

15 Sept

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

①  $p=1$  Model:  $y_i = \beta_0 + \beta_1 x_{i1} + e_i \quad i=1, \dots, n$

OR Model:  $Y = X \beta + e$

$$\begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 & x_{11} \\ \vdots & \vdots \\ 1 & x_{n1} \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix} + e$$

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix}^{-1} = \frac{1}{ad-bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix}$$

$$X^T X = \begin{pmatrix} n & \sum_{i=1}^n x_{i1} \\ \sum_{i=1}^n x_{i1} & \sum_{i=1}^n x_{i1}^2 \end{pmatrix} \quad (X^T X)^{-1} = \frac{1}{n \sum_{i=1}^n x_{i1}^2 - \left( \sum_{i=1}^n x_{i1} \right)^2}$$

$$X^T Y = \begin{pmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n x_{i1} y_i \end{pmatrix} \quad \begin{pmatrix} \sum_{i=1}^n x_{i1}^2 & -\sum_{i=1}^n x_{i1} \\ -\sum_{i=1}^n x_{i1} & n \end{pmatrix}$$

②  $\beta_0$  is known,  $p=1$

Model:  $y_i = \boxed{\beta_0} + \beta_1 x_{i1} + e_i \quad i=1, \dots, n$   
 $\uparrow$   
 known

$$\Rightarrow \underbrace{y_i - \beta_0}_{y_i'} = \beta_1 x_{i1} + e_i$$

$$\text{Model} = \begin{pmatrix} y_1 - \beta_0 \\ \vdots \\ y_n - \beta_0 \end{pmatrix} = \begin{pmatrix} x_{11} \\ \vdots \\ x_{n1} \end{pmatrix}_{n \times 1} \beta_1 + e$$

$$\Rightarrow \hat{\beta}_1 = \left( \sum_{i=1}^n x_{i1}^2 \right)^{-1} \sum_{i=1}^n x_{i1} (y_i - \beta_0)$$

$$= \frac{\sum_{i=1}^n x_{i1} y_i - \beta_0 \sum_{i=1}^n x_{i1}}{\sum_{i=1}^n x_{i1}^2}$$

③ Example 3 in p.7  $\beta_0 = 40$

Model =  $y_i = \boxed{\beta_0} + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + e_i$

$$y_i - \beta_0 = \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + e_i$$

$$\underline{Y} = \begin{pmatrix} y_1 - \beta_0 \\ \vdots \\ y_n - \beta_0 \end{pmatrix} \quad \underline{X} = \begin{pmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & x_{n3} \end{pmatrix} \quad \underline{\beta} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix}$$

$n \times 3$

Can I use the centered model ?

Original model  $y_i' = \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + e_i$

Centered model  $y_i' = \beta_1' (x_{i1} - \bar{x}_1) + \beta_2' (x_{i2} - \bar{x}_2) + \beta_3' (x_{i3} - \bar{x}_3) + e_i$

$$\Rightarrow y_i' = \boxed{-\beta_1' \bar{x}_1 - \beta_2' \bar{x}_2 - \beta_3' \bar{x}_3} + \beta_1' x_{i1} + \beta_2' x_{i2} + \beta_3' x_{i3} + e_i$$

$\uparrow$   
 $\beta_0'$

$$\beta_0 = 40$$

### Example 5: Example in Multiple Linear Regression

The percent survival of a certain type of animal semen after storage was measured at various combinations of concentrations of three materials used to increase chance of survival. The data are as follows:

$y$ (% survival)	$x_1$ (weight %)	$x_2$ (weight %)	$x_3$ (weight %)
25.5	1.74	5.30	10.80
31.2	6.32	5.42	9.40
25.9	6.22	8.41	7.20
38.4	10.52	4.63	8.50
18.4	1.19	11.60	9.40
26.7	1.22	5.85	9.90
26.4	4.10	6.62	8.00
25.9	6.32	8.72	9.10
32.0	4.08	4.42	8.70
25.2	4.15	7.60	9.20
39.7	10.15	4.83	9.40
35.7	1.72	3.12	7.60
26.5	1.70	5.30	8.20

