

GOODNESS OF FIT (PT. 2)

We are considering the simple linear model $Y_i = \beta_1 + \beta_2 x_i + \varepsilon_i$, $\varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$ and the system of hypotheses

$$\begin{cases} H_0: \text{the model does not help to explain the variability of } Y \\ H_1: \text{the model helps to explain the variability of } Y \end{cases}$$

which can be expressed in terms of the coefficient R^2 as

$$\begin{cases} H_0: R^2 = 0 \\ H_1: R^2 > 0 \end{cases}$$

We have seen that we can use the test statistic $(n-2)R^2 / (1-R^2)$, which, under H_0 , has an $F_{2,n-2}$ distribution.

$$\begin{aligned} F &= \frac{R^2}{1-R^2} \cdot (n-2) = \frac{\text{SSR}}{\text{SSE}} (n-2) = \\ &= \left(\frac{\text{SST}}{\text{SSE}} - 1 \right) (n-2) = \\ &= \left(\frac{\sum_{i=1}^n (Y_i - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2} - 1 \right) (n-2) = \\ &= \frac{\sum_{i=1}^n \hat{\varepsilon}_i^2 - \sum_{i=1}^n \hat{\beta}_2^2}{\sum_{i=1}^n \hat{\beta}_2^2} (n-2) \stackrel{H_0}{\sim} F_{2,n-2} \end{aligned}$$

In the case of the SIMPLE linear model, we can prove this result

Preliminary result:

If $T \sim t_n$, and $V = T^2$ then $V \sim F_{2,n}$

PROOF FOR THE CASE OF SIMPLE LM: distribution of F

$$\text{Let's start from } \frac{\text{SSR}}{\text{SSE}} = \frac{\sum_{i=1}^n \hat{\varepsilon}_i^2}{\sum_{i=1}^n \hat{\beta}_2^2} \quad \text{with } \hat{\varepsilon}_i^2 = Y_i - \bar{Y}, \quad \hat{\beta}_2^2 = Y_i - \hat{Y}_i$$

Now, notice that we can write

$$\begin{aligned} \sum_{i=1}^n \hat{\varepsilon}_i^2 &= \sum_{i=1}^n (Y_i - \hat{B}_2 - \hat{B}_2 x_i)^2 = \sum_{i=1}^n (Y_i - \bar{Y} + \hat{B}_2 \bar{x} - \hat{B}_2 x_i)^2 = \\ &= \sum_{i=1}^n [(Y_i - \bar{Y}) - \hat{B}_2(x_i - \bar{x})]^2 = \\ &= \sum_{i=1}^n (Y_i - \bar{Y})^2 + \hat{B}_2^2 \sum_{i=1}^n (x_i - \bar{x})^2 - 2 \hat{B}_2 \sum_{i=1}^n (Y_i - \bar{Y})(x_i - \bar{x}) \quad \rightarrow -\hat{B}_2 \frac{\sum_{i=1}^n (Y_i - \bar{Y})(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \cdot \sum_{i=1}^n (x_i - \bar{x})^2 = \\ &= \sum_{i=1}^n (Y_i - \bar{Y})^2 - \hat{B}_2^2 \sum_{i=1}^n (x_i - \bar{x})^2 \\ &\quad \hat{\varepsilon}_i^2 = \end{aligned}$$

$$\Rightarrow \sum_{i=1}^n \hat{\varepsilon}_i^2 = \sum_{i=1}^n \hat{\varepsilon}_i^2 - \hat{B}_2^2 \sum_{i=1}^n (x_i - \bar{x})^2$$

$$\Rightarrow \sum_{i=1}^n \hat{\varepsilon}_i^2 = \sum_{i=1}^n \hat{\varepsilon}_i^2 + \hat{B}_2^2 \sum_{i=1}^n (x_i - \bar{x})^2$$

Moreover, recall that

$$V(\hat{B}_2) = \frac{\sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad ; \quad \hat{V}(\hat{B}_2) = \frac{S^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad ; \quad \frac{(n-2)S^2}{\sigma^2} \sim \chi^2_{n-2}$$

