

# Homework 3

## Problem 1

5.3 Perform a thorough analysis of the Ski Sales data in Table 5.11 using the ideas presented in Section 5.6.

4 Quarters  $\rightarrow 4 - 1 = 3$  indicator variables

$$\begin{matrix} z_1 & z_2 & z_3 \\ \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} & \begin{matrix} Q_1 \\ Q_2 \\ Q_3 \\ Q_4 \end{matrix} \end{matrix}$$

Reduced model:  $S_t = \beta_0 + \beta_1 \cdot \text{PDI}_t + \epsilon_t$

Full model:  $S_t = \beta_0 + \beta_1 \cdot \text{PDI}_t + \beta_2 \cdot z_1 + \beta_3 \cdot z_2 + \beta_4 \cdot z_3 + \epsilon_t$

$$\begin{cases} H_0: \beta_2 = \beta_3 = \beta_4 = 0 \\ H_a: \text{at least one not zero} \end{cases}$$

F-test  $F^* = \frac{SSE(R) - SSE(F)}{df_R - df_F} \bigg/ \frac{SSE(F)}{df_F} = \frac{47.245 - 346.433}{3} \bigg/ \frac{47.245}{35} = 73.881$

$SSE = Y^T(I - H)Y$   
 $H = X(X^T X)^{-1}X^T$  } calculated in Python

$F_{(p-q, n-p-1)} = F_{(3, 35)} = 2.874$   
when  $\alpha = 0.05$

$F^* > F_{critical}$



We reject the null hypothesis and favor the full model

## Problem 2

5.4 Perform a thorough analysis of the Education Expenditures data in Tables 5.12, 5.13, and 5.14 using the ideas presented in Section 5.7.

1960 1970 1975

$$T_1 = \begin{cases} 1 & \text{if time} = 1960 \\ 0 & \text{otherwise} \end{cases}$$

$$T_2 = \begin{cases} 1 & \text{if time} = 1970 \\ 0 & \text{otherwise} \end{cases}$$

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 T_1 + \beta_5 T_2 + \beta_6 T_1 \cdot X_1 + \beta_7 T_1 \cdot X_2 + \beta_8 T_1 \cdot X_3 + \beta_9 T_2 \cdot X_1 + \beta_{10} T_2 \cdot X_2 + \beta_{11} T_2 \cdot X_3 + \varepsilon$$

$$1960: Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 + \beta_6 X_1 + \beta_7 X_2 + \beta_8 X_3 + \varepsilon$$

$$= (\beta_0 + \beta_4) + (\beta_1 + \beta_6) X_1 + (\beta_2 + \beta_7) X_2 + (\beta_3 + \beta_8) X_3 + \varepsilon$$

$$1970: Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_5 + \beta_9 X_1 + \beta_{10} X_2 + \beta_{11} X_3 + \varepsilon$$

$$= (\beta_0 + \beta_5) + (\beta_1 + \beta_9) X_1 + (\beta_2 + \beta_{10}) X_2 + (\beta_3 + \beta_{11}) X_3 + \varepsilon$$

$$1975: Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

$$\begin{cases} H_0: \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = 0 \\ H_a: \text{at least one of these } \uparrow \text{ is non-zero} \end{cases}$$

$$\begin{cases} SSE = Y^T(I - H)Y \\ H = X(X^T X)^{-1}X^T \end{cases} \text{ calculated in Python}$$

F-test

$$F^* = \frac{SSE(R) - SSE(F)}{df_R - df_F} \bigg/ \frac{SSE(F)}{df_F} = 9.422$$

$$\begin{cases} SSE(R) = 185764.329 \rightarrow n - 3 - 1 = 146 \\ SSE(F) = 120140.176 \rightarrow n - 11 - 1 = 138 \end{cases}$$

$$F_{(p-q, n-p-1)} = F_{(8, 138)} = 2.006$$

↑  
when  $\alpha = 0.05$

$$F^* > F_{\text{critical}}$$

reject  $H_0$  and favor the full model

### Problem 3

5.7 Three types of fertilizer are to be tested to see which one yields more corn crop. Forty similar plots of land were available for testing purposes. The 40 plots are divided at random into four groups, 10 plots in each group. Fertilizer 1 was applied to each of the 10 corn plots in Group 1. Similarly, Fertilizers 2 and 3 were applied to the plots in Groups 2 and 3, respectively. The corn plants in Group 4 were not given any fertilizer; it will serve as the control group. Table 5.17 gives the corn yield  $y_{ij}$  for each of the 40 plots.

