

1.

(a)

Call:

lm(formula = y ~ x)

Residuals:

Min	1Q	Median	3Q	Max
-5.1500	-2.2188	0.1625	2.6875	5.5750

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	168.60000	2.65702	63.45	< 2e-16 ***
x	2.03437	0.09039	22.51	2.16e-12 ***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.234 on 14 degrees of freedom

Multiple R-squared: 0.9731, Adjusted R-squared: 0.9712

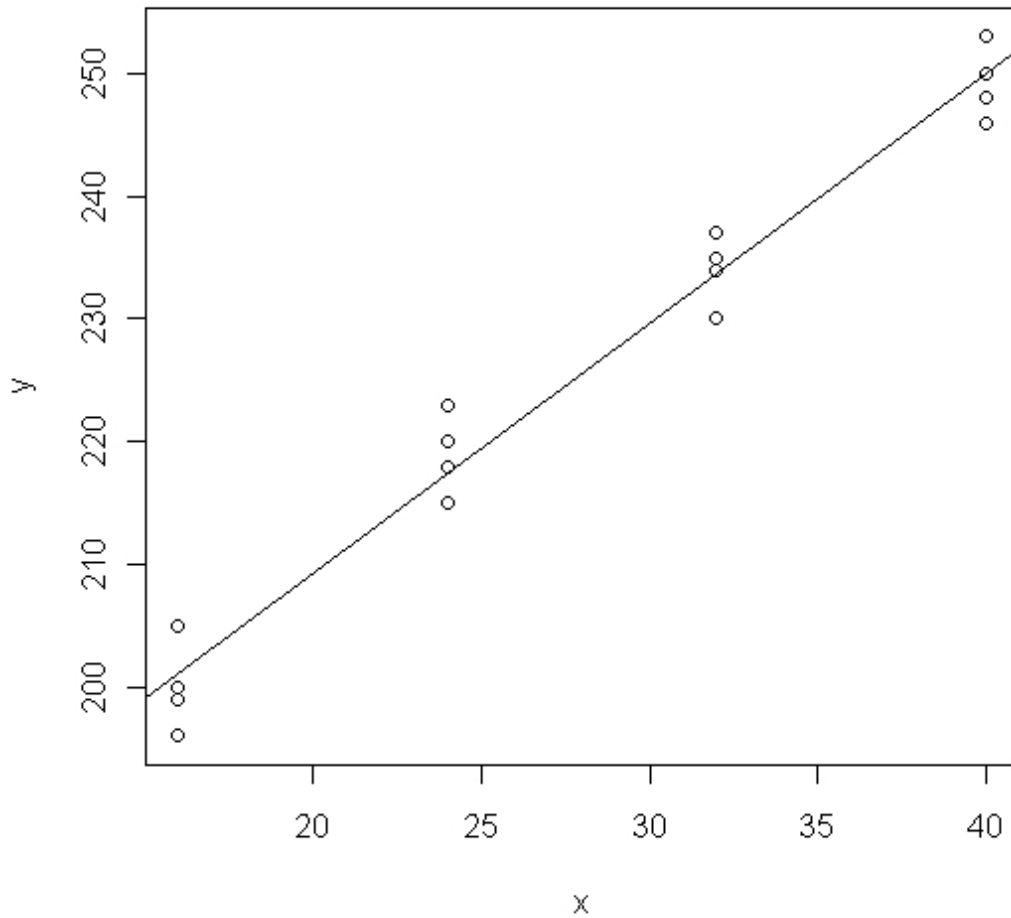
F-statistic: 506.5 on 1 and 14 DF, p-value: 2.159e-12

Estimated regression function:  $\hat{Y} = 168.60000 + 2.03437X$

(b) p-value = 2.16e-12 很小，故 reject  $\beta_0 = 0$

從圖形來看，還滿適合的，而且 Adjusted R-squared: 0.9712 也很高，代表此 regression line 的解釋效力很高，約有 97% 可由此線解釋

**Fitted Line**



(c)  $H_0 : \beta_1 = 2, H_1 : \beta_1 \neq 2$

p-value = 0.7094445 > 0.01, do not reject  $H_0$

(d)