Summary statistics:

$$\begin{aligned} \sum_{i=1}^{13} y_i &= 377.5 & \sum_{i=1}^{13} y_i^2 &= 11,400.15 & \sum_{i=1}^{13} x_{i1} &= 59.43 \\ \sum_{i=1}^{13} x_{i2} &= 81.82 & \sum_{i=1}^{13} x_{i3} &= 115.40 & \sum_{i=1}^{13} x_{i1}^2 &= 394.7255 \\ \sum_{i=1}^{13} x_{i2}^2 &= 576.7264 & \sum_{i=1}^{13} x_{i3}^2 &= 1035.96 & \sum_{i=1}^{13} x_{i1} y_i &= 1877.567 \\ \sum_{i=1}^{13} x_{i2} y_i &= 2246.661 & \sum_{i=1}^{13} x_{i3} y_i &= 3337.78 & \sum_{i=1}^{13} x_{i1} x_{i2} &= 360.6621 \\ \sum_{i=1}^{13} x_{i1} x_{i3} &= 522.078 & \sum_{i=1}^{13} x_{i2} x_{i3} &= 728.31 & n &= 13 \end{aligned}$$

$$\text{Model: } y_i - 40 = \beta_1' x_{i1} + \beta_2' x_{i2} + \beta_3' x_{i3} + e_i \quad i=1, \dots, n$$

$$\begin{pmatrix} 13 & 59.43 & 81.82 & 115.40 \\ 59.43 & 394.7255 & 360.6621 & 522.078 \\ 81.82 & 360.6621 & 576.7264 & 728.31 \\ 115.40 & 522.078 & 728.31 & 1035.96 \end{pmatrix}^{-1} = \begin{pmatrix} 8.06479 & -0.0825927 & -0.0941951 & -0.790527 \\ -0.0825927 & 0.00847982 & 0.00171669 & 0.00372002 \\ -0.0941951 & 0.00171669 & 0.0166294 & -0.00206331 \\ -0.790527 & 0.00372002 & -0.00206331 & 0.0886013 \end{pmatrix}$$

$$\text{Or } \tilde{X}^T \tilde{X} = \begin{pmatrix} 13 & 0 & 0 & 0 \\ 0 & 123.039 & -13.3812 & -5.4775 \\ 0 & -13.3812 & 61.7639 & 2.0002 \\ 0 & -5.4775 & 2.0002 & 11.5631 \end{pmatrix}^{-1} = \begin{pmatrix} 0.0076339722 & 0.007520217 & -0.004375877 & 0.0155272451 \\ 0.0155272451 & -0.011296496 & 0.0111123033 & 0.0769231 \\ 0.0769231 & 0 & 0 & 0 \\ 0 & 0.00847981 & 0.00171669 & 0.00371998 \\ 0 & 0.00171669 & 0.0166294 & -0.00206338 \\ 0 & 0.00371998 & -0.00206338 & 0.0886011 \end{pmatrix}$$

$$\Rightarrow \hat{\beta}_0 = 39.1574, \hat{\beta}_1 = 1.0161, \hat{\beta}_2 = -1.8616, \hat{\beta}_3 = -0.3433.$$

$$\tilde{X}^T \tilde{Y} = \begin{pmatrix} \sum_{i=1}^n x_{i1} (y_i - 40) \\ \sum_{i=1}^n x_{i2} (y_i - 40) \\ \sum_{i=1}^n x_{i3} (y_i - 40) \end{pmatrix} = \begin{pmatrix} \sum_{i=1}^n x_{i1} y_i - 40 \sum_{i=1}^n x_{i1} \\ \sum_{i=1}^n x_{i2} y_i - 40 \sum_{i=1}^n x_{i2} \\ \sum_{i=1}^n x_{i3} y_i - 40 \sum_{i=1}^n x_{i3} \end{pmatrix} = \begin{pmatrix} -499.633 \\ -1026.119 \\ -1278.22 \end{pmatrix}$$

$$\hat{\beta} = (\tilde{X}^T \tilde{X})^{-1} \tilde{X}^T \tilde{Y} = \begin{pmatrix} 1.00748 \\ -1.87149 \\ -0.425862 \end{pmatrix}$$