- Create three indicator variables  $F_1, F_2, F_3$ , one for each of the three fertilizer groups.
- Fit the model  $y_{ij} = \mu_0 + \mu_1 F_{i1} + \mu_2 F_{i2} + \mu_3 F_{i3} + \varepsilon_{ij}$ .
- Test the hypothesis that, on the average, none of the three types of fertilizer has an effect on corn crops. Specify the hypothesis to be tested, the test used, and your conclusions at the 5% significance level.
- Which of the three fertilizers has the greatest effects on corn yield?

$$(a) \quad F_1 = \begin{cases} 1 & \text{if group 1} \\ 0 & \text{otherwise} \end{cases} \quad F_2 = \begin{cases} 1 & \text{if group 2} \\ 0 & \text{otherwise} \end{cases} \quad F_3 = \begin{cases} 1 & \text{if group 3} \\ 0 & \text{otherwise} \end{cases}$$

$$(b) \quad \begin{cases} \hat{\beta} = (X^T X)^{-1} X^T Y \\ SSE = Y^T (I - H) Y \\ H = X (X^T X)^{-1} X^T \end{cases} \quad \begin{matrix} \text{calculated} \\ \text{in Python} \end{matrix} \quad \hat{\beta} = \begin{bmatrix} 29.8 \\ 6.8 \\ 0.1 \\ 5.1 \end{bmatrix}$$

$$\hat{Y} = 29.8 + 6.8 \mu_1 + 0.1 \mu_2 + 5.1 \mu_3$$

$$(c) \quad \begin{aligned} SSE_F &= 845.8 \\ SSE_R &= 1208.4 \\ df_F &= 36 \\ df_R &= 39 \end{aligned} \quad F^* = \frac{SSE(R) - SSE(F)}{df_R - df_F} \bigg/ \frac{SSE(F)}{df_F} = 5.144$$

$$F_{(p-q, n-p-1)} = F_{(3, 36)} = 2.866$$

↑  
when  $\alpha = 0.05$

$$F^* > F_{\text{critical}}$$

→ reject  $H_0$  and favor the full model

(e) Fertilizer 1 has the highest coefficient, and therefore the highest effect.

# Problem 4

4.6 The following graphs are used to verify some of the assumptions of the ordinary least squares regression of  $Y$  on  $X_1, X_2, \dots, X_p$ :

1. The scatter plot of  $Y$  versus each predictor  $X_j$ .
2. The scatter plot matrix of the variables  $X_1, X_2, \dots, X_p$ .
3. The normal probability plot of the internally standardized residuals.
4. The residuals versus fitted values.
5. The potential-residual plot.
6. Index plot of Cook's distance.
7. Index plot of Hadi's influence measure.

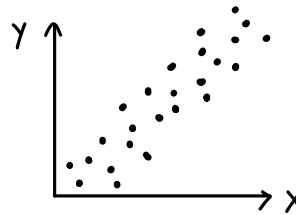
For each of these graphs:

- (a) What assumption can be verified by the graph?
- (b) Draw an example of the graph where the assumption does not seem to be violated.
- (c) Draw an example of the graph which indicates the violation of the assumption.

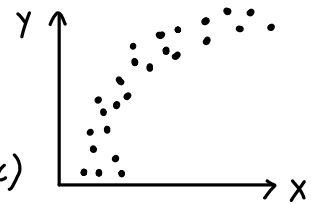
1.  $Y$  vs.  $X$  scatter plot

(a) linearity

(b)



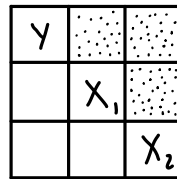
(c)



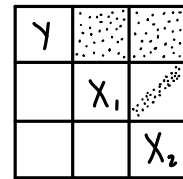
2.  $X_1, \dots, X_p$  scatterplot matrix

(a) linear independence

(b)



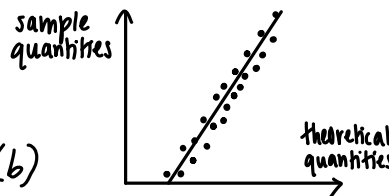
(c)



