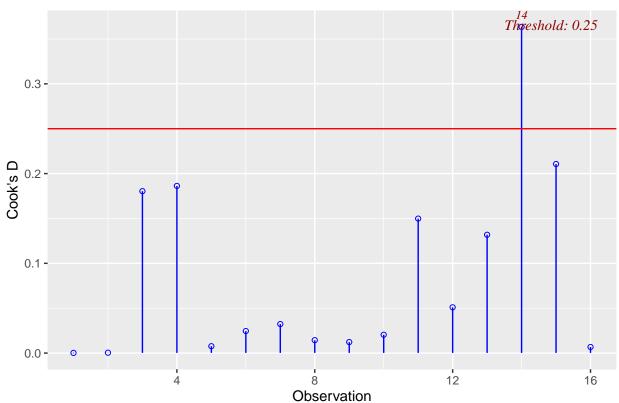
```
## [1] 0.6284827
```

g-) Calculate Cook's distance D; for each case and prepare an index plot. Are any cases influential according to this measure?

Case 14 is an influential point based on the plot.

ols_plot_cooksd_chart(pr1)

Cook's D Chart



h-) Find the two variance inflation factors. Why are they both equal to 1? X1 and X2 are independent, therefore VIF=1.

library(faraway)

```
##
## Attaching package: 'faraway'
## The following object is masked from 'package:olsrr':
##
## hsb

vif(pr1)

## X1 X2
## 1 1
```

cor(Brand.Preference)

```
## Y X1 X2
## Y 1.000000 0.8923929 0.3945807
## X1 0.8923929 1.000000 0.0000000
## X2 0.3945807 0.000000 1.0000000
```

Problem 2

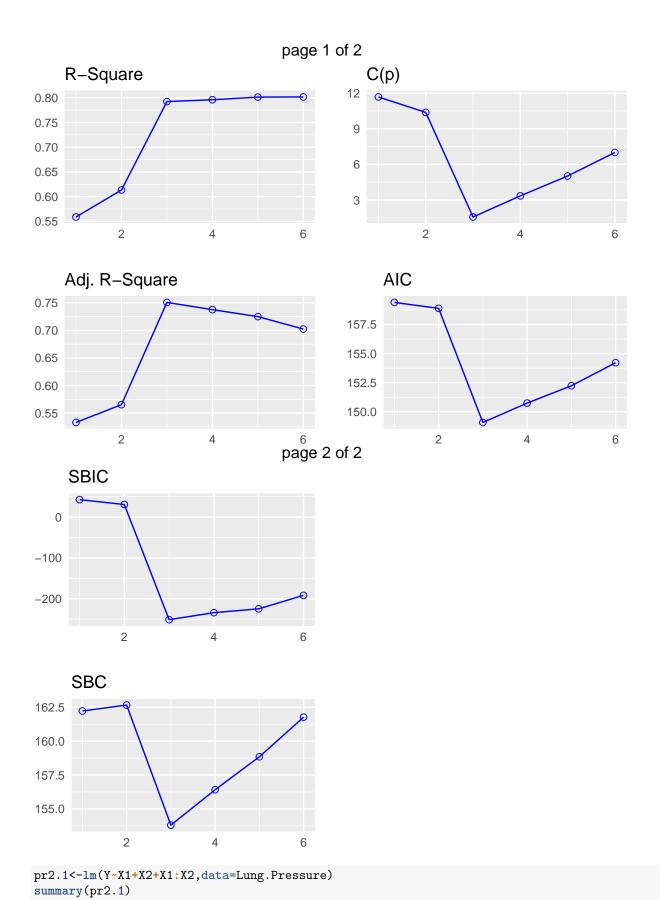
Refer to the Lung pressure Data. Increased arterial blood pressure in the lungs frequently leads to the development of heart failure in patients with chronic obstructive pulmonary disease (COPD). The standard method for determining arterial lung pressure is invasive, technically difficult, and involves some risk to the patient. Radionuclide imaging is a noninvasive, less risky method for estimating arterial pressure in the lungs. To investigate the predictive ability of this method, a cardiologist collected data on 19 mild-to-moderate COPD patients. The data includes the invasive measure of systolic pulmonary arterial pressure (Y) and three potential noninvasive predictor variables. Two were obtained by using radionuclide imaging emptying rate of blood into the pumping chamber or the heart (X_1) and ejection rate of blood pumped out of the heart into the lungs (X_2) and the third predictor variable measures blood gas (X_3) . (35 points, 5 points each)

a-) Find the best regression model by using first-order terms and the cross-product term. Ensure that all variables in the model are significant at 5%.