④ Example in p.7  $\beta_1 = 1$  (one of reg. coeff. is known)

$$\text{Model} = y_i = \beta_0 + \boxed{\beta_1} x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + e_i \quad i=1, \dots, n$$

$$y_i - \boxed{\beta_1} x_{i1} = \beta_0 + \beta_2 x_{i2} + \beta_3 x_{i3} + e_i$$

$$\underbrace{y_i - \beta_1 x_{i1}}_{y_i'}$$

$$\Rightarrow \underbrace{\begin{pmatrix} y_1 - \beta_1 x_{11} \\ \vdots \\ y_n - \beta_1 x_{n1} \end{pmatrix}}_{\underline{Y}} = \underbrace{\begin{pmatrix} 1 & x_{12} & x_{13} \\ \vdots & x_{22} & \vdots \\ \vdots & \vdots & \vdots \\ 1 & x_{n2} & x_{n3} \end{pmatrix}}_{\underline{X}} \underbrace{\begin{pmatrix} \beta_0 \\ \beta_2 \\ \beta_3 \end{pmatrix}}_{\underline{\beta}} + \underbrace{e}_{\underline{e}}$$



$B_1 = 1$  Model =  $y_i - x_{i1} = \beta_0 + \beta_2 x_{i2} + \beta_3 x_{i3} + e_i$   
 Centred model =  $y_i - x_{i1} = \beta'_0 + \beta'_2 (x_{i2} - \bar{x}_2) + \beta'_3 (x_{i3} - \bar{x}_3) + e_i$   
 Example 5: Example in Multiple Linear Regression

The percent survival of a certain type of animal semen after storage was measured at various combinations of concentrations of three materials used to increase chance of survival. The data are as follows:

$\hat{\beta}'_0 = \bar{y}' \Rightarrow \hat{\beta}_0 = \bar{y} - \beta_2 \bar{x}_2 - \beta_3 \bar{x}_3$

y (% survival)	x <sub>1</sub> (weight %)	x <sub>2</sub> (weight %)	x <sub>3</sub> (weight %)
25.5	1.74	5.30	10.80
31.2	6.32	5.42	9.40
25.9	6.22	8.41	7.20
38.4	10.52	4.63	8.50
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35.7	1.72	3.12	7.60
26.5	1.70	5.30	8.20

$\bar{y}' = \bar{y} - \bar{x}_1$

Summary statistics:

$$\begin{aligned} \sum_{i=1}^{13} y_i &= 377.5 & \sum_{i=1}^{13} y_i^2 &= 11,400.15 & \sum_{i=1}^{13} x_{i1} &= 59.43 \\ \sum_{i=1}^{13} x_{i2} &= 81.82 & \sum_{i=1}^{13} x_{i3} &= 115.40 & \sum_{i=1}^{13} x_{i1}^2 &= 394.7255 \\ \sum_{i=1}^{13} x_{i2}^2 &= 576.7264 & \sum_{i=1}^{13} x_{i3}^2 &= 1035.96 & \sum_{i=1}^{13} x_{i1} y_i &= 1877.567 \\ \sum_{i=1}^{13} x_{i2} y_i &= 2246.661 & \sum_{i=1}^{13} x_{i3} y_i &= 3337.78 & \sum_{i=1}^{13} x_{i1} x_{i2} &= 360.6621 \\ \sum_{i=1}^{13} x_{i1} x_{i3} &= 522.078 & \sum_{i=1}^{13} x_{i2} x_{i3} &= 728.31 & n &= 13 \end{aligned}$$