2.5 %    97.5 %

x 1.840500 2.228250

(e)

Lower    Upper

242.4562 257.4938

(f)

Lower    Upper

242.4562 257.4938

(g)  $H_0 : \beta_1 = 0, H_1 : \beta_1 \neq 0$

p-value =  $2.159e-12 < 0.01$ , reject  $H_0$

(h)  $R^2 = 0.9731, r = \sqrt{0.9731} = 0.9864583$  (slope > 0)

2.

$$(a) H^2 = (X(X^T X)^{-1} X^T)^2 = X(X^T X)^{-1} X^T X(X^T X)^{-1} X^T = X(X^T X)^{-1} X^T = H$$

$$(I - H)^2 = I - 2H + H^2 = I - 2H + H = I - H$$

$$HX = X(X^T X)^{-1} X^T X = X$$

$$(b) A(I - H) = (X^T X)^{-1} X^T (I - X(X^T X)^{-1} X^T)$$

$$= (X^T X)^{-1} X^T - (X^T X)^{-1} X^T X(X^T X)^{-1} X^T$$

$$= (X^T X)^{-1} X^T - (X^T X)^{-1} X^T X(X^T X)^{-1} X^T$$

$$= (X^T X)^{-1} X^T - (X^T X)^{-1} X^T = O$$

$$(I - H)A^T = (I - X(X^T X)^{-1} X^T)((X^T X)^{-1} X^T)^T$$

$$= (I - X(X^T X)^{-1} X^T)X((X^T X)^{-1})^T$$

$$= X((X^T X)^{-1})^T - X(X^T X)^{-1} X^T X((X^T X)^{-1})^T$$

$$= X((X^T X)^{-1})^T - X((X^T X)^{-1})^T = O$$

$$H(I - H) = H - H^2 = H - H = O$$

$$(I - H)^T H^T = H(I - H)^T = O^T = O$$

3.characteristic polynomial:

$$f(t) = \det(tI - A) = \begin{vmatrix} t-1 & -\rho \\ -\rho & t-1 \end{vmatrix} = (t-1)^2 - \rho^2 = [t - (1+\rho)][t - (1-\rho)]$$

Eigenvalue:  $1 + \rho, 1 - \rho$

Eigenvector:

$t = 1 + \rho$ :

$$A - (1 + \rho)I = \begin{bmatrix} -\rho & \rho \\ \rho & -\rho \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -1 \\ 0 & 0 \end{bmatrix} \Rightarrow x - y = 0$$

$$\text{取 } \bar{u}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \bar{e}_1 = \frac{\bar{e}_1}{|\bar{e}_1|} = \begin{bmatrix} \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{bmatrix}$$

$t = 1 - \rho$ :

$$A - (1 - \rho)I = \begin{bmatrix} \rho & \rho \\ \rho & \rho \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} \Rightarrow x + y = 0$$

$$\text{取 } \bar{u}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}, \bar{e}_2 = \frac{\bar{e}_2}{|\bar{e}_2|} = \begin{bmatrix} \frac{\sqrt{2}}{2} \\ -\frac{\sqrt{2}}{2} \end{bmatrix}$$

4.

$$(a) \text{ 令 } \mathbf{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix}, \mathbf{A} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -1 & 0 \\ 1 & -1 & -1 \end{bmatrix}, \text{ 則 } \mathbf{W} = \mathbf{A}\mathbf{Y}$$