The best subet algorithm is suggesting that the third model is the best model based on Adjusted R square values, CP, SBC and AIC. The model is significant and all variables are significant at 5% level.

```
Lung.Pressure <- read.csv("/cloud/project/Lung Pressure.csv")
pr2<-lm(Y~.^2,data=Lung.Pressure)
summary(pr2)</pre>
```

```
##
## Call:
## lm(formula = Y ~ .^2, data = Lung.Pressure)
##
## Residuals:
##
       Min
                1Q
                   Median
                                3Q
                                        Max
##
  -14.908
           -4.817
                   -2.612
                              4.623
                                    23.476
##
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 144.97317
                           78.36891
                                       1.850
                                             0.08910
## X1
                -2.95130
                            2.76019
                                     -1.069
                                              0.30600
## X2
                -1.28415
                                     -1.772
                            0.72475
                                              0.10179
                -0.23106
## X3
                            1.84130
                                      -0.125
                                              0.90222
## X1:X2
                 0.03381
                            0.01017
                                       3.325
                                             0.00605 **
## X1:X3
                 0.02099
                            0.06416
                                       0.327
                                              0.74922
## X2:X3
                -0.01247
                            0.01712
                                     -0.729
                                             0.48025
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 11.56 on 12 degrees of freedom
## Multiple R-squared: 0.8016, Adjusted R-squared: 0.7023
## F-statistic: 8.079 on 6 and 12 DF, p-value: 0.001179
library(olsrr)
library(datasets)
k1<-ols_step_best_subset(pr2)
plot(k1)
```

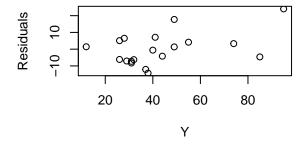


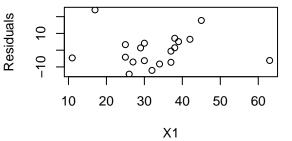
```
##
## Call:
##
  lm(formula = Y ~ X1 + X2 + X1:X2, data = Lung.Pressure)
##
##
  Residuals:
##
        Min
                  1Q
                       Median
                                     3Q
                                             Max
   -14.3075 -6.6602 -0.5824
                                4.6284
                                         24.0398
##
##
##
  Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
##
##
   (Intercept) 134.399866
                           15.981599
                                       8.410 4.63e-07 ***
                                       -4.085 0.000975 ***
                -2.133022
                            0.522157
## X1
## X2
                -1.699330
                            0.363669
                                       -4.673 0.000300 ***
## X1:X2
                 0.033347
                            0.009283
                                       3.592 0.002667 **
## ---
                   0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
##
## Residual standard error: 10.58 on 15 degrees of freedom
## Multiple R-squared: 0.7922, Adjusted R-squared: 0.7507
## F-statistic: 19.06 on 3 and 15 DF, p-value: 2.233e-05
```

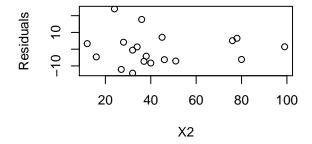
b-) Obtain the residuals and plot them separately against Y and each of the three predictor variables. On the basis of these plots. should any further modification of the regression model be attempted?

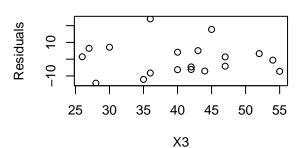
No pattern with residuals and X3, indicating that X3 would not increase the power. There are couple of potential outliers in the data.

```
par(mfrow=c(2,2))
plot(Lung.Pressure$Y,pr2.1$residuals,ylab="Residuals",xlab="Y")
plot(Lung.Pressure$X1,pr2.1$residuals,ylab="Residuals",xlab="X1")
plot(Lung.Pressure$X2,pr2.1$residuals,ylab="Residuals",xlab="X2")
plot(Lung.Pressure$X3,pr2.1$residuals,ylab="Residuals",xlab="X3")
```









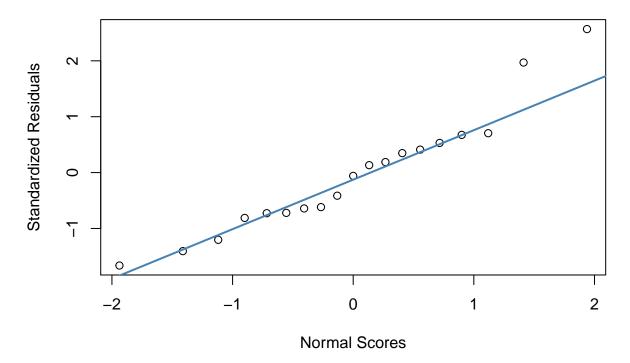
c-)

Prepare a normal probability plot of the residuals. Also obtain the coefficient of correlation between the ordered residuals and their expected values under normality. Does the normality assumption appear to be reasonable here?

The correlation is 96%, and graph indicates that the assumption is reasonable.

```
stdei<- rstandard(pr2.1)
qqnorm(stdei,ylab="Standardized Residuals",xlab="Normal Scores", main="QQ Plot")
qqline(stdei,col = "steelblue", lwd = 2)</pre>
```

QQ Plot



```
a2<-anova(pr2.1)
mse<-a2$'Mean Sq'[4]
ei<-pr2.1$residuals
ei.rank<-rank(ei)
z1<-(ei.rank-0.375)/(19+0.375)
exp.rank<-sqrt(mse)*qnorm(z1)
cor(exp.rank,ei)</pre>
```

[1] 0.9606285

d-) Obtain the variance inflation factors. Are there any indications that serious multicollinearity problems are present? Explain.