Original model

$$\begin{pmatrix} 13 & 59.43 & 81.82 & 115.40 \\ 59.43 & 394.7255 & 360.6621 & 522.078 \\ 81.82 & 360.6621 & 576.7264 & 728.31 \\ 115.40 & 522.078 & 728.31 & 1035.96 \end{pmatrix}^{-1} = \begin{pmatrix} 8.06479 & -0.0825927 & -0.0941951 & -0.790527 \\ -0.0825927 & 0.00847982 & 0.00171669 & 0.00372002 \\ -0.0941951 & 0.00171669 & 0.0166294 & -0.00206331 \\ -0.790527 & 0.00372002 & -0.00206331 & 0.0886013 \end{pmatrix}$$

Or  $X^T X = \begin{pmatrix} 13 & 81.82 & 115.40 \\ 81.82 & 576.7264 & 728.31 \\ 115.40 & 728.31 & 1035.96 \end{pmatrix}$   $(X^T X)^{-1} X^T Y = \begin{pmatrix} \sum_{i=1}^{13} (y_i - x_{i1}) \\ \sum_{i=1}^{13} x_{i2} (y_i - x_{i1}) \\ \sum_{i=1}^{13} x_{i3} (y_i - x_{i1}) \end{pmatrix}$

Centred model

$$(X_c^T X_c)^{-1} = \begin{pmatrix} 13 & 0 & 0 & 0 \\ 0 & 122.039 & -13.3812 & 5.4775 \\ 0 & -13.3812 & 61.7639 & 2.0002 \\ 0 & 5.4775 & 2.0002 & 11.5631 \end{pmatrix}^{-1} = \begin{pmatrix} 0.0769231 & 0 & 0 & 0 \\ 0 & 0.00847981 & 0.00171669 & 0.00371998 \\ 0 & 0.00171669 & 0.0166294 & -0.00206338 \\ 0 & 0.00371998 & -0.00206338 & 0.0886011 \end{pmatrix}$$

$$= \begin{pmatrix} \sum_{i=1}^{13} y_i - \sum_{i=1}^{13} x_{i1} \\ \sum_{i=1}^{13} x_{i2} y_i - \sum_{i=1}^{13} x_{i1} x_{i2} \\ \sum_{i=1}^{13} x_{i3} y_i - \sum_{i=1}^{13} x_{i1} x_{i3} \end{pmatrix}$$

$\Rightarrow \hat{\beta}_0 = 39.1574, \hat{\beta}_1 = 1.0161, \hat{\beta}_2 = -1.8616, \hat{\beta}_3 = -0.3433.$

$X^T Y = \begin{pmatrix} \sum_{i=1}^{13} (y_i - x_{i1}) \\ \sum_{i=1}^{13} (x_{i2} - \bar{x}_2) (y_i - x_{i1}) \\ \sum_{i=1}^{13} (x_{i3} - \bar{x}_3) (y_i - x_{i1}) \end{pmatrix}$

$\sum_{i=1}^{13} (x_{i2} - \bar{x}_2) (y_i - x_{i1})$   
 $= \left[ \sum_{i=1}^{13} (x_{i2} - \bar{x}_2) y_i \right] - \sum_{i=1}^{13} (x_{i2} - \bar{x}_2) x_{i1}$   
 $= \sum_{i=1}^{13} x_{i2} y_i - \sum_{i=1}^{13} x_{i1} x_{i2} - \left[ \bar{y} \sum_{i=1}^{13} (x_{i2} - \bar{x}_2) \right] = 0$

$\hat{\beta}_0 = 39.3147, \hat{\beta}_2 = -1.86491, \hat{\beta}_3 = -0.35032$

Fitted line =  $y' = y - x_1 = 39.3147 - 1.86491 x_2 - 0.35032 x_3$  (5)

# Method of maximum likelihood (3413)

$p=1$  Model:  $y_i = \beta_0 + \beta_1 x_{i1} + e_i$  Assume  $e_i \sim N(0, \sigma^2)$

$\text{cov}(e_i, e_j) = 0$

$\Rightarrow y_i \sim N(\beta_0 + \beta_1 x_{i1}, \sigma^2)$

$i=1, \dots, n$

likelihood  $(\beta_0, \beta_1, \sigma^2)$

$$= \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ - \frac{(y_i - (\beta_0 + \beta_1 x_{i1}))^2}{2\sigma^2} \right\}$$

increasing  
function

$$= \left( \frac{1}{2\pi} \right)^{n/2} (\sigma^2)^{-n/2} \exp \left\{ - \frac{\sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_{i1}))^2}{2\sigma^2} \right\}$$

