# Lesson 9 R Activity

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#### Lesson 9 - Install packages

```
knitr::opts_chunk$set(echo = TRUE)

library(e1071)
library(xtable)
library("xlsx") # Needed to read data
```

Perform data housekeeping - upload, name columns, display to make sure it reads properly, etc.

```
## Warning: package 'xlsx' was built under R version 4.0.3
```

```
library(MASS) # Needed for ginv() function
rm(list = ls())
```

Upload data-ex-3-1.xlsx data file and label columns time

cases

distance

16.68

11.50

12.03

14.88

13.75

18.11

8.00

17.83

79.24

21.50

40.33

21.00

13.50

19.75

24.00

29.00

15.35

19.00

9.50

35.10

17.90

52.32

18.75

19.83

10.75

# # Output data structure and dimensions str(exL9)

'data.frame': 25 obs. of 3 variables: \$ time : num 16.7 11.5 12 14.9 13.8 . . . \$ cases : num 7 3 3 4 6 7 2 7 30 5 . . . \$ distance: num 560 220 340 80 150 330 110 210 1460 605 . . .

#### dim(exL9)

[1] 25 3

#### Example 6.1 (p.213-214)

```
X <- cbind(matrix(1,length(distance),1),as.matrix(cases),as.matrix(distance))
y <- as.matrix(time)

xTx <- t(X) %*% X
H_matrix <- X %*% ginv(xTx, tol=.Machine$double.eps) %*% t(X)

# get the diagonal diag(H_matrix)</pre>
```

#### Calculate hat matrix values (by hand)

```
## [1] 0.10180178 0.07070164 0.09873476 0.08537479 0.07501050 0.04286693

## [7] 0.08179867 0.06372559 0.49829216 0.19629595 0.08613260 0.11365570

## [13] 0.06112463 0.07824332 0.04111077 0.16594043 0.05943202 0.09626046

## [19] 0.09644857 0.10168486 0.16527689 0.39157522 0.04126005 0.12060826

## [25] 0.06664345
```

```
# perform multiple least squares regression
model <- lm(time ~ cases+distance)

# calculate hat matrix automatically
hat_diags <- lm.influence(model)$hat
hat_diags</pre>
```

#### Calculate hat matrix values automatically

```
## 1 2 3 4 5 6 7
## 0.10180178 0.07070164 0.09873476 0.08537479 0.07501050 0.04286693 0.08179867
## 8 9 10 11 12 13 14
## 0.06372559 0.49829216 0.19629595 0.08613260 0.11365570 0.06112463 0.07824332
## 15 16 17 18 19 20 21
## 0.04111077 0.16594043 0.05943202 0.09626046 0.09644857 0.10168486 0.16527689
## 22 23 24 25
## 0.39157522 0.04126005 0.12060826 0.06664345
```

```
# sequence of observations
Obs <- seq(1, length(time))

influence_stats <- data.frame(cbind(Obs, hat_diags))

out <- influence_stats
colnames(out) <- c("Obs $i$", "$h_{ii}$")
tab <- (xtable(out, digits=c(0,0,5)))
print(tab, type="html")</pre>
```

Create data frame to reproduce Table 6.1 on p. 214 - start with column for Observation at h_ii Obs $i$	nd
$h_{ii}$	
1	
1	
0.10180	
2	
2	
0.07070	
3	
3	
0.09873	
4	
4	
0.08537	
5	
5	
0.07501	
6	
6	
0.04287	
7	
7	
0.08180	
8	
8	
0.06373	
9	
9	
0.49829	
10	
10	
0.19630	
11	
11	
0.08613	

0.11366

0.06112

0.07824

0.04111

0.16594

0.05943

0.09626

0.09645

0.10168

0.16528

0.39158

0.04126

```
240.1206125250.06664
```

```
Run <- c("9 \text{ and } 22 \text{ in"},
          "9 out",
          "22 out",
          "9 and 22 out")
beta_0 <- c(" "," "," "," ")
beta_1 <- c(" "," "," "," ")
beta_2 <- c(" "," "," "," ")
MS_Res <- c(" "," "," "," ")
R_sqrd <- c(" "," "," "," ")</pre>
unnamed_table <- data.frame(cbind(Run,</pre>
                                        beta_0,
                                        beta_1,
                                        beta_2,
                                        MS_Res,
                                        R_sqrd))
out <- unnamed_table</pre>
colnames(out) <- c("Run",</pre>
                      "beta_hat_0",
                      "beta_hat_1",
                      "beta_hat_2",
                      "$MS_{Res}$",
                      "$R_2$")
tab <- (xtable(out, digits=c(0,0,0,0,0,0,0)))
print(tab, type="html")
```