Multicollinearity present VIF>10 for X2 and the interaction term.

```
library(faraway)
vif(pr2.1)
```

```
## X1 X2 X1:X2
## 5.431477 11.639560 22.474469
```

e-) Obtain the studentized deleted residuals and identify outlying Y observations. Use the Bonferroni outlier test procedure with $\alpha = .05$. State the decision rule and conclusion.

No outliers based on the bonforeni test. the largest deleted residual is observation 7, which larger than 3.

```
drst<-rstudent(pr2.1)
tb<-qt(1-0.05/(2*19),19-4-1)
sum(abs(drst)>abs(tb))
```

[1] 0

f-) Obtain the diagonal elements of the hat matrix. Are there any outlying X observations? Discuss. Indicating 3 outliers in X. Observations 3,8 and 15.

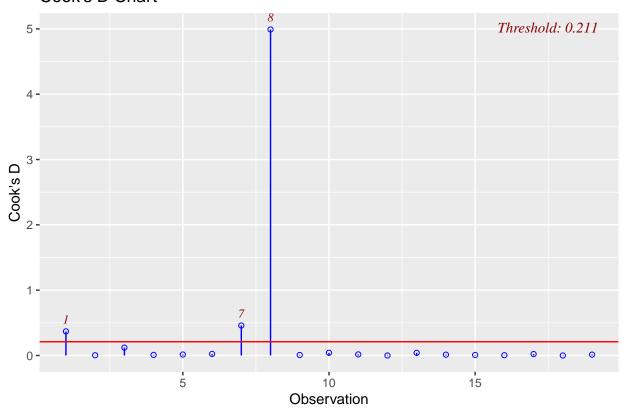
```
hii <- hatvalues(pr2.1)
hii
##
            1
                                  3
                                              4
                                                         5
                                                                    6
## 0.27569243 0.08336965 0.53886673 0.08482945 0.17565769 0.17374756 0.21775095
                                                        12
                                                                   13
                                 10
                                            11
## 0.87827870 0.19254581 0.10171037 0.11155424 0.06796196 0.07530137 0.09294148
           15
                      16
                                 17
                                            18
## 0.47982100 0.08967339 0.14443764 0.13905081 0.07680876
summary(hii)
      Min. 1st Qu. Median
                              Mean 3rd Qu.
## 0.06796 0.08725 0.13905 0.21053 0.20515 0.87828
sum(hii>(2*4/19))
## [1] 3
(hii>(2*4/19))
       1
             2
                   3
                               5
                                     6
                                           7
                                                  8
                                                             10
                                                                   11
                                                                         12
                                                                               13
  FALSE FALSE
                TRUE FALSE FALSE FALSE
                                              TRUE FALSE FALSE FALSE FALSE
##
      14
            15
                  16
                        17
                              18
                                    19
         TRUE FALSE FALSE FALSE
## FALSE
```

g-) Cases 3, 8, and 15 are moderately far outlying with respect to their X values, and case 7 is relatively far outlying with respect to its Y value. Obtain DFFITS, DFBETAS, and Cook's distance values for these cases to assess their influence. What do you conclude? Case 8 has the largest cooks distance, it is an influential point. Cases 1 and 7 are outliers.

```
cd2<-influence.measures(pr2.1)
cd2</pre>
```

```
## Influence measures of
    lm(formula = Y ~ X1 + X2 + X1:X2, data = Lung.Pressure) :
##
                     dfb.X2 dfb.X1.X dffit cov.r cook.d
##
      dfb.1_
               dfb.X1
## 1 -0.74721 1.086986 0.22392 -0.59551 1.3632 0.550 0.369041 0.2757
    0.00722 0.030375 -0.00594 -0.02091 0.1203 1.374 0.003833 0.0834
## 3 -0.65194 0.591913 0.43337 -0.48191 -0.6802 2.556 0.120516 0.5389
    0.04063 -0.040524 -0.10592 0.09287 -0.1842 1.299 0.008854 0.0848
## 4
## 5
    -0.04872 -0.000561 0.10888 -0.04217 0.2387 1.482 0.014982 0.1757
    -0.02764 -0.026282 0.07195 0.01040 0.3035 1.410 0.023920 0.1737
## 7
     1.45413 -1.277609 -0.74152 0.84752 1.7486 0.166 0.458917 0.2178
## 8 -1.54691 1.186623 3.16227 -3.28579 -4.7798 4.790 4.990815 0.8783
     0.10208 -0.046089 -0.10509 0.07011 0.1650 1.580 0.007236 0.1925
## 10 0.03588 -0.171698 0.00924 0.10165 -0.4116 0.977 0.040999 0.1017
## 11 0.10895 -0.171977 -0.06084 0.11835 -0.2534 1.285 0.016600 0.1116
## 12 0.00127 0.006001 0.00576 -0.00950 0.0346 1.407 0.000320 0.0680
## 15 -0.01551 -0.035251 0.07715 -0.01570 0.1749 2.510 0.008170 0.4798
## 17  0.05185  -0.018569  -0.19203  0.14258  -0.2914  1.337  0.021956  0.1444
## 18  0.00912 -0.015709 -0.00358  0.00987 -0.0230 1.529 0.000142 0.1391
cd3<-cd2\sinfmat
cd3[c(3,7,8,15),]
        dfb.1_{-}
                  dfb.X1
                            dfb.X2
                                     dfb.X1:X
                                                 dffit
                                                         cov.r
## 3 -0.6519371 0.59191342 0.43337176 -0.48191103 -0.6801824 2.5561254
     1.4541305 -1.27760852 -0.74151968 0.84752328 1.7485509 0.1661137
## 8 -1.5469080 1.18662253 3.16226530 -3.28579003 -4.7797848 4.7895257
## 15 -0.0155059 -0.03525106 0.07714703 -0.01569977 0.1748573 2.5095274
##
         cook.d
## 3 0.120515509 0.5388667
## 7 0.458917058 0.2177509
## 8 4.990814979 0.8782787
## 15 0.008170411 0.4798210
ols_plot_cooksd_chart(pr2.1)
```

