

$$\begin{array}{ccccc}
 Y & \hat{Y} & \bar{Y} & e & \hat{e} \\
 | & | & | & | & \swarrow \text{ } Y-\hat{Y} \\
 N(x\beta, \sigma^2) & HY & JY & N(0, \sigma^2 I) & (I-H)Y
 \end{array}$$

$$J = \frac{1}{n} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{pmatrix}_{n \times n}$$

$$JH = J = HJ$$

$$JJJJJJ = J$$

$$JJ = J$$

$$\frac{1}{n^2} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{pmatrix} = \begin{pmatrix} n & n & n & n \\ n & n & n & n \\ n & n & n & n \\ n & n & n & n \end{pmatrix} \frac{1}{n^2} = \frac{1}{n} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{pmatrix} = J$$

$$\begin{aligned}
 \text{Cov}(Y, \hat{e}) &= \text{Cov}(Y, Y)(I-H) \\
 \text{Cov}(Y, \hat{Y}) &= \text{Cov}(Y, Y)H \\
 \text{Cov}(\bar{Y}, \hat{e}) &= J \text{Cov}(Y, Y)(I-H) \\
 &= \sigma^2 J(I-H) \\
 &= \sigma^2 (J - \underbrace{JH}) = 0
 \end{aligned}$$

$$\begin{aligned}
 \text{Sum of col } & \frac{1}{n} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{pmatrix} H \\
 \text{of } H = 1 \downarrow &= \frac{1}{n} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{pmatrix} = J
 \end{aligned}$$

Sum of Squares

Ch3 : $\sum (Y_i - \bar{Y})^2 \stackrel{\text{want}}{=} \sum (Y_i - \hat{Y}_i)^2 + \sum (\hat{Y}_i - \bar{Y})^2$

$\text{TSS} \quad \leftarrow \text{scalar} \quad \text{RSS} \quad \quad \text{SS reg} \quad \leftarrow \text{scalar}$

$\downarrow x_i \hat{\beta}$

Pf $(Y - \bar{Y})'(Y - \bar{Y}) \stackrel{?}{=} (Y - \hat{Y})'(Y - \hat{Y}) + (\hat{Y} - \bar{Y})'(\hat{Y} - \bar{Y})$

$H = X(X'X)^{-1}X' \quad J = \frac{1}{n} \begin{pmatrix} 1 & 1 & \dots & 1 \\ 1 & 1 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & 1 \end{pmatrix} \Rightarrow H=H, J'=J$

$Y'(I - J)(I - J)Y \stackrel{?}{=} Y'(I - H)(I - H)Y + Y'(H - J)(H - J)Y$

$Y'(I - J - J + \frac{JJ}{J})Y \stackrel{?}{=} Y'(I - H - H + \frac{HH}{H})Y + Y'(\frac{HH}{H} - \frac{JH}{J} - \frac{HJ}{J} + \frac{JJ}{J})Y$

$\text{TSS} \rightarrow Y'(I - J)Y = Y'(I - H)Y + Y'(H - J)Y$

$Y'(I - H + H - J)Y \checkmark = Y'(I - H)Y + Y'(H - J)Y$

$$e.g. E \left(\sum_{i=1}^n (Y_i - \hat{Y}_i) (Y_i - \bar{Y}) \right)$$

↑
model you used
↓

$$= E \left(Y' (I - H_2) (I - J) Y \right)$$

$$= E \left(Y' (I - H_2 - \cancel{J} + \cancel{HJ}) Y \right) = E \left(Y' (I - H) Y \right)$$

$$H_1 = X_1 (X_1' X_1)^{-1} X_1'$$

$$= E \left(\text{tr} (Y' (I - H_2) Y) \right) = E \left(\text{tr} ((I - H) Y Y') \right)$$