(log)-likelihood

$$= - \frac{n}{2} \log(2\pi) - \frac{n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_{i1}))^2$$

$$\frac{\partial \log L}{\partial \beta_0} = - \frac{1}{2\sigma^2} \times 2 \left[ \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_{i1})) (-1) \right] = 0$$

$$\frac{\partial \log L}{\partial \beta_1} = - \frac{1}{2\sigma^2} \times 2 \left[ \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_{i1})) (-x_{i1}) \right] = 0$$

from  
method  
of least  
squares

$$\frac{\partial \log L}{\partial \sigma^2} = - \frac{n}{2} \frac{1}{\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_{i1}))^2 = 0$$

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^n (y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_{i1}))^2}{n} \leftarrow \frac{\sum_{i=1}^n \hat{e}_i^2}{n} = \frac{\text{Res S.S.}}{n}$$

$\hat{\beta}_0, \hat{\beta}_1$

Is  $\hat{\sigma}^2$  unbiased? NO

Res S.S. =  $\sum_{i=1}^n \hat{e}_i^2$   $\hat{e}_i = y_i - \hat{y}_i$

$$= \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$= (\underline{Y} - \underline{\hat{Y}})^T (\underline{Y} - \underline{\hat{Y}})$$

$$\underline{\hat{Y}} = \underline{X} \underline{\hat{\beta}}$$

$$= (\underline{Y} - \underline{X} \underline{\hat{\beta}})^T (\underline{Y} - \underline{X} \underline{\hat{\beta}}) = \underline{Y}^T \underbrace{(\underline{I} - \underline{X}(\underline{X}^T \underline{X})^{-1} \underline{X}^T)}_{\underline{H}} \underline{Y}$$

(6)

$$\hat{Y} = H Y$$

↑  
hat matrix

Symmetric? Yes

$$H \stackrel{\text{def}}{=} X(X^T X)^{-1} X^T$$

$$\begin{aligned} H^T &= (X(X^T X)^{-1} X^T)^T \\ &= (X^T)^T ((X^T X)^{-1})^T X^T \\ &= X (X^T X)^{-1} X^T \\ &= H \end{aligned}$$

+

Is  $H H^T = H$ ? Yes

$$\begin{aligned} H H^T &= (X(X^T X)^{-1} X^T) (X(X^T X)^{-1} X^T)^T \\ &= X(X^T X)^{-1} \boxed{X^T X} (X^T X)^{-1} X^T \\ &= X(X^T X)^{-1} X^T \\ &= H \end{aligned}$$

⇒ Idempotent

Is  $(I - H)$  idempotent?

$$\text{Res S.S.} = Y^T (I - H)^T (I - H) Y$$

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

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

$$= Y^T Y - \boxed{Y^T X (X^T X)^{-1} X^T} Y$$

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

$$= Y^T Y - \hat{\beta}^T X^T Y$$



① Assuming  $\beta_0$  is unknown

$$\text{Res S.S.} = \sum_{i=1}^n y_i^2 - (\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_p) \begin{pmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n x_{i1} y_i \\ \vdots \\ \sum_{i=1}^n x_{ip} y_i \end{pmatrix}$$

$$= \sum_{i=1}^n y_i^2 - \hat{\beta}_0 \sum_{i=1}^n y_i - \hat{\beta}_1 \sum_{i=1}^n x_{i1} y_i - \dots - \hat{\beta}_p \sum_{i=1}^n x_{ip} y_i$$