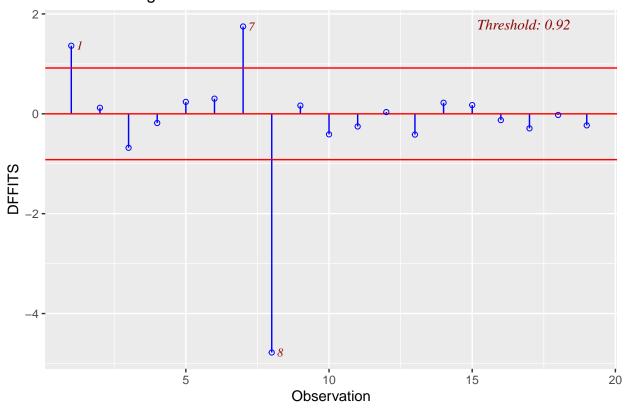
Cook's D Chart



ols_plot_dfbetas(pr2.1)

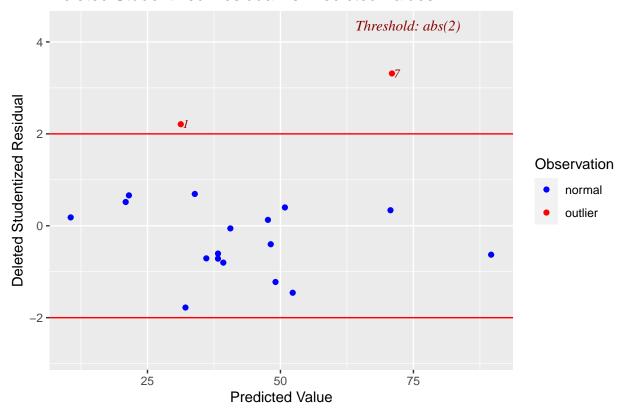
page 1 of 1 Influence Diagnostics for (Intercept Influence Diagnostics for X2 3 **-**Threshold: 0.46 Threshold: 0.46 DFBETAS DFBETAS 10 15 10 5 15 20 5 20 Observation Observation Influence Diagnostics for X1 Influence Diagnostics for X1:X2 Threshold: 0.46 1.0 -0 -1 -2 0.5 DFBETAS 0.0 -0.5-1.0 -3 **-**5 15 20 5 10 10 15 20 Observation Observation ols_plot_dffits(pr2.1)

Influence Diagnostics for Y



ols_plot_resid_stud_fit(pr2.1)

Deleted Studentized Residual vs Predicted Values



Problem 3

Refer to the Prostate cancer data set. Serum prostate-specific antigen (PSA) was determined in 97 men with advanced prostate cancer. PSA (Y) is a well-established screening test for prostate cancer and the oncologists wanted to examine the correlation between level of PSA and a number of clinical measures for men who were about to undergo radical prostatectomy. The measures are cancer volume (X_1) , prostate weight (X_2) , patient age (X_3) , the amount of benign prostatic hyperplasia (X_4) , seminal vesicle invasion (X_5) , capsular penetration (X_6) , and Gleason score (X_7) . (20 points, 5 points each)

a-) Select a random sample of 65 observations to use as the model-building data set. Develop a best subset model for predicting PSA. Justify your choice of model. Assess your model's ability to predict and discuss its usefulness to the oncologists.

We tried two variable selection methodologies, best subset and stepwise. Both methods are suggesting Y=X1+X6 to be the best model.

```
library(olsrr)
PROSTATE.CANCER <- read.csv("/cloud/project/PROSTATE.CANCER.csv")
set.seed(567)
sample.ind <- sample(1:nrow(PROSTATE.CANCER), size = 65)
devq5 <- PROSTATE.CANCER[sample.ind,]
holdoutq5 <- PROSTATE.CANCER[-sample.ind,]
pr3<-lm(Y~X1+X2+X3+X4+X5+X6+X7,data=devq5)
ols_step_both_p(pr3,prem=0.05,details=TRUE)</pre>
```

