

# HOMEWORK 6

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## PROBLEM 1 (Ch9, Q9)

Let us load the data:

```
data = read.table("C:/Users/eagle/OneDrive/Course/CU Stats/STATS GR6101 - Applied Statistics I/Data/CH09Data.txt")
colnames(data) = c("Y", "X1", "X2", "X3")
datacopy = data
performance = rbind()
```

(1) Let us compute the evaluation criteria:

```
for (i in c("0", "1", "2", "3", "1_2", "1_3", "2_3", "1_2_3")) {
  i = as.numeric(unlist(strsplit(i, "_")))
  if (as.numeric(i) == 0) {
    MODEL = lm(Y~1L, data = data)
  } else {
    data = data.frame(cbind(data[,1], datacopy[, -1][, i]))
    colnames(data) = c("Y", paste0("X", i))
    MODEL = lm(Y~., data = data)
  }
  eval_R2 = summary(MODEL)$r.squared
  eval_AIC = nrow(data) * log(sum(MODEL$residuals^2)) - nrow(data) * log(nrow(data)) + 2*ncol(data)
  eval_Cp = olsrr::ols_mallows_cp(MODEL, lm(Y~., data = datacopy))
  performance = rbind(performance, cbind(
    Formula = paste0("Y=", paste0(paste0("X", i), collapse = "+")),
    R2 = eval_R2,
    AIC = eval_AIC,
    Cp = eval_Cp ))
}; performance
```

```
## Warning in if (as.numeric(i) == 0) {: the condition has length > 1 and only the
## first element will be used

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```

	Formula	R2	AIC	Cp
## [1,]	"Y=X0"	"0"	"268.915461105549"	"88.1562338191455"
## [2,]	"Y=X1"	"0.618984251996021"	"220.529390822719"	"8.35360628199045"
## [3,]	"Y=X2"	"0.363538735911057"	"244.13120196195"	"42.1123236337672"
## [4,]	"Y=X3"	"0.415497545878045"	"240.21372332691"	"35.2456429948055"
## [5,]	"Y=X1+X2"	"0.654955853888437"	"217.967647227459"	"5.59973485144706"
## [6,]	"Y=X1+X3"	"0.67608638253165"	"215.060654177041"	"2.80720376735253"
## [7,]	"Y=X2+X3"	"0.46845446298584"	"237.845006316576"	"30.2470562751665"
## [8,]	"Y=X1+X2+X3"	"0.68219433328074"	"216.184962183753"	"4"

Similar results can be found from the following:

```
olsrr::ols_step_all_possible(lm(Y~., data=data))
```

##	Index	N	Predictors	R-Square	Adj. R-Square	Mallow's Cp
## 1	1	1	X1	0.6189843	0.6103248	8.353606
## 3	2	1	X3	0.4154975	0.4022134	35.245643
## 2	3	1	X2	0.3635387	0.3490737	42.112324
## 5	4	2	X1 X3	0.6760864	0.6610206	2.807204
## 4	5	2	X1 X2	0.6549559	0.6389073	5.599735
## 6	6	2	X2 X3	0.4684545	0.4437314	30.247056
## 7	7	3	X1 X2 X3	0.6821943	0.6594939	4.000000

- (2) The *R-square* tends to go up as we increase the number of features. This is not necessarily true for AIC. As a matter of fact, AIC penalizes the model more as we increase the number of parameters. We can see this from the formula of AIC.
- (3) If we start with  $X_1$ , we get AIC of 220. Then we start adding  $X_2$  or  $X_3$ . Here  $X_1 + X_3$  has lower AIC at 215. Then we see if we can keep adding in order to lower AIC. In this example, we can no longer do that. Hence, the optimal model is  $Y \sim X_1 + X_3$ .

The other direction is the following. We start with the full model  $Y \sim X_1 + X_2 + X_3$  with AIC of 216. We subtract the variables one by one. Subtracting  $X_1$  gives us AIC of 237. Subtracting  $X_2$  gives us AIC of 215. Subtracting  $X_3$  gives us AIC of 217. The lowest AIC is model  $Y \sim X_1 + X_3$ .

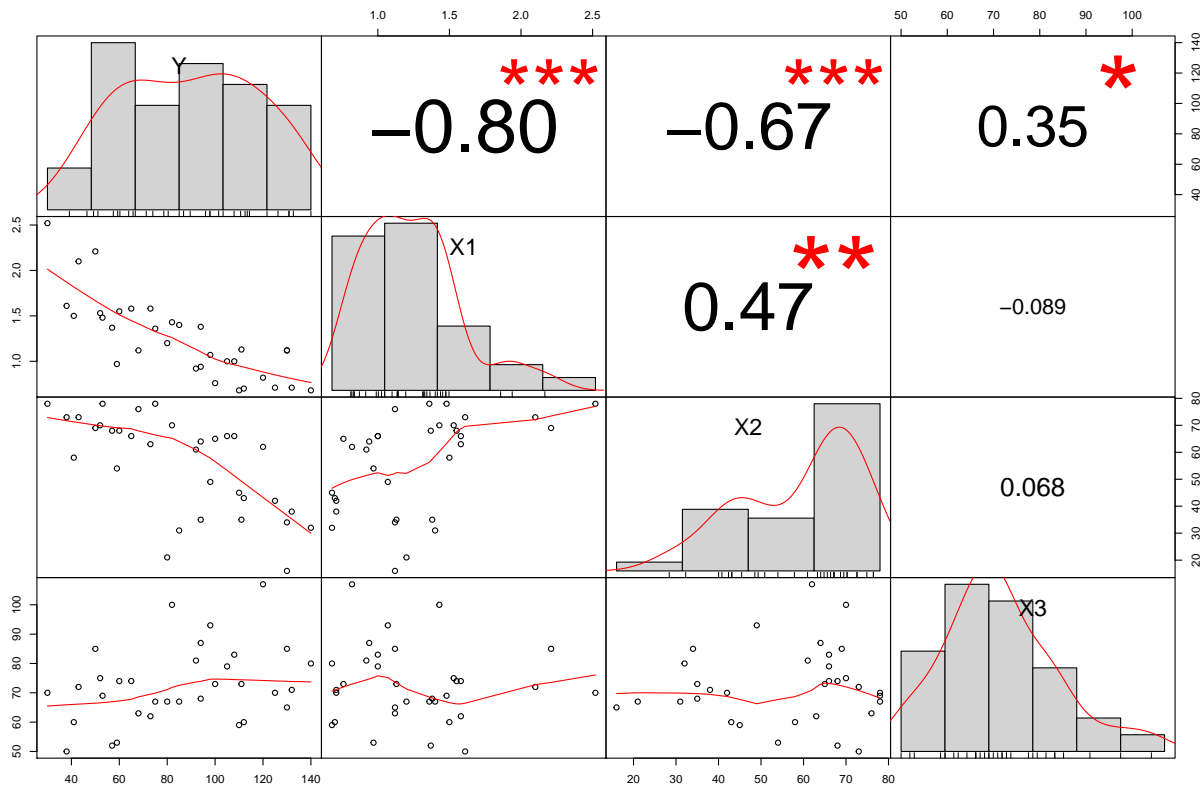
## PROBLEM 2 (Ch9, Q15b,c)

Let us load the data first

```
data2 = read.table("C:/Users/eagle/OneDrive/Course/CU Stats/STATS GR6101 - Applied Statistics I/Data/CH
colnames(data2) = c("Y", paste0("X", 1:3))
```

(1) Correlation and Scatter Plot

```
PerformanceAnalytics::chart.Correlation(data2)
```



From results above, we have correlation matrix of the  $X$  variables to be the following

$$\begin{bmatrix} 1 & 0.47 & -0.089 \\ 0.47 & 1 & 0.068 \\ -0.089 & 0.068 & 1 \end{bmatrix}$$

and the scatter plot are above as well.

From the results, we can say that there is some correlation between  $X_1$  and  $X_2$ , i.e.  $\text{cor}(X_1, X_2) = 0.47$ . We can also confirm this idea from  $\text{cor}(Y, X_1) = -0.8$  and  $\text{cor}(Y, X_2) = -0.67$ . In other words, the response variable  $Y$  is both correlated with  $X_1$  and  $X_2$ .

(2) Fit multiple linear regression model:

```
MODEL2 = lm(Y~., data = data2)
summary(MODEL2)
```

```
##
## Call:
```

```
## lm(formula = Y ~ ., data = data2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -28.668  -7.002   1.518   9.905  16.006
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 120.0473    14.7737   8.126 5.84e-09 ***
## X1          -39.9393     5.6000  -7.132 7.55e-08 ***
## X2           -0.7368     0.1414  -5.211 1.41e-05 ***
## X3           0.7764     0.1719   4.517 9.69e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.46 on 29 degrees of freedom
## Multiple R-squared:  0.8548, Adjusted R-squared:  0.8398
## F-statistic: 56.92 on 3 and 29 DF,  p-value: 2.885e-12
```

From above regression results, we have the following model

$$Y = 120.0473 - 39.9393X_1 - 0.7368X_2 + 0.7764X_3$$

We observe that both  $X_1$  and  $X_2$  have regression coefficients to be negative and they both have significantly high  $t$ -value. Since from part (1) we discussed the potential of multicollinearity, it is with doubt that we should keep both of these covariates.

To see if our doubts need to be put in action, we can confirm the idea by the following:

```
data2copy = data2
performance2 = rbind()
for (i in c("0", "1", "2", "3", "1_2", "1_3", "2_3", "1_2_3")) {
  i = as.numeric(unlist(strsplit(i, "_")))
  if (as.numeric(i) == 0) {
    MODEL = lm(Y~1L, data = data2)
  } else {
    data2 = data.frame(cbind(data2[,1], data2copy[,-1][,i]))
    colnames(data2) = c("Y", paste0("X", i))
    MODEL = lm(Y~., data = data2)
  }
  eval_R2 = summary(MODEL)$r.square
  eval_AIC = nrow(data2) * log(sum(MODEL$residuals^2)) - nrow(data2) * log(nrow(data2)) + 2*ncol(data2)
  eval_Cp = olsrr::ols_mallows_cp(MODEL, lm(Y~., data = data2copy))
  performance2 = rbind(performance2, cbind(
    Formula = paste0("Y=", paste0(paste0("X", i), collapse = "+")),
    R2 = eval_R2,
    AIC = eval_AIC,
    Cp = eval_Cp ))
}; performance2
```

```
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## Warning in if (as.numeric(i) == 0) {: the condition has length > 1 and only the
## first element will be used

##      Formula      R2      AIC      Cp
## [1,] "Y=X0"      "0"      "233.887977887098" "168.750046029594"
## [2,] "Y=X1"      "0.642900659975658" "195.906515893374" "42.330609607"
## [3,] "Y=X2"      "0.446053532146372" "210.395299451315" "81.6508324516934"
## [4,] "Y=X3"      "0.119657096239573" "225.682333013619" "146.848535547972"
## [5,] "Y=X1+X2"    "0.752670606738983" "185.785847477995" "22.4040576883597"
## [6,] "Y=X1+X3"    "0.718889720038503" "190.010706255522" "29.1517913617011"
## [7,] "Y=X2+X3"    "0.600167376151661" "201.636572312908" "52.866585017839"
## [8,] "Y=X1+X2+X3" "0.854818556608976" "170.205535378933" "4"
```

We observe that the model  $Y \sim X_1 + X_2 + X_3$  have the best *R-square*, *AIC*, and *Cp* scores.

## PROBLEM 3 (Ch9, Q16)

(1) Fit model and select the best three according to *Mallow's Cp*:

```
Y = data2$Y
X1 = data2$X1; X2 = data2$X2; X3 = data2$X3
center1 = X1 - mean(X1); center1_sq = center1^2
center2 = X2 - mean(X2); center2_sq = center2^2
center3 = X3 - mean(X3); center3_sq = center3^2
MODEL3 = lm(
  Y~center1+center2+center3+center1*center2+center1*center3+center2*center3+
  center1*center3+center1_sq+center2_sq+center3_sq)
MODELLIST = olsrr::ols_step_all_possible(MODEL3)
MODELLIST[order(MODELLIST$cp, decreasing = FALSE), ][1:3, ]
```

