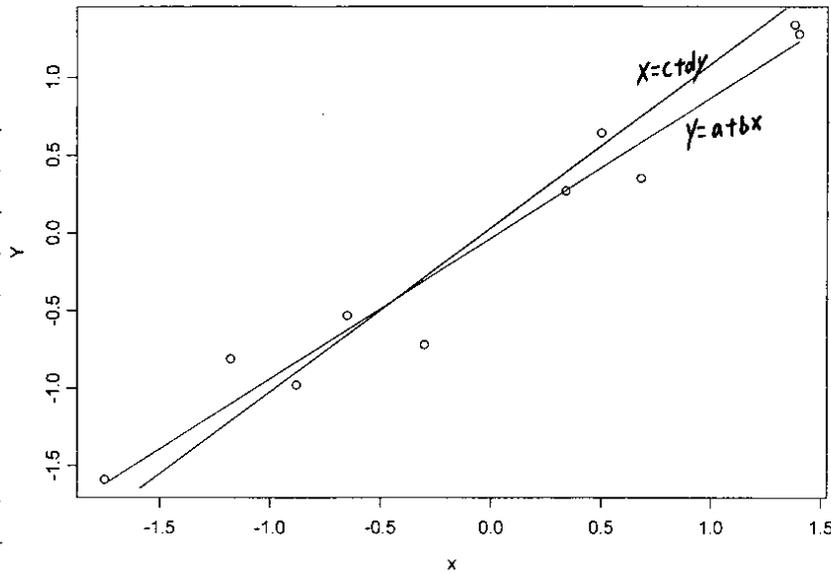


Liang Chen

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a. Fit $y = atbx$ by the method of least squares:

$$a = \frac{(\sum_{i=1}^n x_i^2)(\sum_{i=1}^n y_i) - (\sum_{i=1}^n x_i)(\sum_{i=1}^n x_i y_i)}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$= \frac{10.4342 \times (-0.75) - (-0.46) \times 9.4522}{10 \times 10.4342 - (-0.46)^2}$$

$$= -0.0334$$

$$b = \frac{n \sum_{i=1}^n x_i y_i - (\sum_{i=1}^n x_i)(\sum_{i=1}^n y_i)}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$= \frac{10 \times 9.4522 - (-0.46) \times (-0.75)}{10 \times 10.4342 - (-0.46)^2}$$

$$= 0.9044$$

$$\therefore y = -0.0334 + 0.9044x$$

b. Fit $x = ctdy$ by the method of least squares

$$c = \frac{(\sum_{i=1}^n y_i^2)(\sum_{i=1}^n x_i) - (\sum_{i=1}^n y_i)(\sum_{i=1}^n y_i x_i)}{n \sum_{i=1}^n y_i^2 - (\sum_{i=1}^n y_i)^2} \quad d = \frac{n \sum_{i=1}^n y_i x_i - (\sum_{i=1}^n y_i)(\sum_{i=1}^n x_i)}{n \sum_{i=1}^n y_i^2 - (\sum_{i=1}^n y_i)^2}$$

$$= \frac{8.9829 \times (-0.46) - (-0.75) \times 9.4522}{10 \times 8.9829 - (-0.75)^2}$$

$$= 0.0331$$

$$x = 0.0331 + 1.0550y$$

$$= \frac{10 \times 9.4522 - (-0.46) \times (-0.75)}{10 \times 8.9829 - (-0.75)^2}$$

$$= 1.0550$$

c They are not the same. For the first line, X is independent. The line minimizes the sum of squared vertical distance. For the second line, Y is independent. The line minimizes the sum of squared horizontal distance. So they are different.

4. a set up a linear model $y_i = \beta_0 + \beta_1 x_i + e_i$ $e_i \sim \text{Norm}(0, \sigma^2)$