Stepwise Selection Method

```
##
## Candidate Terms:
##
## 1. X1
## 2. X2
## 3. X3
## 4. X4
## 5. X5
## 6. X6
## 7. X7
## We are selecting variables based on p value...
##
##
## Stepwise Selection: Step 1
##
## - X6 added
##
##
                  Model Summary
## -----
                  0.696 RMSE
0.485 Coef. Var
## R-Squared
                                      121.436
                       MSE
MAE
                 0.477
## Adj. R-Squared
                                       861.994
## Pred R-Squared
                 0.263
                                       17.101
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##
                       ANOVA
##
              Sum of
            Squares DF Mean Square
##
                                      F
                                             Sig.
## -----
## Regression 51158.364 1 51158.364
## Residual 54305.592 63 861.994
                                     59.349 0.0000
## Residual 54305.592
## Total 105463.956
                     64
##
                       Parameter Estimates
## -----
      model Beta Std. Error Std. Beta
                                     t
                                            Sig
                                                 lower
## (Intercept) 8.258
                    4.187
                                    1.972 0.053
                                                 -0.110 16.625
                    X6 7.469
##
##
##
##
## Stepwise Selection: Step 2
## - X1 added
##
```

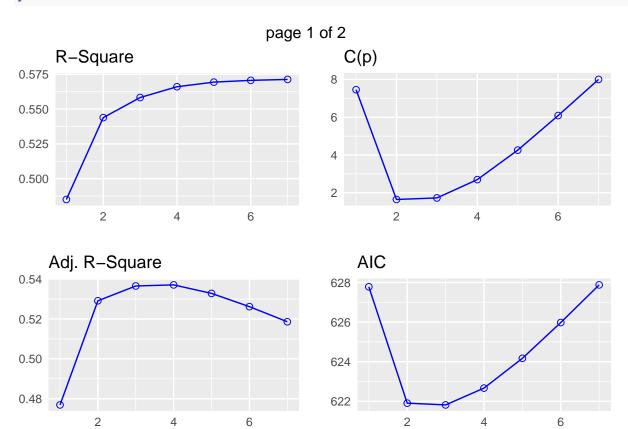
##			Mod	el Summ	ary								
## ##					RMSE	27.8							
	R-Squared				Coef. Var								
	Adj. R-Square	d	0.52	9	MSE	775.9	976						
##	Pred R-Square	d	0.30	5	MAE	15.2	294						
## ##	RMSE: Root M MSE: Mean Sq MAE: Mean Ab												
## ##		_											
##		Sum of	:										
##		Squares	3	DF	Mean Square	F	Sig.						
##	Regression	57353.472	2	2	28676.736	36.956	0.0000	_					
##	Residual	48110.483	3	62	28676.736 775.976								
##	Total	105463.956	5	64									
##								=					
	Parameter Estimates												
##	model	Beta 	Std.	Error 	Std. Beta	t 	Sig 	lower	upper				
					0.457 0.340								
##	X6	4.906		1.292	0.457	3.797	0.000	2.324	7.489				
##	Y1	1.507		0.555 	0.340	2.020		0.456 	2.070				
##													
##													
## ##			Mod	el Summ	arv								
##				7		27.8							
##	R-Squared				Coef. Var 115.218 MSE 775.976								
	Pred R-Square				MAE	15.2							
##													
##	RMSE: Root M		Erro	r									
##	MSE: Mean Sq MAE: Mean Ab												
##	MAE. Mean AD	solute Ell)1										
##													
	G f												
## ##	Sum of Squares			DE	Mean Square	┎	Sig.						
								_					
##	Regression	57353.472	2	2	28676.736	36.956	0.0000						
	Residual	48110.483 105463.956	3		775.976								
	Total) 	64 				_					
##													

Parameter Estimates

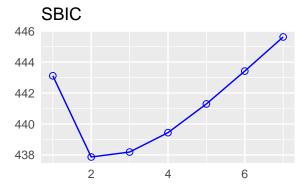
##

## model Beta Std. Error Std. Beta t			
#	Sig 	lower	uppe:
t (Intercent) 2 012 4 546 0 442	0.660	-7.076	11.10
(Intercept) 2.012 4.546 0.442 X6 4.906 1.292 0.457 3.797	0.000	2.324	7.48
X6 4.906 1.292 0.457 3.797 X1 1.567 0.555 0.340 2.826	0.006	0.458	2.67
No more variables to be added/removed.			
Final Model Output			
Model Summary			
R 0.737 RMSE 27	 7.856		
R-Squared 0.544 Coef. Var 115 Adj. R-Squared 0.529 MSE 775 Pred R-Squared 0.305 MAE 15			
Adj. R-Squared 0.529 MSE 775	5.976		
Pred R-Squared 0.305 MAE 15	5.294		
RMSE: Root Mean Square Error			
MSE: Mean Square Error			
MAE: Mean Absolute Error			
ANOVA			
Sum of Squares DF Mean Square F	C:	-	
Squares Dr mean Square r	DI,	g. 	
Regression 57353.472 2 28676.736 36.98	56 0.00	00	
Residual 48110.483 62 775.976			
Total 105463.956 64			
Parameter Estimates model Beta Std. Error Std. Beta t	 Sig	lower	 uppe
Parameter Estimates model Beta Std. Error Std. Beta t			
Parameter Estimates model Beta Std. Error Std. Beta t (Intercept) 2.012 4.546 0.442	0.660	-7.076	11.10
Parameter Estimates	0.660 0.000	-7.076 2.324	11.10 7.48
Parameter Estimates	0.660 0.000	-7.076	11.10 7.48
Parameter Estimates	0.660 0.000	-7.076 2.324	11.10 7.48
Parameter Estimates	0.660 0.000	-7.076 2.324	11.10 7.48
Parameter Estimates	0.660 0.000	-7.076 2.324	11.10 7.48
Parameter Estimates	0.660 0.000 0.006	-7.076 2.324	11.10 7.48
model Beta Std. Error Std. Beta t (Intercept) 2.012 4.546 0.442 X6 4.906 1.292 0.457 3.797 X1 1.567 0.555 0.340 2.826 Stepwise Selection Summary Added/ Step Variable Removed R-Square R-Square	0.660 0.000 0.006	-7.076 2.324 0.458	11.10 7.48 2.67