Note that  $\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}_1 - \dots - \hat{\beta}_p \bar{x}_p$

$$\text{Res S.S.} = \sum_{i=1}^n y_i^2 - (\bar{y} - \hat{\beta}_1 \bar{x}_1 - \dots - \hat{\beta}_p \bar{x}_p) \left( \sum_{i=1}^n y_i \right) - \hat{\beta}_1 \sum_{i=1}^n x_{i1} y_i - \dots - \hat{\beta}_p \sum_{i=1}^n x_{ip} y_i$$

$$= \left( \sum_{i=1}^n y_i^2 - n \bar{y}^2 \right) - \hat{\beta}_1 \left( \sum_{i=1}^n x_{i1} y_i - n \bar{x}_1 \bar{y} \right) - \hat{\beta}_2 \left( \sum_{i=1}^n x_{i2} y_i - n \bar{x}_2 \bar{y} \right) - \dots - \hat{\beta}_p \left( \sum_{i=1}^n x_{ip} y_i - n \bar{x}_p \bar{y} \right)$$

$$= S_{yy} - \left( \hat{\beta}_1 S_{x_1 y} + \dots + \hat{\beta}_p S_{x_p y} \right)$$

$$\boxed{S_{uv} = \sum_{i=1}^n (u_i - \bar{u})(v_i - \bar{v}) = \sum_{i=1}^n u_i v_i - n \bar{u} \bar{v} = \sum_{i=1}^n (u_i - \bar{u}) v_i}$$

$$\text{Res S.S.} = \boxed{S_{yy}} - \left( \hat{\beta}_1 S_{x_1 y} + \dots + \hat{\beta}_p S_{x_p y} \right)$$

$\sum_{i=1}^n (y_i - \bar{y})^2$  corrected Total S.S.

Reg S.S.

$\beta_1, \dots, \beta_p$  reg. coeff of  $x_1, \dots, x_p$ , respectively



p=1 Res S.S. =  $S_{yy} - \hat{\beta}_1 S_{x_1 y}$        $\hat{\beta}_1 = \frac{S_{x_1 y}}{S_{x_1 x_1}}$

$\Rightarrow S_{x_1 y} = \boxed{\hat{\beta}_1 S_{x_1 x_1}}$

$$= S_{yy} - \hat{\beta}_1 (\hat{\beta}_1 S_{x_1 x_1})$$

$$= S_{yy} - \hat{\beta}_1^2 S_{x_1 x_1} \quad \leftarrow$$

$$\boxed{\text{Res S.S.} = S_{yy} - (\hat{\beta}_1^2 S_{x_1 x_1} + \dots + \hat{\beta}_p^2 S_{x_p x_p})} \quad \times$$

$$E(\text{Res S.S.}) = E(S_{yy}) - S_{x_1 x_1} E(\hat{\beta}_1^2)$$

$\nearrow$   $\text{Var}(\hat{\beta}_1) + E(\hat{\beta}_1)^2$

$$E(S_{yy}) = E\left(\sum_{i=1}^n (y_i - \bar{y})^2\right) \neq (n-1) \sigma^2$$

$\sum_{i=1}^n y_i^2 - n \bar{y}^2$        $\uparrow$  diff. means

Then,  $E(S_{yy}) = ?$

②  $\beta_0$  is known

$$\underline{Y} = \begin{pmatrix} y_1' \\ \vdots \\ y_n' \end{pmatrix} = \begin{pmatrix} y_1 - \beta_0 \\ \vdots \\ y_n - \beta_0 \end{pmatrix}$$

$$\text{Res S.S.} = \underline{Y}^T \underline{Y} - \hat{\beta}^T \underline{X}^T \underline{Y}$$

$$= \sum_{i=1}^n y_i'^2 - \hat{\beta}_1 \sum_{i=1}^n x_{i1} y_i' - \dots - \hat{\beta}_p \sum_{i=1}^n x_{ip} y_i' \quad \underline{\beta} = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}$$

$$= \sum_{i=1}^n (y_i - \beta_0)^2 - \hat{\beta}_1 \sum_{i=1}^n x_{i1} (y_i - \beta_0) - \dots - \hat{\beta}_p \sum_{i=1}^n x_{ip} (y_i - \beta_0)$$