Y : the measurement value

X : because the two objects are weighed 3 g. so we can denote

$X=1$ just one object is weighed

$X=0$ object 1 mimics object 2

$X=2$ two objects are weighed

so	Y	X
	3	1
	1	0
	7	2

$$\bar{Y} = 3.67 \quad \bar{X} = 1$$

b. the least squares estimates of the slope and intercept are

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$= \frac{0 + (-1)(1-3.67) + 1 \times (7-3.67)}{0^2 + 1^2 + 1^2}$$

$$= 3$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} = 3.67 - 3 \times 1 = 0.67$$

$$\hat{y} = \hat{\beta}_1 x + \hat{\beta}_0 = 3x + 0.67 \quad \text{estimate wr. } w_2 \quad \text{thus } X=0$$

$$\hat{w}_1 = \hat{w}_2 = 3 \times 1 + 0.67 = 3.67$$

c. the estimate of σ^2 is

$$S^2 = \frac{\sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2}{n-2}$$

$$= \frac{(3-0.67-3)^2 + (1-0.67)^2 + (7-0.67-6)^2}{1}$$

$$= 0.6667$$

$$d \quad \hat{w}_1 = \hat{w}_2 = \hat{\beta}_0 + \hat{\beta}_1$$

$$\text{Var}(\hat{w}_1) = \text{Var}(\hat{w}_2) = \text{Var}(\hat{\beta}_0) + \text{Var}(\hat{\beta}_1) + 2\text{Cov}(\hat{\beta}_0, \hat{\beta}_1) = \frac{\sum_{i=1}^n x_i^2}{n} \sigma^2 + \frac{\sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2} - \frac{2\sigma^2 \bar{x}}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{\left[\frac{\sum_{i=1}^n x_i^2}{n} + 1 - 2\bar{x} \right] \sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$\therefore S_{\hat{w}_1} = S_{\hat{w}_2} = \sqrt{\frac{\frac{\sum_{i=1}^n x_i^2}{n} + 1 - 2\bar{x}}{\sum_{i=1}^n (x_i - \bar{x})^2} S^2} = \sqrt{\frac{5 + 1 - 2}{2} \times 0.6667} = 0.4714$$

$$e. \quad \widehat{w_1 w_2} = \hat{\beta}_1 x_0 + \hat{\beta}_0 = 0.67$$

$$\text{Var}(\widehat{w_1 w_2}) = \text{Var}(\hat{\beta}_1) + \text{Var}(x_0 \hat{\beta}_1) + 2\text{Cov}(\hat{\beta}_0, x_0 \hat{\beta}_1) = \text{Var}(\hat{\beta}_1) = \frac{\frac{\sum_{i=1}^n x_i^2}{n} \sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$\therefore S_{\widehat{w_1 w_2}} = \sqrt{\frac{\frac{\sum_{i=1}^n x_i^2}{n} S^2}{\sum_{i=1}^n (x_i - \bar{x})^2}} = \sqrt{\frac{5 \times 0.6667}{2}} = 0.7454$$

$$f. \quad \because w_1 - w_2 = \hat{\beta}_1 x_0 + \hat{\beta}_0 = \beta_0 \quad \widehat{w_1 - w_2} = \hat{\beta}_1 x_0 + \hat{\beta}_0 = \hat{\beta}_0 \quad S_{\hat{\beta}_0} = S_{\widehat{w_1 - w_2}}$$

$H_0: w_1 = w_2$ thus $w_1 - w_2 = 0$

$$\therefore \frac{\hat{\beta}_0 - \beta_0}{S_{\hat{\beta}_0}} \sim t_{n-2} \quad \text{thus} \quad \frac{\widehat{w_1 - w_2} - (w_1 - w_2)}{S_{\widehat{w_1 - w_2}}} \sim t_{n-2}$$

$$t = \frac{\hat{\beta}_0 - \beta_0}{S_{\hat{\beta}_0}} = \frac{0.67}{0.7454} = 0.8988$$

under H_0 , $t \sim t_1$, because $t_{10} = 0.727$ $t_{80} = 1.376$, the p-value should be greater than 0.2 and less than 0.3. It's significant. So we can't reject H_0 .

$$11a \quad \text{Var}(\hat{w}_0) = \text{Var}(\hat{\beta}_0) + \text{Var}(x_0 \hat{\beta}_1) + 2\text{Cov}(\hat{\beta}_0, x_0 \hat{\beta}_1)$$

$$= \text{Var}(\hat{\beta}_0) + x_0^2 \text{Var}(\hat{\beta}_1) + 2x_0 \text{Cov}(\hat{\beta}_0, \hat{\beta}_1)$$

$$\therefore \text{Var}(\hat{\beta}_0) = \frac{\frac{\sum_{i=1}^n x_i^2}{n} \sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$\text{Var}(\hat{\beta}_1) = \frac{\sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$\text{Cov}(\hat{\beta}_0, \hat{\beta}_1) = \frac{-\sigma^2 \bar{x}}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$\text{Var}(\hat{w}_0) = \frac{\frac{\sum_{i=1}^n x_i^2}{n} \sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2} + \frac{x_0^2 \sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2} - \frac{2x_0 \sigma^2 \bar{x}}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$= \frac{\sigma^2 \left(\frac{\sum_{i=1}^n x_i^2}{n} + x_0^2 - 2x_0 \bar{x} \right)}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