#### Create shell of unnamed table on p. 213 Run

```
beta_hat_0
beta_hat_1
beta_hat_2
MS_{Res}
R_2
1
9 and 22 in
2
9 out
3
22 out
```

9 and 22 out

Create models for the four scenarios in the unnamed table on p. 213

```
# scenario 1, points 9 and 22 in
time.s1 <- time
cases.s1 <- cases
distance.s1 <- distance
model.s1 <- lm(time.s1 ~ cases.s1 + distance.s1)</pre>
# scenario 2, point 9 out
time.s2 <- time[1:length(time)][-9]</pre>
cases.s2 <- cases[1:length(cases)][-9]</pre>
distance.s2 <- distance[1:length(distance)][-9]</pre>
model.s2 <- lm(time.s2 ~ cases.s2 + distance.s2)</pre>
# scenario 3, point 22 out
time.s3 <- time[1:length(time)][-22]</pre>
cases.s3 <- cases[1:length(cases)][-22]</pre>
distance.s3 <- distance[1:length(distance)][-22]</pre>
model.s3 <- lm(time.s3 ~ cases.s3 + distance.s3)</pre>
# scenario 4, points 9 and 22 out
time.s4 <- time[1:length(time)][-9][-21]</pre>
cases.s4 <- cases[1:length(cases)][-9][-21]</pre>
distance.s4 <- distance[1:length(distance)][-9][-21]</pre>
model.s4 <- lm(time.s4 ~ cases.s4 + distance.s4)</pre>
```

Note: Deletions using subset= are done sequentially. So, subset=(1:N)[-1][-2] removes the first observation and then the second of the remaining observations.

```
model.s2$coeff[2],
             model.s3$coeff[2],
             model.s4$coeff[2]))
beta_2 <- as.data.frame(c(model.s1$coeff[3],</pre>
            model.s2$coeff[3],
            model.s3$coeff[3],
             model.s4$coeff[3]))
MS_Res <- as.data.frame(c(anova(model.s1)$'Mean Sq'[3],</pre>
             anova(model.s2)$'Mean Sq'[3],
             anova(model.s3) $'Mean Sq'[3],
             anova(model.s4)$'Mean Sq'[3]))
R_sqrd <- as.data.frame(c(summary(model.s1)$r.squared,</pre>
             summary(model.s2)$r.squared,
             summary(model.s3)$r.squared,
             summary(model.s4)$r.squared))
unnamed_table2 <- data.frame(cbind(Run,</pre>
                                    beta_0,
                                    beta_1,
                                    beta_2,
                                    MS_Res,
                                    R_sqrd))
out2 <- unnamed_table2</pre>
colnames(out2) <- c("Run",</pre>
                    "beta_hat_0",
                    "beta_hat_1",
                    "beta_hat_2",
                    "$MS_{Res}$",
                    "$R_2$")
rownames(out2) <- c("1","2","3","4")
tab2 <- (xtable(out2, digits=c(0,0,3,3,3,3,4)))
print(tab2, type="html")
```

#### Display completed (unnamed) table on bottom of p. 213 Run

```
beta_hat_0
beta_hat_1
beta_hat_2
MS_{Res}
R_2
1
9 and 22 in
2.341
1.616
0.014
```

```
10.624
0.9596
2
9 out
4.447
1.498
0.010
5.905
0.9487
3
22 out
1.916
1.786
0.012
10.066
0.9564
9 and 22 out
4.643
1.456
0.011
6.163
0.9072
```

## Example 6.2 (p.216)

```
# rstudent residual calculation
model.1 <- lm(time ~ cases + distance)

# Calculate studentized residuals, r_i (eqn 4.8)
e_i <- model.1$residuals
MS_Res <- anova(model.1)$'Mean Sq'[3]
r_i <- e_i/sqrt(MS_Res * (1-hat_diags))

p <- sum(hat_diags)

D_i <- ((r_i)^2/p) * (hat_diags/(1-hat_diags))

D_i</pre>
```