$$(b) \text{ 令 } E[Y_1] = \mu_1, E[Y_2] = \mu_2, E[Y_3] = \mu_3$$

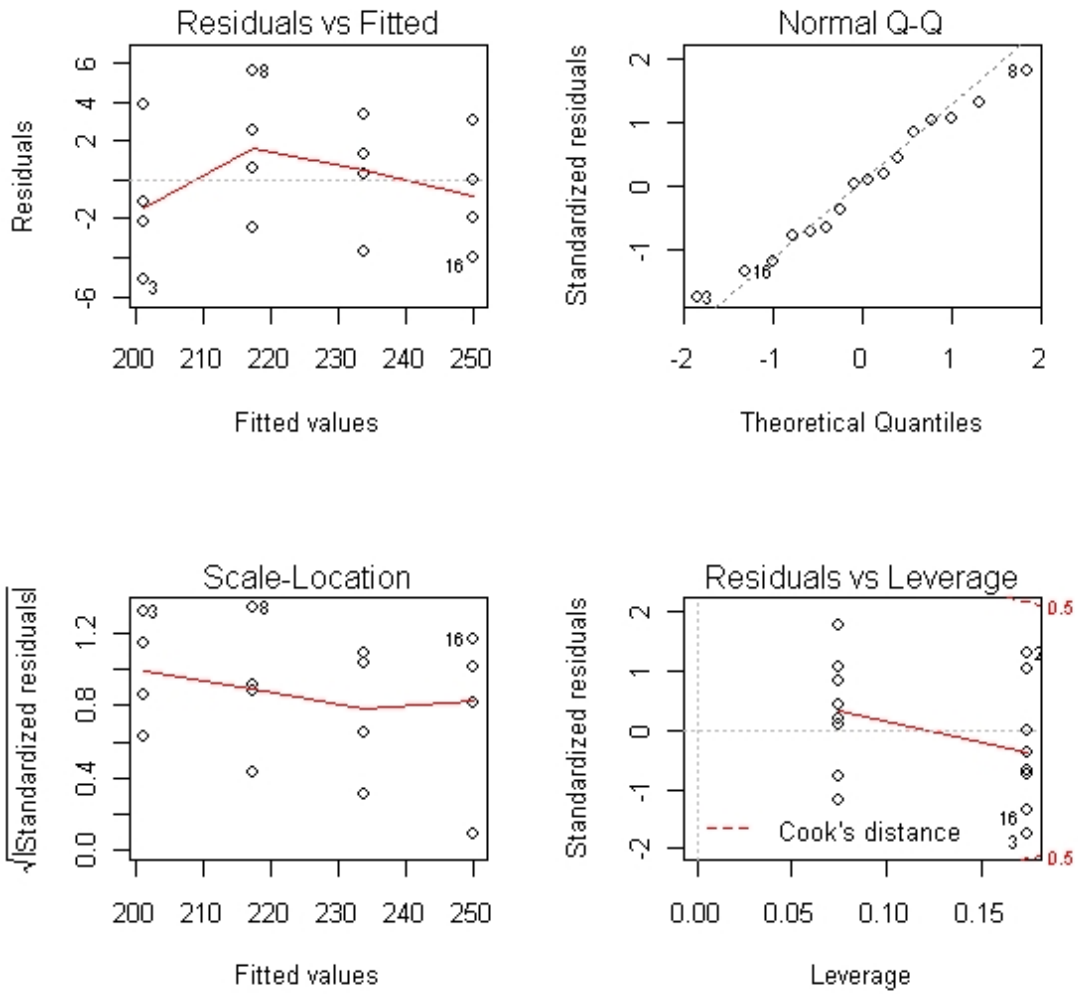
$$\text{則 } E[\mathbf{Y}] = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} \Rightarrow E[\mathbf{W}] = E[\mathbf{A}\mathbf{Y}] = \mathbf{A}E[\mathbf{Y}] = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -1 & 0 \\ 1 & -1 & -1 \end{bmatrix} \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} = \begin{bmatrix} \mu_1 + \mu_2 + \mu_3 \\ \mu_1 - \mu_2 \\ \mu_1 - \mu_2 - \mu_3 \end{bmatrix}$$