$\underline{X}^T \underline{Y} = \begin{pmatrix} \sum_{i=1}^n x_{i1} y_i' \\ \vdots \\ \sum_{i=1}^n x_{ip} y_i' \end{pmatrix}$

$$= \sum_{i=1}^n y_i^2 - 2 \boxed{\beta_0} \sum_{i=1}^n y_i + \boxed{\beta_0^2} - \hat{\beta}_1 \left( \sum_{i=1}^n x_{i1} y_i - \boxed{\beta_0} \sum_{i=1}^n x_{i1} \right) - \dots - \hat{\beta}_p \left( \sum_{i=1}^n x_{ip} y_i - \boxed{\beta_0} \sum_{i=1}^n x_{ip} \right)$$

If  $\beta_0 = 0$ , Res S.S. =  $\sum_{i=1}^n y_i^2 - \hat{\beta}_1 \sum_{i=1}^n x_{i1} y_i - \dots - \hat{\beta}_p \sum_{i=1}^n x_{ip} y_i$  ⑨

Example in p.7

Assume  $\beta_0, \beta_1, \beta_2, \beta_3$  are unknown

$$\text{Res S.S.} = S_{yy} - \hat{\beta}_1 S_{x_1 y} - \hat{\beta}_2 S_{x_2 y} - \hat{\beta}_3 S_{x_3 y}$$

$\uparrow$                        $\uparrow$                        $\uparrow$   
 1.0161                  -1.8616                  -0.3433

$$= 38.68289$$

Assume  $\beta_0 = 40$        $\hat{\beta}_1 = 1.00748$ ,  $\hat{\beta}_2 = -1.871149$ ,  $\hat{\beta}_3 = -0.425863$

$$\begin{aligned} \text{Res S.S.} &= \sum_{i=1}^n (y_i - \beta_0)^2 - \hat{\beta}_1 \sum_{i=1}^n x_{i1} (y_i - \beta_0) - \hat{\beta}_2 \sum_{i=1}^n x_{i2} (y_i - \beta_0) \\ &\quad - \hat{\beta}_3 \sum_{i=1}^n x_{i3} (y_i - \beta_0) \\ &= \sum_{i=1}^n y_i^2 - 2\beta_0 \sum_{i=1}^n y_i + \beta_0^2 - \hat{\beta}_1 \left( \sum_{i=1}^n x_{i1} y_i - \beta_0 \sum_{i=1}^n x_{i1} \right) \\ &\quad - \hat{\beta}_2 \left( \sum_{i=1}^n x_{i2} y_i - \beta_0 \sum_{i=1}^n x_{i2} \right) - \hat{\beta}_3 \left( \sum_{i=1}^n x_{i3} y_i - \beta_0 \sum_{i=1}^n x_{i3} \right) \\ &= 38.76445 \end{aligned}$$

Assume  $\beta_1 = 1$        $\hat{\beta}_0 = 39.3147$ ,  $\hat{\beta}_2 = -1.86491$ ,  $\hat{\beta}_3 = -0.35032$   
 $\uparrow$  model with intercept

$$\begin{aligned} \text{Res S.S.} &= S_{y'y'} - \hat{\beta}_2 \boxed{S_{x_2 y'}} - \hat{\beta}_3 S_{x_3 y'} \\ &\quad \uparrow \sum_{i=1}^n (y_i' - \bar{y}')^2 \quad \sum_{i=1}^n (x_{i2} - \bar{x}_2)(y_i' - \bar{y}') \\ &\quad \quad \quad = \sum_{i=1}^n (x_{i2} - \bar{x}_2) [(y_i - \bar{y}) - (x_{i1} - \bar{x}_1)] \\ &= \sum_{i=1}^n [(y_i - x_{i1}) - (\bar{y} - \bar{x}_1)]^2 \quad = S_{x_2 y} - S_{x_1 x_2} \\ &= \sum_{i=1}^n [(y_i - \bar{y}) - (x_{i1} - \bar{x}_1)]^2 \\ &= S_{yy} - 2S_{x_1 y} + S_{x_1 x_1} \end{aligned}$$

$$\text{Res S.S.} = 38.70697$$