#### Calculate Cook's D using Equation 6.5

```
2
## 1.000921e-01 3.375704e-03 9.455785e-06 7.764718e-02 5.432217e-04 1.231067e-04
              7
                           8
                                        9
                                                     10
## 2.171604e-03 3.051135e-03 3.419318e+00 5.384516e-02 1.619975e-02 1.596392e-03
##
             13
                          14
                                       15
                                                     16
                                                                  17
## 2.294737e-03 3.292786e-03 6.319880e-04 3.289086e-03 4.013419e-04 4.397807e-02
             19
                          20
                                       21
                                                     22
                                                                  23
## 1.191868e-02 1.324449e-01 5.086063e-02 4.510455e-01 2.989892e-02 1.023224e-01
##
## 1.084694e-04
```

```
D_i_auto <- cooks.distance(model.1)
D_i_auto</pre>
```

Calculate Cook's D using cooks.distance(). Does this give the same answer as the "by hand" approach?

```
##
                                                      4
                           2
                                         3
                                                                   5
                                                                                 6
              1
## 1.000921e-01 3.375704e-03 9.455785e-06 7.764718e-02 5.432217e-04 1.231067e-04
                                                     10
              7
                           8
                                        9
                                                                  11
## 2.171604e-03 3.051135e-03 3.419318e+00 5.384516e-02 1.619975e-02 1.596392e-03
                                       15
                                                     16
             13
                          14
                                                                  17
## 2.294737e-03 3.292786e-03 6.319880e-04 3.289086e-03 4.013419e-04 4.397807e-02
                                                     22
                                                                  23
## 1.191868e-02 1.324449e-01 5.086063e-02 4.510455e-01 2.989892e-02 1.023224e-01
##
             25
## 1.084694e-04
```

cooks.distance() matches the output from the by-hands approach.

```
# obtain and add Cook's D to table 6.1 dataframe
influence_stats$Cooks_D <- c(D_i_auto)</pre>
```

Add Cook's D to the Table 6.1 dataframe

Example 6.3 (p.218-219)

```
influence_stats$DFFITS <- c(dffits(model.1))
dfbetas.col <- dfbetas(model.1)
influence_stats$DFBETAS_0 <- c(dfbetas.col[,1])
influence_stats$DFBETAS_1 <- c(dfbetas.col[,2])
influence_stats$DFBETAS_2 <- c(dfbetas.col[,3])</pre>
```

Calculate DFFITS and DFBETAS using R

```
out <- influence_stats</pre>
colnames(out) <- c("Obs $i$",</pre>
                     "$h_{ii}$",
                     "$D_i$",
                     "$DFFITS_i$",
                     "$DFBETAS_{0i}$",
                     "$DFBETAS_{1i}$",
                     "$DFBETAS_{2i}$")
tab <- (xtable(out, digits=c(0,0,5,5,4,4,4,4)))</pre>
print(tab, type="html")
Update Table 6.1 Obs i
h_{ii}
D_i
DFFITS_i
DFBETAS_{0i}
DFBETAS_{1i}
DFBETAS_{2i}
1
1
0.10180
0.10009
-0.5709
-0.1873
0.4113
-0.4349
2
2
0.07070
0.00338
0.0986
0.0898
-0.0478
0.0144
3
0.09873
0.00001
```