$$(c) \text{ 令 } \text{Cov}(Y_i, Y_j) = \sigma_{ij}, i = 1, 2, 3, j = 1, 2, 3$$

$$\begin{aligned} \text{Cov}(\mathbf{W}) &= \text{Cov}(\mathbf{A}\mathbf{Y}) = \mathbf{A}\text{Cov}(\mathbf{Y})\mathbf{A}^T = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -1 & 0 \\ 1 & -1 & -1 \end{bmatrix} \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_2^2 & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & -1 & -1 \\ 1 & 0 & -1 \end{bmatrix} \\ &= \begin{bmatrix} \sigma_1^2 + \sigma_{12} + \sigma_{13} & \sigma_{12} + \sigma_2^2 + \sigma_{23} & \sigma_{13} + \sigma_{23} + \sigma_3^2 \\ \sigma_1^2 - \sigma_{12} & \sigma_{12} - \sigma_2^2 & \sigma_{13} - \sigma_{23} \\ \sigma_1^2 - \sigma_{12} - \sigma_{13} & \sigma_{12} - \sigma_2^2 - \sigma_{23} & \sigma_{13} - \sigma_{23} - \sigma_3^2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & -1 & -1 \\ 1 & 0 & -1 \end{bmatrix} \\ &= \begin{bmatrix} \sigma_1^2 + \sigma_2^2 + \sigma_3^2 + 2\sigma_{12} + 2\sigma_{13} + 2\sigma_{23} & \sigma_1^2 + \sigma_{13} - \sigma_2^2 - \sigma_{23} & \sigma_1^2 - \sigma_2^2 - 2\sigma_{23} - \sigma_3^2 \\ \sigma_1^2 - \sigma_{12} + \sigma_{12} - \sigma_2^2 + \sigma_{13} - \sigma_{23} & \sigma_1^2 - 2\sigma_{12} + \sigma_2^2 & \sigma_1^2 - 2\sigma_{12} + \sigma_2^2 - \sigma_{13} + \sigma_{23} \\ \sigma_1^2 - \sigma_2^2 - 2\sigma_{23} - \sigma_3^2 & \sigma_1^2 - 2\sigma_{12} - \sigma_{13} + \sigma_2^2 + \sigma_{23} & \sigma_1^2 - 2\sigma_{12} - 2\sigma_{13} + \sigma_2^2 + 2\sigma_{23} + \sigma_3^2 \end{bmatrix} \end{aligned}$$

5.(a)

- i. 由圖形(右上角)看來，第 3, 8, 16 個資料點，是 unusual data points(超過 2 個 standard error)
- ii. 由圖形(左上角)看來，第 3, 8, 16 個資料點，是 unusual data points(超過 2 個 standard error)



iii.  $h_{ii} - 2\bar{h}$ :

[1] -0.075 -0.075 -0.075 -0.075 -0.175 -0.175 -0.175 -0.175 -0.175 -0.175

[11] -0.175 -0.175 -0.075 -0.075 -0.075 -0.075

都是 negative, 故由 leverage 判別並無 outliers

iv. 由圖形(右下角)知, 並沒有比例超過很多的值, 故由 Cook's distance 判別並無 outliers.

v. 由圖形(右下角)知, 並沒有超過 2 的值, 故由 studentized deleted residuals 判別並無 outliers.

(b)

Analysis of Variance Table

Model 1:  $y \sim x$

Model 2:  $y \sim \text{factor}(x)$

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	14	146.425			
2	12	128.750	2	17.675	0.8237 0.4622

p-value = 0.4622 > 0.05, do not reject  $H_0 : E[Y] = \beta_0 + \beta_1 x$

(c)

Analysis of Variance Table

Model 1:  $y \sim x$

Model 2:  $y \sim x + I(x^2)$

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	14	146.425			
2	13	132.362	1	14.063	1.3812 0.261

p-value = 0.4622 > 0.05, do not reject  $H_0 : E[Y] = \beta_0 + \beta_1 x + \beta_2 x^2$

但是 linear regression 的 fitness 比較好

6.(a)

$\lambda$	SSE
-0.2	0.733
-0.1	0.3326
0	0.1718
0.1	0.1671
0.2	0.2664

建議可以用  $\lambda = 0$ ，因為其在 95% 的 confidence interval 內

(b)

Call:

lm(formula = log(Y) ~ X)

Residuals:

Min	1Q	Median	3Q	Max
-0.19102	-0.10228	0.01569	0.07716	0.19699

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.50792	0.06028	25.01	2.22e-12 ***
X	-0.44993	0.01049	-42.88	2.19e-15 ***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