k1<-ols_step_best_subset(pr3) plot(k1)</pre>







SBC 645 640 635 630 2 4 6

```
pr31<-lm(Y~X1+X6,data=devq5)
summary(pr31)</pre>
```

```
##
## Call:
## lm(formula = Y \sim X1 + X6, data = devq5)
##
##
   Residuals:
##
       Min
                1Q
                    Median
                                 3Q
                                        Max
##
   -83.117
            -5.059
                     1.852
                              6.041 123.528
##
##
  Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
##
   (Intercept)
                 2.0117
                             4.5463
                                      0.442 0.659674
## X1
                 1.5673
                             0.5547
                                      2.826 0.006343 **
## X6
                 4.9062
                             1.2920
                                      3.797 0.000335 ***
##
                  0 '*** 0.001 '** 0.01 '* 0.05 '. ' 0.1 ' ' 1
## Signif. codes:
##
## Residual standard error: 27.86 on 62 degrees of freedom
## Multiple R-squared: 0.5438, Adjusted R-squared: 0.5291
## F-statistic: 36.96 on 2 and 62 DF, p-value: 2.711e-11
```

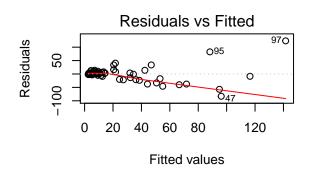
b-) Perform appropriate diagnostic checks to evaluate outliers and assess their influence.

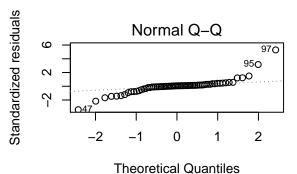
The model is significant with 54% R-Square. QQ plot show problem with the normal distribution. Residual vs Fitted graph shows a megaphone shape indicating un equal variances. Cook's distance graph show that observation 33 and 8 are influential points. Observations 33,61,8, and 44 are outliers.