```
##      Index N      Predictors  R-Square
## 133    130 4      center1 center2 center3 center1:center2 0.8788215
## 265    256 5 center1 center2 center3 center3_sq center1:center2 0.8876545
## 262    257 5 center1 center2 center3 center2_sq center1:center2 0.8827571
##      Adj. R-Square Mallow's Cp
## 133      0.8615103      3.302215
## 265      0.8668497      3.384990
## 262      0.8610455      4.447976
```

From above results, we conclude that the models are

$$Y \sim (X_1 - \bar{X}_1) + (X_2 - \bar{X}_2) + (X_3 - \bar{X}_3) + (X_1 - \bar{X}_1) * (X_2 - \bar{X}_2) \text{ with } Cp=3.30$$

$$Y \sim (X_1 - \bar{X}_1) + (X_2 - \bar{X}_2) + (X_3 - \bar{X}_3) + (X_3 - \bar{X}_3)^2 + (X_1 - \bar{X}_1) * (X_2 - \bar{X}_2) \text{ with } Cp=3.38$$

$$Y \sim (X_1 - \bar{X}_1) + (X_2 - \bar{X}_2) + (X_3 - \bar{X}_3) + (X_2 - \bar{X}_2)^2 + (X_1 - \bar{X}_1) * (X_2 - \bar{X}_2) \text{ with } Cp=4.45$$

(2) In terms of the measure of *Mallow's Cp*, the numerical difference is quite small.

## PROBLEM 4 (Ch9, Q19a)

Let us conduct forward stepwise regression. First, let us reconstruct the data with the appropriate columns.

```
data4 = data.frame(cbind(
  Y,
  center1, center2, center3,
  center1*center2, center1*center3, center2*center3,
  center1^2, center2^2, center3^2 ))
colnames(data4) = c("Y", "C1", "C2", "C3",
  "C12", "C13", "C23", "C1_sq", "C2_sq", "C3_sq")
```

Next, let us screen models using stepwise regression and set to *forward*. Note alpha level is 0.1.

```
MODEL4 <- lm(Y~1, data = data4)
summary(SignifReg::SignifReg(MODEL4, alpha = 0.1, scope = data4, criterion = "AIC", direction = "forward"))

##
## Call:
## lm(formula = Y ~ C1 + C2 + C3 + C12, data = data4)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -25.198  -4.867   0.761   5.074  17.657
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  82.0934     2.4122  34.033  < 2e-16 ***
## C1          -47.3114     6.0752  -7.788 1.75e-08 ***
## C2           -0.6760     0.1340  -5.046 2.44e-05 ***
## C3           0.7951     0.1600   4.969 3.02e-05 ***
## C12          0.8620     0.3660   2.355  0.0258 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.58 on 28 degrees of freedom
## Multiple R-squared:  0.8788, Adjusted R-squared:  0.8615
## F-statistic: 50.77 on 4 and 28 DF,  p-value: 1.959e-12
```

Last, let us repeat the above and set alpha level to 0.15.

```
MODEL4 <- lm(Y~1, data = data4)
summary(SignifReg::SignifReg(MODEL4, alpha = 0.15, scope = data4, criterion = "AIC", direction = "forward"))

##
## Call:
## lm(formula = Y ~ C1 + C2 + C3 + C12, data = data4)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -25.198  -4.867   0.761   5.074  17.657
##
```

```
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)  82.0934     2.4122  34.033 < 2e-16 ***
## C1          -47.3114     6.0752  -7.788 1.75e-08 ***
## C2           -0.6760     0.1340  -5.046 2.44e-05 ***
## C3            0.7951     0.1600   4.969 3.02e-05 ***
## C12           0.8620     0.3660   2.355  0.0258 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.58 on 28 degrees of freedom
## Multiple R-squared:  0.8788, Adjusted R-squared:  0.8615
## F-statistic: 50.77 on 4 and 28 DF,  p-value: 1.959e-12
```

We observe that both alpha levels produce the same stepwise results. The optimal model is the following:

$$Y \sim (X_1 - \bar{X}_1) + (X_2 - \bar{X}_2) + (X_3 - \bar{X}_3) + (X_1 - \bar{X}_1) * (X_2 - \bar{X}_2)$$

with regression coefficients produced we have

$$Y = 82.09 - 47.31(X_1 - \bar{X}_1) - 0.67(X_2 - \bar{X}_2) + 0.795(X_3 - \bar{X}_3) + 0.86(X_1 - \bar{X}_1) * (X_2 - \bar{X}_2)$$

and we are done.