$$= \text{tr} [(I - H_2) E(Y Y')]$$

e.g. (True model) $Y = X\beta + e$ $e \sim N(0, \sigma^2 I)$

$$= \text{tr} [(I - H_2) \cdot E((X_1\beta + e)(X_1\beta + e'))]$$

$$= \text{tr} [(I - H_2) \cdot (X_1\beta\beta'X_1' + \sigma^2 I)] = \text{tr} \left(\underbrace{(I - H_2) X_1}_{n \times n} \underbrace{\beta\beta' X_1'}_{1 \times n} \right) + \sigma^2 \text{tr}(I - H_2)$$

$$= \underbrace{\beta' X_1' (I - H_2) X_1 \beta}_{\text{scalar}} + \sigma^2 (n - p_2 - 1)$$

$$\sum a_i b_i = (a_1 \dots a_n) \begin{pmatrix} b_1 \\ \vdots \\ b_n \end{pmatrix}$$

$$\text{True: } Y = X_1 \beta + e$$

$$\text{Use: } Y = X_2 \beta + e$$

$\text{tr}(I) = n$
 $\text{tr}(H_2) = \text{tr}(X_2' X_2) X_2' X_2$

8.1.3. Residuals when the model is correct

- Look at residual plot

- y-axis = residuals

- x-axis = term / combination of terms / fitted values

- Let U be any combinations of terms, we expect the Null Plot

- $E(\hat{e}_i | U) = 0$

- mean level = 0

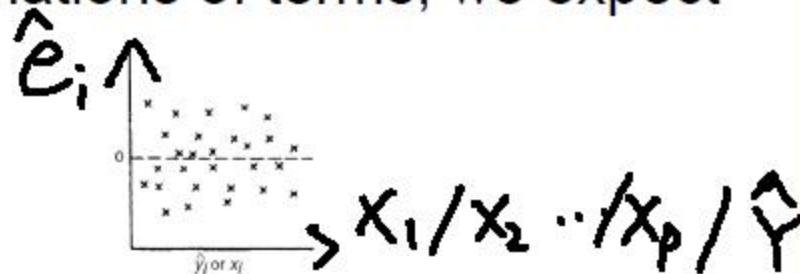
- $Var(\hat{e}_i | U) = \sigma^2(1 - h_{ii})$

- variance is roughly constant (since h_{ii} are usually small)

- The point with high leverage ($h_{ii} \sim 1$) have small variance

$$e \sim N(0, \sigma^2 I)$$

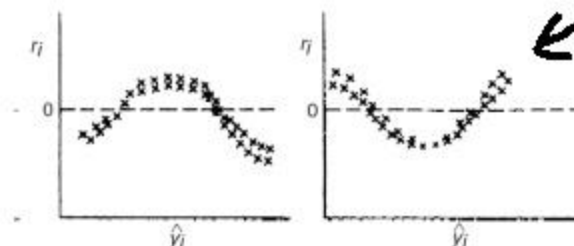
$$\hat{e} \sim N(0, \sigma^2(I - H))$$



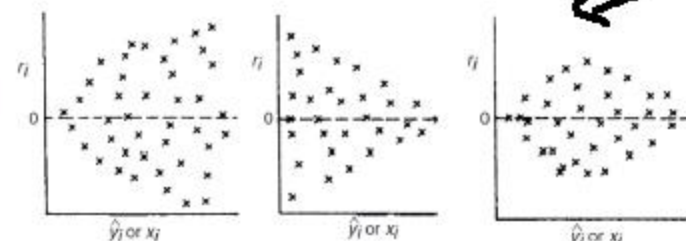
8.1.4. Residuals when the model is NOT correct

- Residual plot far from the Null Plot

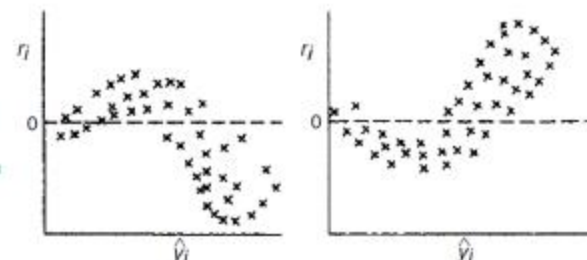
- Mean level not 0



- Variance not constant



- Both



transformation

Weighted least square

both