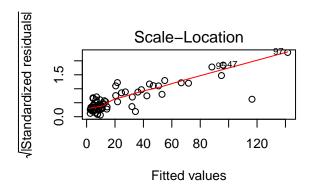
```
## Influence measures of
##
    lm(formula = Y \sim X1 + X6, data = devq5):
##
##
        dfb.1_
                 dfb.X1
                           dfb.X6
                                     dffit cov.r
                                                  cook.d
                                                           hat inf
      0.038312 -1.53e-02 4.77e-03
                                  0.039858 1.066 5.38e-04 0.0191
## 73
      0.069107 -3.31e-02 2.48e-02
                                  0.078374 1.053 2.07e-03 0.0187
      0.068109 -2.20e-02 -7.62e-03
                                  0.069283 1.063 1.62e-03 0.0226
      0.010425 2.36e-03 -6.31e-03
                                  0.013449 1.072 6.13e-05 0.0210
## 46
      0.007133 -2.39e-03 -7.21e-04
                                  0.007238 1.074 1.77e-05 0.0228
     0.014668 -6.31e-03 -2.37e-04 0.014698 1.076 7.32e-05 0.0249
    -0.016318 4.30e-03 2.71e-03 -0.016841 1.073 9.61e-05 0.0218
## 47 -0.160876 1.03e+00 -1.95e+00 -2.074925 0.735 1.19e+00 0.2342
      0.026063 -1.41e-02 5.45e-03 0.026644 1.073 2.40e-04 0.0231
## 48 0.013864 -3.85e-03 -9.17e-04 0.014385 1.070 7.01e-05 0.0191
## 30 -0.088578 3.10e-02 -1.18e-01 -0.221547 0.982 1.61e-02 0.0252
## 24 -0.088232 5.35e-02 -5.85e-02 -0.115993 1.041 4.51e-03 0.0213
     0.002809 -1.25e-03 1.44e-04 0.002822 1.075 2.70e-06 0.0230
      0.018118 -3.67e-03 -2.89e-03 0.019133 1.070 1.24e-04 0.0192
     -0.010160 4.58e-03 -2.60e-05 -0.010168 1.077 3.50e-05 0.0255
               1.06e-03 -1.04e-05 -0.002338 1.078 1.85e-06 0.0256
     -0.002336
## 43 0.012176 -5.38e-03 8.95e-04 0.012290 1.073 5.12e-05 0.0220
     0.049607 -8.02e-03 -1.27e-02 0.052916 1.065 9.47e-04 0.0208
     -0.012075 5.17e-03 2.14e-04 -0.012101 1.076 4.96e-05 0.0249
## 92 0.064361
               2.64e-01 -2.62e-01 0.343506 0.990 3.85e-02 0.0494
## 10 -0.006098 2.20e-03 4.77e-04 -0.006160 1.075 1.29e-05 0.0233
     0.000504 -2.21e-04 4.93e-05 0.000512 1.073 8.87e-08 0.0211
## 17 -0.007979 4.26e-03 -1.11e-03 -0.008030 1.077 2.18e-05 0.0252
## 29 -0.026201
               1.09e-02 -2.82e-03 -0.026907 1.069 2.45e-04 0.0199
     0.004558 1.78e-02 -1.37e-02 0.024340 1.086 2.01e-04 0.0336
## 80 -0.000330 -6.80e-03 5.34e-03 -0.008102 1.110 2.22e-05 0.0537
      0.010699 9.71e-03 -1.30e-02 0.020137 1.078 1.37e-04 0.0265
## 59
      ## 28
      0.017795 -7.49e-03 -4.28e-04
                                 0.017844 1.076 1.08e-04 0.0247
      0.026856 -3.24e-03 -5.35e-03
                                 0.029397 1.067 2.93e-04 0.0180
## 66
      0.001225 -5.35e-05 -4.45e-04
                                  0.001373 1.072 6.39e-07 0.0204
      0.148772 -7.12e-02 5.34e-02
                                 0.168721 0.995 9.41e-03 0.0187
## 97 -1.005084 -2.64e-01 3.37e+00
                                  4.603614 0.247 3.94e+00 0.2971
      0.066976 -8.02e-03 -1.97e-02 0.072630 1.059 1.78e-03 0.0206
## 72
      0.127646 -2.62e-01 1.09e-01 -0.289155 1.625 2.83e-02 0.3587
      0.010453 -6.00e-03 3.37e-03 0.011083 1.073 4.16e-05 0.0221
     0.026703 -7.79e-03 -3.75e-03 0.027358 1.072 2.53e-04 0.0221
## 18 -0.051454 -5.16e-02 4.81e-02 -0.106189 1.045 3.79e-03 0.0208
    -0.012898 5.58e-03 1.82e-04 -0.012922 1.077 5.66e-05 0.0250
## 19 0.010665 -4.60e-03 -1.61e-04 0.010686 1.077 3.87e-05 0.0250
## 84 -0.020188 -1.53e-02 -4.44e-02 -0.112711 1.061 4.28e-03 0.0303
      ## 86 0.196062 -2.97e-01 -2.44e-01 -0.760963 0.924 1.81e-01 0.1036
## 39 -0.060084 -3.98e-03 -1.64e-01 -0.317919 0.946 3.27e-02 0.0337
## 13 -0.037709 -7.79e-04 1.27e-02 -0.043896 1.064 6.52e-04 0.0181
## 16 -0.021717 -2.49e-03 1.10e-02 -0.026355 1.070 2.35e-04 0.0205
```

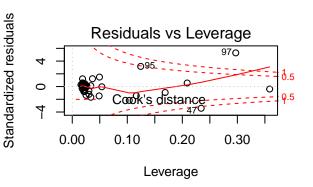
```
## 91 -0.053970 2.71e-01 -2.22e-01
                                     0.285168 1.307 2.74e-02 0.2089
      0.023927 -7.74e-03 -2.68e-03
                                     0.024339 1.073 2.01e-04 0.0226
      0.035525 -2.33e-03 -1.22e-02
                                     0.039426 1.068 5.26e-04 0.0204
      0.019766 -7.24e-03 -1.45e-03
                                     0.019951 1.074 1.35e-04 0.0234
##
  32
                -1.54e-01 -5.80e-02 -0.337188 0.992 3.72e-02 0.0488
     -0.018241 -1.07e-01 -1.18e-03 -0.216101 1.007 1.54e-02 0.0304
       0.008995
                 2.95e-03 -6.26e-03
                                     0.012293 1.073 5.12e-05 0.0216
                2.54e-02 -3.67e-02 -0.071800 1.060 1.74e-03 0.0208
      -0.047842
  55
       0.064157 -3.94e-01
                           3.28e-01 -0.420206 1.211 5.90e-02 0.1688
      0.011264 -5.42e-03
                           9.20e-04
                                     0.011303 1.076 4.33e-05 0.0240
      -0.014651
                 4.04e-03
                           2.27e-03 -0.015070 1.073 7.69e-05 0.0219
      0.026657
                 4.43e-03 -6.35e-03
                                     0.035901 1.063 4.36e-04 0.0159
                 3.96e-02 -6.71e-02 -0.118515 1.044 4.71e-03 0.0229
     -0.069321
      0.015090 -3.48e-01
                          1.07e+00
                                     1.292260 0.707 4.74e-01 0.1244
  82 -0.093129
                 2.60e-01 -4.78e-01 -0.525584 1.074 9.05e-02 0.1163
  33 -0.000866
                 5.22e-05
                          3.01e-04 -0.000963 1.072 3.14e-07 0.0204
      0.006438
                 1.72e-01 -7.28e-02
                                     0.241858 1.012 1.93e-02 0.0368
                 2.47e-04 -2.81e-03
                                    0.007507 1.072 1.91e-05 0.0204
```

par(mfrow=c(2,2)) plot(pr31)







