

$$e_i = y_i - \hat{y}_i \sim N(0, \sigma^2(1 - h_{ii}))$$

$$\Rightarrow \frac{e_i}{\sqrt{\sigma^2(1 - h_{ii})}} = \frac{e_i}{\sqrt{V(e_i)}} \sim N(0, 1)$$

$$e_{(i)} = \frac{e_i}{1 - h_{ii}} \sim N\left(0, \frac{\sigma^2}{1 - h_{ii}}\right)$$

$$\Rightarrow \frac{e_i}{\sqrt{V(e_i)}} = \frac{e_i}{\sqrt{\sigma^2(1 - h_{ii})}} = \frac{e_i}{\sqrt{V(e_i)}}$$

(Even if we leave one out we get the same expression but there are some differences)

$$(A + \underset{\substack{\downarrow \\ n \times 1}}{\underline{u}} \underset{\substack{\downarrow \\ (1 \times 1)^T = 1 \times n}}{\underline{u}^T})^{-1} = A^{-1} - \frac{A^{-1} \underline{u} \underline{u}^T A^{-1}}{1 + \underline{u}^T A^{-1} \underline{u}}$$

X matrix when i^{th} row is removed $= X_{(i)}$.

$$[X_{(i)}^T X_{(i)}]^{-1} = (X^T X - X_i^T X_i)^{-1} \quad \text{--- (1)}$$

$$X^T Y = X_{(i)}^T Y_{(i)} + X_i^T y_i$$

$$\Rightarrow X_{(i)}^T Y_{(i)} = X^T Y - X_i^T y_i$$

$$\begin{aligned} e_{(i)} &= y_i - \hat{y}_{(i)} \\ &= y_i - \underline{x}_i^T \hat{\beta}_{(i)} \\ &= y_i - \underline{x}_i^T [X_{(i)}^T X_{(i)}]^{-1} X_{(i)}^T Y_{(i)} \\ &= y_i - \underline{x}_i^T \left[(X^T X)^{-1} + \frac{(X^T X)^{-1} \underline{x}_i \underline{x}_i^T (X^T X)^{-1}}{1 - \underline{x}_i^T (X^T X)^{-1} \underline{x}_i} \right] X_{(i)}^T Y_{(i)} \end{aligned}$$

$$= y_i - \underline{x}_i^T \left[(X^T X)^{-1} + \frac{(X^T X)^{-1} \underline{x}_i \underline{x}_i^T (X^T X)^{-1}}{1 - h_{ii}} \right] X_{(i)}^T Y_{(i)}$$

$$= \left[(1 - h_{ii}) y_i - \underline{x}_i^T (X^T X)^{-1} X_{(i)}^T Y_{(i)} (1 - h_{ii}) - (\underline{x}_i^T (X^T X)^{-1} \underline{x}_i) \underline{x}_i^T (X^T X)^{-1} X_{(i)}^T Y_{(i)} \right]$$

$$= \left[\frac{(1 - h_{ii}) y_i - \underline{x}_i^T (X^T X)^{-1} X_{(i)}^T Y_{(i)}}{1 - h_{ii}} \right]$$

$$= \frac{(1 - h_{ii}) y_i - \underline{x}_i^T (X^T X)^{-1} [X^T Y - X_i^T y_i]}{1 - h_{ii}}$$

$$= \frac{(1 - h_{ii}) y_i - \underline{x}_i^T \hat{\beta} + h_{ii} y_i}{1 - h_{ii}}$$

$$= \frac{(y_i - \hat{y}_i)}{1 - h_{ii}} = \frac{e_i}{1 - h_{ii}}$$

When all data are used then

$$\hat{\sigma}^2 = \frac{SS_{Res}}{n - k - 1} = MS_{Res}$$

When the i^{th} observation is removed then

$$\hat{\sigma}^2 = s_{(i)}^2 = \frac{(n - k - 1) MS_{Res} - \frac{e_i^2}{1 - h_{ii}}}{n - k - 2}$$

For proof see C.8 Montgomery

Test that i^{th} observation is an outlier
 $H_0: \mu = 0$
 $H_1: \mu \neq 0$

$$y_i - \hat{y}_i = e_{(i)} \sim N\left(0, \frac{\sigma^2}{1 - h_{ii}}\right)$$

$$\frac{e_i}{\sqrt{\sigma^2 / (1 - h_{ii})}} \sim N(0, 1)$$

$$\Rightarrow \frac{e_{(i)}}{\sqrt{s_{(i)}^2 / (1 - h_{ii})}} \sim t_{n - k - 2}$$