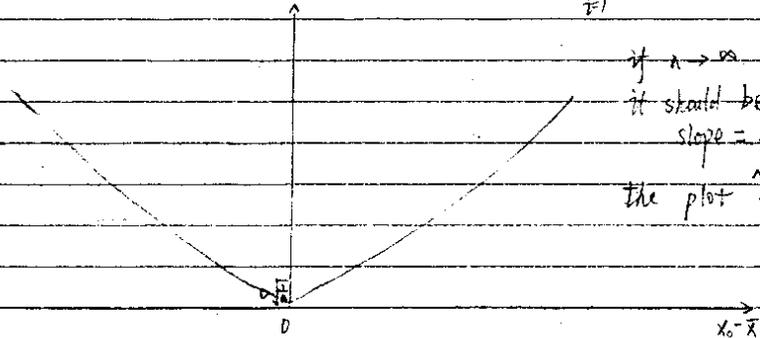
$$= \frac{\sigma^2 \sum_{i=1}^n (x_i - \bar{x})^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$= \frac{\sigma^2 \sum_{i=1}^n (x_i - \bar{x})^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$= \sigma^2 \left[\frac{\sum_{i=1}^n (X_i - \bar{X})^2 + n(X_0 - \bar{X})^2}{n \sum_{i=1}^n (X_i - \bar{X})^2} \right]$$

$$= \sigma^2 \left[\frac{1}{n} + \frac{(X_0 - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \right]$$

b) the standard deviation of $\hat{\mu}_0$ is $\sigma_{\hat{\mu}_0} = \sigma \left[\frac{1}{n} + \frac{(X_0 - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \right]^{\frac{1}{2}}$ if $n \rightarrow \infty$ $\propto \frac{|X_0 - \bar{X}|}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2}}$



if $n \rightarrow \infty$ for the $X_0 - \bar{X} \neq 0$ region
it should be a line with
slope = $\frac{\sigma}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2}}$ And
the plot is symmetry.

c) $S_{\hat{\mu}_0} = S \left[\frac{1}{n} + \frac{(X_0 - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \right]^{\frac{1}{2}}$ $S = \left\{ \frac{1}{n-2} \left[\sum_{i=1}^n (Y_i - \hat{\mu}_0 - \hat{\beta}_1 X_i)^2 \right] \right\}^{\frac{1}{2}}$

the 95% confidence interval is

$$\hat{\mu}_0 \pm S_{\hat{\mu}_0} t_{n-2} (0.025)$$

16. Under these assumptions, the Y_i are independent and normally distributed with means $\beta_0 + \beta_1 X_i$ and variance σ^2

$$f(y_1, y_2, \dots, y_n | \beta_0, \beta_1) = \frac{1}{n!} \frac{1}{\sigma \sqrt{2\pi}} \exp \left[-\frac{1}{2} \left(\frac{Y_i - \beta_0 - \beta_1 X_i}{\sigma} \right)^2 \right]$$

the log likelihood is

$$l(\beta_0, \beta_1) = -n \log \sigma - \frac{n}{2} \log 2\pi - \frac{1}{2\sigma^2} \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i)^2$$

$$\frac{\partial l}{\partial \beta_0} = -\frac{1}{2\sigma^2} \times (-2) \times \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i) \quad \text{let } \frac{\partial l}{\partial \beta_0} = 0$$

$$\text{thus } \sum_{i=1}^n Y_i = n \hat{\beta}_0 + \hat{\beta}_1 \sum_{i=1}^n X_i = 0$$

$$\frac{\partial f}{\partial \beta_1} = -\frac{1}{20^2} (-2) \left[\sum_{i=1}^n X_i (Y_i - \beta_0 - \beta_1 X_i) \right] \quad \text{let } \frac{\partial f}{\partial \beta_1} = 0$$