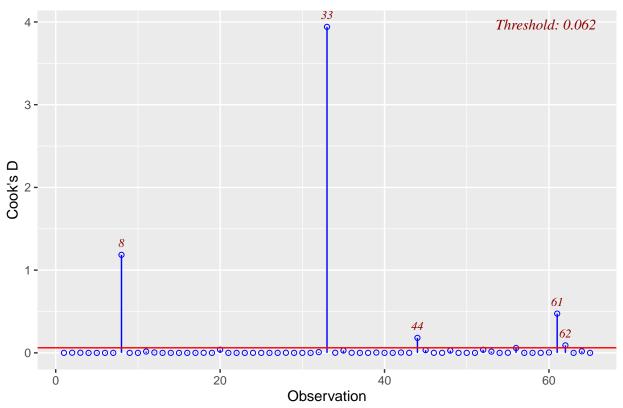


vif(pr31)

X1 X6 ## 1.972479 1.972479

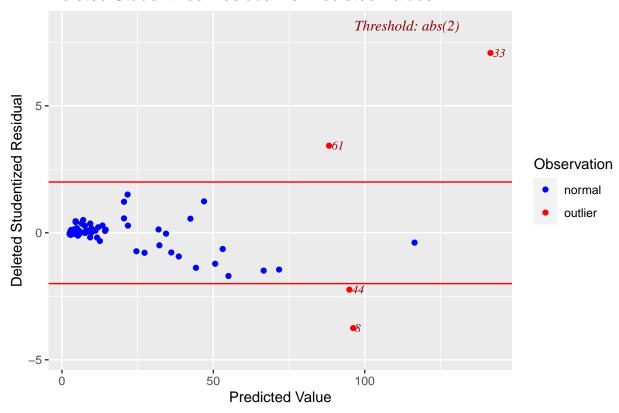
ols_plot_cooksd_chart(pr31)

Cook's D Chart



ols_plot_resid_stud_fit(pr31)

Deleted Studentized Residual vs Predicted Values



c-) Fit the regression model identified in part a to the validation data set. Compare the estimated regression coefficients and their estimated standard errors with those obtained in part a. Also compare the error mean square and coefficients of multiple determination. Does the model fitted to the validation data set yield similar estimates as the model fitted to the model-building data set?

Capsular.penetration (X_6) becomes insignificant and Rsquare decreases. MSE increased from 776 to 1149.8.Indicating problem with the model stability.

```
f31<-lm(Y~X1+X6,data=holdoutq5)
summary(f31)
```

```
##
## Call:
  lm(formula = Y ~ X1 + X6, data = holdoutq5)
##
##
## Residuals:
##
       Min
                1Q
                    Median
                                 3Q
                                        Max
  -68.762 -9.941
                     0.629
                              6.181 150.292
##
##
##
  Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
  (Intercept)
                 -6.010
                                    -0.659
                                           0.51504
##
                              9.118
## X1
                  6.467
                              1.682
                                      3.844
                                            0.00061 ***
## X6
                 -4.129
                              2.424
                                    -1.703
                                            0.09918 .
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 33.91 on 29 degrees of freedom
## Multiple R-squared: 0.3844, Adjusted R-squared: 0.342
## F-statistic: 9.055 on 2 and 29 DF, p-value: 0.0008805
anova(f31)
## Analysis of Variance Table
##
## Response: Y
##
            Df Sum Sq Mean Sq F value
                                        Pr(>F)
## X1
             1 17486 17486.2 15.2074 0.000525 ***
## X6
                 3337 3336.6 2.9017 0.099180 .
             1
## Residuals 29 33346 1149.8
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
anova(pr31)
## Analysis of Variance Table
##
## Response: Y
            Df Sum Sq Mean Sq F value
                        46164 59.491 1.246e-10 ***
## X1
             1 46164
## X6
             1 11190
                        11190 14.420 0.0003352 ***
## Residuals 62 48110
                          776
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
MSPR<-sum(f31\$residuals^2)/length(f31\$residuals)
MSPR
```

[1] 1042.05

d-) Calculate the mean squared prediction error and compare it to MSE obtained from the model-building data set. Is there evidence of a substantial bias problem in MSE here?

MSPR=1042.05 and MSE=776. Indicating problem with the model stability.

```
MSPR<-sum(f31\$residuals^2)/length(f31\$residuals)
MSPR
```

[1] 1042.05