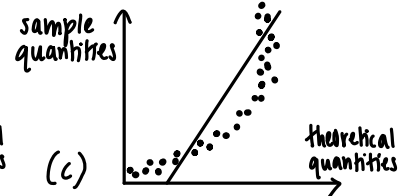
3. normal probability plot of internally-standardized residuals

(a) normal distribution of error terms

(b)



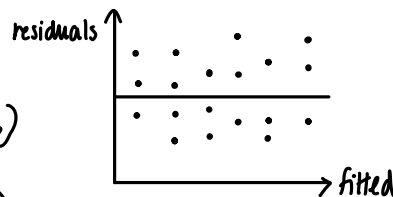
(c)



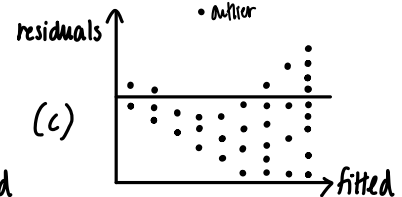
4. residuals vs. fitted values

(a) linearity  
equal variance  
(can also help detect outliers)

(b)



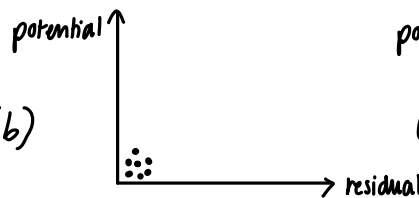
(c)



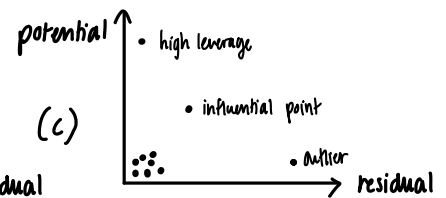
5. potential-residual plot

(a) can detect { outliers  
high-leverage points  
influential observations

(b)



(c)



6. index plot - Cook's Distance

(a) can detect influence in the data

(b)



(c)



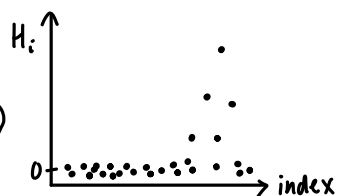
7. index plot - Hadi's influence

(a) can detect influence in the data

(b)



(c)



# Problem 5

4.8 Consider again the Examination Data used in Exercise 3.3 and given in Table 3.10:

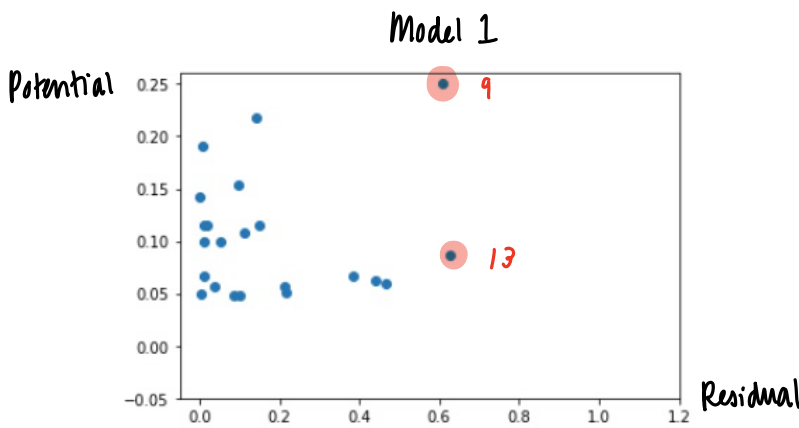
- (a) For each of the three models, draw the P-R plot. Identify all unusual observations (by number) and classify as outlier, high-leverage point, and/or influential observation.

