

Recall, from class notes, that

$$\begin{aligned}\tilde{\sigma}^2 &= \frac{1}{n} \sum_{i=1}^n \hat{u}_i^2 = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{\alpha} - \hat{\beta}X_i)^2 = \frac{1}{n} \sum_{i=1}^n (\alpha - \beta X_i + u_i - \hat{\alpha} - \hat{\beta}X_i)^2 \\ &= \frac{1}{n} \sum_{i=1}^n \left(-(\hat{\alpha} - \alpha) - (\hat{\beta} - \beta)X_i + u_i \right)^2.\end{aligned}$$

Since $\hat{\alpha} = \bar{Y} - \bar{X}\hat{\beta} = \alpha + \bar{X}\beta + \bar{u} - \bar{X}\hat{\beta} = \alpha - (\hat{\beta} - \beta)\bar{X} + \bar{u}$, we have $\hat{\alpha} - \alpha = -(\hat{\beta} - \beta)\bar{X} + \bar{u}$.

Then,

$$\begin{aligned}\tilde{\sigma}^2 &= \frac{1}{n} \sum_{i=1}^n \left((\hat{\beta} - \beta)\bar{X} - \bar{u} - (\hat{\beta} - \beta)X_i + u_i \right)^2 \\ &= \frac{1}{n} \sum_{i=1}^n \left(-(\hat{\beta} - \beta)(X_i - \bar{X}) + (u_i - \bar{u}) \right)^2 \\ &= \frac{1}{n} \sum_{i=1}^n \left((\hat{\beta} - \beta)^2(X_i - \bar{X})^2 + (u_i - \bar{u})^2 - 2(\hat{\beta} - \beta)(X_i - \bar{X})(u_i - \bar{u}) \right) \\ &= (\hat{\beta} - \beta)^2 \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 + \frac{1}{n} \sum_{i=1}^n (u_i - \bar{u})^2 - 2(\hat{\beta} - \beta) \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})(u_i - \bar{u}).\end{aligned}$$

Since, from class notes, $\hat{\beta} - \beta = \frac{\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})(u_i - \bar{u})}{\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2}$, we have that

$$2(\hat{\beta} - \beta) \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})(u_i - \bar{u}) = 2(\hat{\beta} - \beta)^2 \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2.$$

Then,

$$\tilde{\sigma}^2 = (\hat{\beta} - \beta)^2 \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 + \frac{1}{n} \sum_{i=1}^n (u_i - \bar{u})^2 - 2(\hat{\beta} - \beta)^2 \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2.$$

In class, we obtained that

$$\begin{aligned}E \left((\hat{\beta} - \beta)^2 \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 | X_1, \dots, X_n \right) &= \frac{\sigma^2}{n}, \text{ and} \\ E \left(\frac{1}{n} \sum_{i=1}^n (u_i - \bar{u})^2 | X_1, \dots, X_n \right) &= \sigma^2 - \frac{\sigma^2}{n}.\end{aligned}$$

Therefore,

$$E(\tilde{\sigma}^2 | X_1, \dots, X_n) = \frac{\sigma^2}{n} + \sigma^2 - \frac{\sigma^2}{n} - 2 \frac{\sigma^2}{n} = \sigma^2 \left(\frac{n-2}{n} \right). \quad (1)$$

Hence, we define the unbiased estimator

$$\hat{\sigma}^2 = \frac{1}{n-2} \sum_{i=1}^n \hat{u}_i^2 = \frac{n-1}{n-2} \frac{1}{n} \sum_{i=1}^n \hat{u}_i^2 = \frac{n-1}{n-2} \tilde{\sigma}^2.$$

Then, using (1)

$$E(\hat{\sigma}^2 | X_1, \dots, X_n) = \frac{n-1}{n-2} E(\tilde{\sigma}^2 | X_1, \dots, X_n) = \frac{n-1}{n-2} \sigma^2 \left(\frac{n-2}{n} \right) = \sigma^2.$$

Also, by the Law of Iterated Expectations,

$$E(E(\hat{\sigma}^2 | X_1, \dots, X_n)) = E(\hat{\sigma}^2) = \sigma^2.$$