$$\text{thus } \sum_{i=1}^n X_i Y_i - \beta_0 \sum_{i=1}^n X_i - \beta_1 \sum_{i=1}^n X_i^2 = 0$$

$$\therefore \hat{\beta}_0 = \frac{\left(\sum_{i=1}^n X_i \right) \left(\sum_{i=1}^n Y_i \right) - \left(\sum_{i=1}^n X_i \right) \left(\sum_{i=1}^n X_i Y_i \right)}{n \sum_{i=1}^n X_i^2 - \left(\sum_{i=1}^n X_i \right)^2}$$

$$\hat{\beta}_1 = \frac{n \sum_{i=1}^n X_i Y_i - \left(\sum_{i=1}^n X_i \right) \left(\sum_{i=1}^n Y_i \right)}{n \sum_{i=1}^n X_i^2 - \left(\sum_{i=1}^n X_i \right)^2}$$

They are the same as the least squares estimates.

2) Let Y denote the final score and X is the midterm score

$$\text{For } Y = \beta_0 + \beta_1 X$$

$$\hat{\beta}_1 = \frac{S_{XY}}{S_{XX}}$$

$$= \frac{S_{XY}}{\sqrt{S_{XX} S_{YY}}} \cdot \sqrt{\frac{S_{YY}}{S_{XX}}}$$

$$= r \sqrt{\frac{S_{YY}}{S_{XX}}}$$

$$= 0.5 \sqrt{\frac{10}{10}}$$

$$= 0.5$$

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{X}$$

$$= 75 - 0.5 \times 75$$

$$= 37.5$$

$$\therefore \hat{Y} = 37.5 + 0.5X$$

$$\text{For } X = \beta_0 + \beta_1 Y$$

$$\hat{\beta}_1 = \frac{S_{XY}}{S_{YY}} = \hat{\beta}_1 = 0.5$$

$$\hat{\beta}_0 = \bar{X} - \hat{\beta}_1 \bar{Y} = 75 - 0.5 \times 75 = 37.5$$

$$\therefore \hat{X} = 37.5 + 0.5Y$$

$$\begin{aligned} \therefore \text{for (a)} \quad X &= 95 & Y &= 37.5 + 0.5 \times 95 = 85. \\ \text{for (b)} \quad Y &= 85 & X &= 37.5 + 0.5 \times 85 = 80. \end{aligned}$$

33 denote $Y = P_n$ (pressure)

$$X = \frac{1}{T}$$

$$\text{then } \hat{B} = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

$$= \frac{-0.01620}{7.60431 \times 10^{-7}}$$

$$= -2.13 \times 10^4$$

$$\therefore \hat{A} = \bar{Y} - \hat{B}\bar{X}$$

$$= -4.2715 - (-2.13 \times 10^4) \times 0.001051713$$

$$= 18.18$$

$$\begin{aligned} \therefore S_{\hat{B}} &= S \frac{1}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2}} \\ &= \frac{0.1160}{\sqrt{7.60436 \times 10^{-7}}} \end{aligned}$$

$$S = \sqrt{\frac{\sum_{i=1}^n (Y_i - \hat{A} - \hat{B}X_i)^2}{n-2}}$$

$$= 0.1160$$

$$= 1.33 \times 10^2$$

\therefore 95% confidence interval for B is

$$\hat{B} \pm t_{n-2}(0.025) S_{\hat{B}} = \hat{B} \pm t_{30}(0.025) S_{\hat{B}}$$

$$= -2.13 \times 10^4 \pm 2.042 \times 1.33 \times 10^2$$

$$= -2.13 \times 10^4 \pm 2.72 \times 10^2$$

$$\therefore S_{\hat{A}} = S \sqrt{\frac{\sum_{i=1}^n X_i^2}{n \sum_{i=1}^n (X_i - \bar{X})^2}}$$

$$= 0.1160 \times \sqrt{\frac{3.61536 \times 10^{-3}}{32 \times 7.60436 \times 10^{-7}}} = 0.14$$

∴ 95% confidence interval for A is

$$\hat{A} \pm t_{30}(1-\alpha/2) S_A$$

$$= 18.18 \pm 2.042 \times 0.14$$

$$= 18.18 \pm 0.29$$