-0.0052

-0.0035

0.0039

-0.0028

4

4

0.08537

0.07765

0.5008

0.4520

0.0883

-0.2734

5

5

0.07501

0.00054

-0.0395

-0.0317

-0.0133

0.0242

6

6

0.04287

0.00012

-0.0188

-0.0147

0.0018

0.0011

7

7

0.08180

0.00217

0.0790

0.0781

-0.0223

-0.0110

8

0.06373

0.00305

0.0938

0.0712

0.0334

-0.0538

9

9

0.49829

3.41932

4.2961

-2.5757

0.9287

1.5076

10

10

0.19630

0.05385

0.3987

0.1079

-0.3382

0.3413

11

11

0.08613

0.01620

0.2180

-0.0343

0.0925

-0.0027

12

12

0.11366

-0.0677

-0.0303

-0.0487

0.0540

13

13

0.06112

0.00229

0.0813

0.0724

-0.0356

0.0113

14

14

0.07824

0.00329

0.0974

0.0495

-0.0671

0.0618

15

15

0.04111

0.00063

0.0426

0.0223

-0.0048

0.0068

16

16

0.16594

0.00329

-0.0972

-0.0027

0.0644

-0.0842

17

0.05943

0.00040

0.0339

0.0289

0.0065

-0.0157

18

18

0.09626

0.04398

0.3653

0.2486

0.1897

-0.2724

19

19

0.09645

0.01192

0.1862

0.1726

0.0236

-0.0990

20

20

0.10168

0.13244

-0.6718

0.1680

-0.2150

-0.0929

21

21

0.16528

-0.3885

-0.1619

-0.2972

0.3364

22

22

0.39158

0.45105

-1.1950

0.3986

-1.0254

0.5731

23

23

0.04126

0.02990

-0.3075

-0.1599

0.0373

-0.0527

24

24

0.12061

0.10232

-0.5711

-0.1197

0.4046

-0.4654

25

25

0.06664

0.00011

-0.0176

-0.0168

0.0008

### Example 6.4 (p. 219)

```
influence_stats$covratio <- c(covratio(model.1))</pre>
```

#### Calculate Covariance Ratio using R

#### Update Table 6.1 Obs i

```
h_{ii}
D_i
DFFITS_i
DFBETAS_{0i}
DFBETAS_{1i}
DFBETAS_{2i}
COVRATIO_i
1
1
0.10180
0.10009
-0.5709
-0.1873
0.4113
-0.4349
0.8711
2
```

0.0986

0.0898

-0.0478

0.0144

1.2149

3

3

0.09873

0.00001

-0.0052

-0.0035

0.0039

-0.0028

1.2757

4

4

0.08537

0.07765

0.5008

0.4520

0.0883

-0.2734

0.8760

5

5

0.07501

0.00054

-0.0395

-0.0317

-0.0133

0.0242

1.2396

6

6

-0.0188

-0.0147

0.0018

0.0011

1.1999

7

7

0.08180

0.00217

0.0790

0.0781

-0.0223

-0.0110

1.2398

8

8

0.06373

0.00305

0.0938

0.0712

0.0334

-0.0538

1.2056

9

9

0.49829

3.41932

4.2961

-2.5757

0.9287

1.5076

0.3422

10

10

0.3987

0.1079

-0.3382

0.3413

1.3054

11

11

0.08613

0.01620

0.2180

-0.0343

0.0925

-0.0027

1.1717

12

12

0.11366

0.00160

-0.0677

-0.0303

-0.0487

0.0540

1.2906

13

13

0.06112

0.00229

0.0813

0.0724

-0.0356

0.0113

1.2070

14

14

0.0974

0.0495

-0.0671

0.0618

1.2277

15

15

0.04111

0.00063

0.0426

0.0223

-0.0048

0.0068

1.1918

16

16

0.16594

0.00329

-0.0972

-0.0027

0.0644

-0.0842

1.3692

17

17

0.05943

0.00040

0.0339

0.0289

0.0065

-0.0157

1.2192

18

18

0.3653

0.2486

0.1897

-0.2724

1.0692

19

19

0.09645

0.01192

0.1862

0.1726

0.0236

-0.0990

1.2153

20

20

0.10168

0.13244

-0.6718

0.1680

-0.2150

-0.0929

0.7598

21

21

0.16528

0.05086

-0.3885

-0.1619

-0.2972

0.3364

1.2377

22

22

-1.1950

0.3986

-1.0254

0.5731

1.3981

23

23

0.04126

0.02990

-0.3075

-0.1599

0.0373

-0.0527

0.8897

24

24

0.12061

0.10232

-0.5711

-0.1197

0.4046

-0.4654

0.9476

25

25

0.06664

0.00011

-0.0176

-0.0168

0.0008

0.0056

```
n <- length(time)
limit_plus <- (1 + 3*p/n)
limit_minus <- (1 - 3*p/n)
points <- which(influence_stats$covratio > limit_plus | influence_stats$covratio < limit_minus)</pre>
```

Identify observations that exceed limits of 1 + /- 3p/n for COVRATIO using which() and the "or" logical operator (|). Are these the same points identified in the textbook? Points 9, 16, 22 exceed the cutoff  $COVRATIO_i$  limits of 0.64 and 1.36. The textbook identified points 9 and 22, but not point 16. For my calculations, point 16 barely exceeds the 1.36 limit.