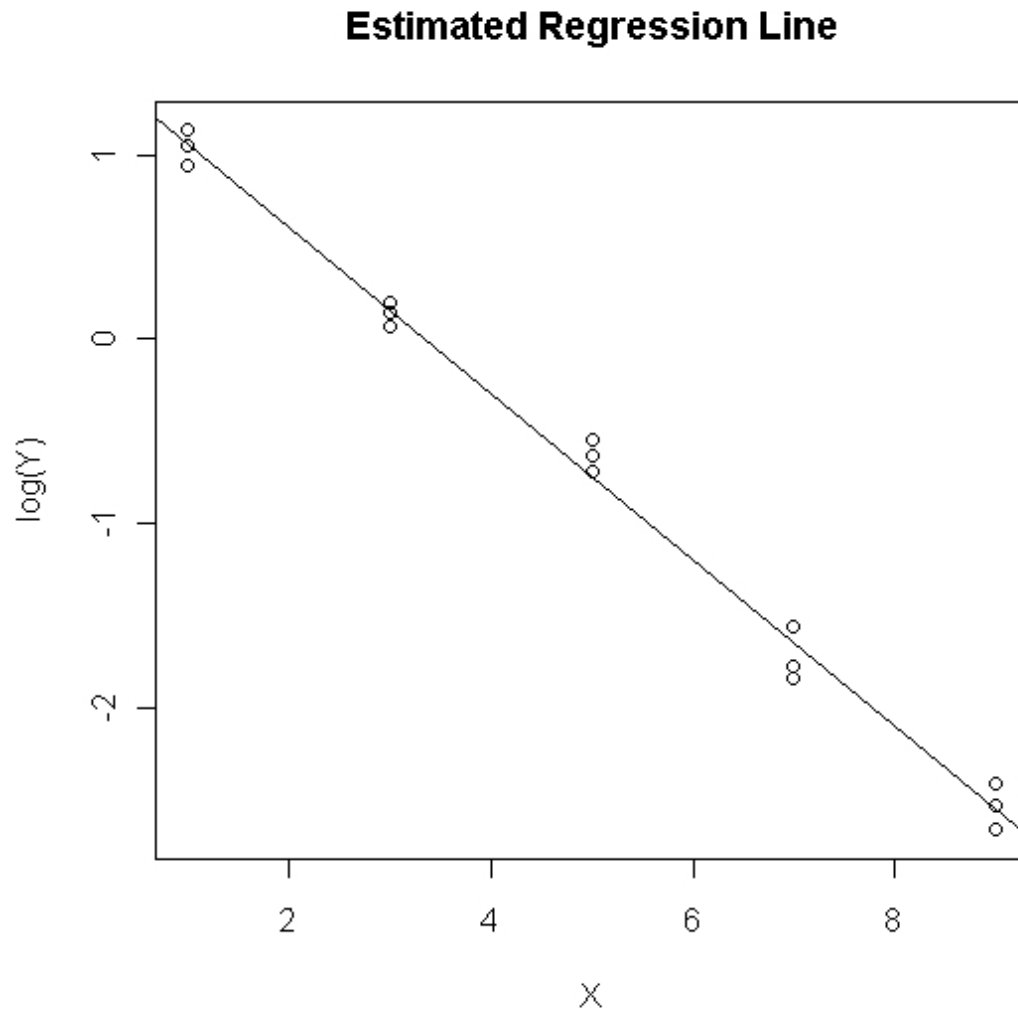
Residual standard error: 0.115 on 13 degrees of freedom

Multiple R-squared: 0.993, Adjusted R-squared: 0.9924

F-statistic: 1838 on 1 and 13 DF, p-value: 2.188e-15

regression function:  $\ln \hat{Y} = 1.50792 - 0.44993X$

(c)從圖形來看，似乎沒有 unusual data points



(d)

Call:

`lm(formula = Y ~ X)`

Residuals:

Min	1Q	Median	3Q	Max
-0.5333	-0.4043	-0.1373	0.4157	0.8487

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	2.5753	0.2487	10.354	1.20e-07	***
X	-0.3240	0.0433	-7.483	4.61e-06	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4743 on 13 degrees of freedom

Multiple R-squared: 0.8116, Adjusted R-squared: 0.7971

F-statistic: 55.99 on 1 and 13 DF, p-value: 4.611e-06

estimated regression function in the original units:  $\hat{Y} = 2.5753 - 0.3240X$