Going now back to the test statistic

$$\begin{aligned} \frac{R^2}{1-R^2} &= \frac{\sum_{i=1}^n \hat{\varepsilon}_i^2}{\sum_{i=1}^n \hat{\beta}_2^2} - 1 = \frac{\sum_{i=1}^n \hat{\varepsilon}_i^2 + \hat{B}_2^2 \sum_{i=1}^n (x_i - \bar{x})^2}{\sum_{i=1}^n \hat{\beta}_2^2} - 1 = \\ &= \cancel{+} + \frac{\hat{B}_2^2 \sum_{i=1}^n (x_i - \bar{x})^2}{\sum_{i=1}^n \hat{\varepsilon}_i^2} \cancel{-} = \\ &= \frac{\hat{B}_2^2 \sum_{i=1}^n (x_i - \bar{x})^2}{(n-2)S^2} = \quad \sum_{i=1}^n \hat{\varepsilon}_i^2 = \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 = \\ &= \frac{\hat{B}_2^2 \cdot \frac{1}{\sigma^2}}{\left(\frac{(n-2)S^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \right) \cdot \frac{1}{\sigma^2}} = \quad = n \sum_{i=1}^n \hat{\varepsilon}_i^2 = (n-2)S^2 \\ &= \frac{\hat{B}_2^2}{\left(\frac{(n-2)S^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \right)} \cdot \frac{1}{\sigma^2} = \\ &= \frac{\hat{B}_2^2}{\left(\frac{(n-2)S^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \right)} \cdot \frac{1}{\sigma^2} \cdot \frac{1}{(n-2)} = \quad \text{where } \hat{B}_2 \stackrel{H_0}{\sim} N(0, 1)^2 \\ &= \frac{\hat{B}_2^2}{\text{var}(\hat{B}_2)} \cdot \frac{1}{(n-2)} = \frac{\hat{B}_2^2}{\frac{(n-2)S^2}{\sigma^2} \cdot \frac{1}{(n-2)}} \cdot \frac{1}{(n-2)} = \quad \text{var}(\hat{B}_2) = \frac{(n-2)S^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \\ &= \frac{\hat{B}_2^2}{\frac{(n-2)S^2}{\sigma^2}} \cdot \frac{1}{(n-2)} = \quad \text{var}(\hat{B}_2) \sim \frac{\chi^2_{n-2}}{n-2} \\ &= \frac{\hat{B}_2^2}{\frac{(n-2)S^2}{\sigma^2}} \cdot \frac{1}{(n-2)} = \quad \text{var}(\hat{B}_2) \sim \frac{\chi^2_{n-2}}{n-2} = T^2 \cdot \frac{1}{n-2} \end{aligned}$$

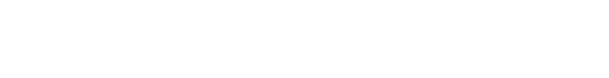
$$\text{where } T = \frac{\hat{B}_2 \sqrt{\sum_{i=1}^n (x_i - \bar{x})^2}}{\sqrt{S^2}} = \frac{\hat{B}_2}{\sqrt{\frac{S^2}{\sum_{i=1}^n (x_i - \bar{x})^2}}} = \frac{\hat{B}_2}{\sqrt{\text{var}(\hat{B}_2)}} \stackrel{H_0}{\sim} t_{n-2}$$

$$\Rightarrow F = \frac{R^2}{1-R^2} \cdot (n-2) = T^2 \stackrel{H_0}{\sim} F_{1,n-2}$$

So, we have derived the distribution of the test statistic (in the case of simple lm).

Remark: connection with the p-value of the test $H_0: \beta_2 = 0$ vs $H_1: \beta_2 \neq 0$

$$\begin{aligned} P_{H_0}(F > f_{\text{obs}}) &= P_{H_0}(T^2 \geq (t_{\text{obs}})^2) \\ &= P_{H_0}(|T| \geq |t_{\text{obs}}|) \\ &= 2 P_{H_0}(T \geq |t_{\text{obs}}|) \stackrel{H_0}{\sim} T \sim t_{n-2} \end{aligned}$$



where T is exactly the test statistic we derived to test β_2