$$d_i = \frac{e_i}{\sqrt{SSE}}$$

$$\text{potential} = \frac{h_{ii}}{1 - h_{ii}}$$

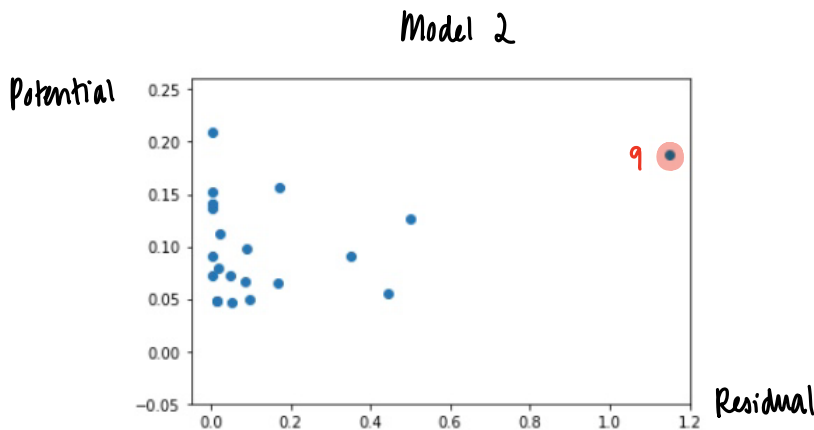
$$\text{residual} = \left( \frac{p+1}{1 - h_{ii}} \right) \left( \frac{d_i^2}{(1 - d_i)^2} \right)$$

No single observation has a value of  $|r_i^*| > 3$ , but highlighted in red below are the observations with values of  $|r_i^*| > 2$ .



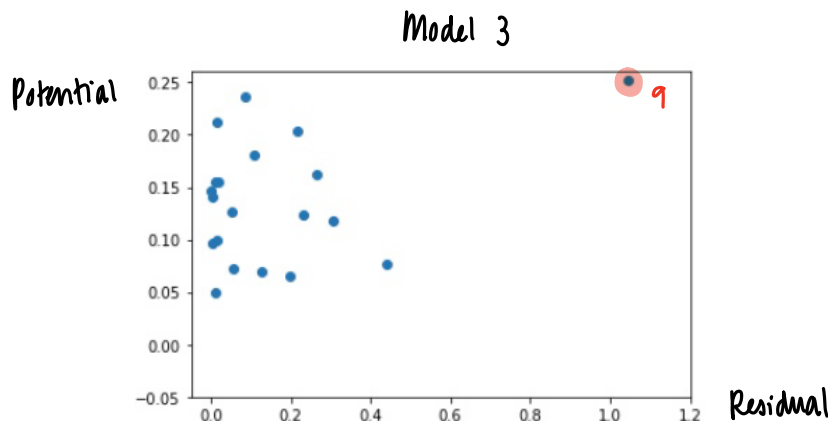
$|r^*|$

Potential	Residual	$r_i$
1	0.062699	0.440821
2	0.107420	0.112028
3	0.048218	0.101113
4	0.100110	0.052788
5	0.066098	0.011404
6	0.100110	0.009389
7	0.048218	0.086418
8	0.142857	0.000637
9	0.250000	0.610012
10	0.218027	0.142723
11	0.114827	0.012415
12	0.057082	0.036958
13	0.086957	0.626116
14	0.153403	0.097401
15	0.066098	0.384801
16	0.114827	0.018035
17	0.059322	0.467592
18	0.114827	0.150157
19	0.049318	0.004634
20	0.051525	0.217850
21	0.190476	0.005980
22	0.057082	0.211667



$|r^*|$

Potential	Residual	$r_i$
1	0.097695	0.087439
2	0.071811	0.002656
3	0.054852	0.442875
4	0.140251	0.002290
5	0.072961	0.047983
6	0.090513	0.001545
7	0.126126	0.499537
8	0.152074	0.001639
9	0.187648	1.147900
10	0.136364	0.001610
11	0.066098	0.085543
12	0.078749	0.018817
13	0.048218	0.014931
14	0.156069	0.170586
15	0.064963	0.167864
16	0.140251	0.002290
17	0.112347	0.022031
18	0.090513	0.352175
19	0.048218	0.015753
20	0.047120	0.051501
21	0.209190	0.003601
22	0.049318	0.096104



$|r^*|$

Potential	Residual	$r_i$
1	0.123596	0.232790
2	0.126126	0.053373
3	0.076426	0.441358
4	0.146789	0.000087
5	0.072961	0.056092
6	0.100110	0.014216
7	0.447178	0.224346
8	0.154734	0.011657
9	0.251564	1.045974
10	0.236094	0.085944
11	0.154734	0.016484
12	0.096491	0.003351
13	0.203369	0.216184
14	0.161440	0.263085
15	0.481481	0.001564
16	0.140251	0.004016
17	0.180638	0.109663
18	0.117318	0.304112
19	0.049318	0.010693
20	0.069519	0.127936
21	0.212121	0.015377
22	0.064963	0.196477