

Understanding the F-Test

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1 F-Distribution

Definition 1. Suppose $X_1, \dots, X_n \sim \mathcal{N}(\mu_X, \sigma_X^2)$ and $Y_1, \dots, Y_m \sim \mathcal{N}(\mu_Y, \sigma_Y^2)$. Then the random variable,

$$F = \frac{S_X^2/\sigma_X^2}{S_Y^2/\sigma_Y^2}$$

where $S_X^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$ and $S_Y^2 = \frac{1}{m-1} \sum_{i=1}^m (Y_i - \bar{Y})^2$. This random variable then has F distribution with $n-1$ and $m-1$ degrees of freedom.

Remark 2. Equivalently we can write,

$$F = \frac{X/d_1}{Y/d_2}$$

where $X \sim \chi_{d_1}^2$ and $Y \sim \chi_{d_2}^2$.

2 F-Test under Homoscedasticity

Suppose now that we consider the regression,

$$Y = X'\beta_0 + \epsilon$$

where $X \in \mathbb{R}^{k \times n}$ and $Y \in \mathbb{R}^n$. Under homoscedasticity we are well aware of the fact that,

$$\text{Var}(\hat{\beta}_{OLS}) = \sigma^2 (X'X)^{-1}$$

Furthermore, we know,

$$\sqrt{n} (\hat{\beta}_{OLS} - \beta_0) \sim N(0, \sigma^2 (XX)^{-1})$$

Define the linear transformation,

$$r(\beta) = R'\beta$$

where $R \in \mathbb{R}^{k \times q}$ which represents the k covariates in the above linear regression and q linear restrictions.

Consider the hypothesis test,

$$H_0 : R'\beta = \theta_0 \longleftrightarrow H_1 : R'\beta \neq \theta_0$$

By the delta method we have that,

$$R'(\hat{\beta}_{OLS} - \beta_0) \sim N(0, R'\sigma^2 (XX)^{-1} R)$$

So we have,

$$A = \frac{[R'(X'X)^{-1}R]^{-1/2}}{\sigma^2} R'(\hat{\beta}_{OLS} - \beta_0) \sim N(0, I_{q \times q})$$

Claim 3. In the model defined above,

$$B = (n - k) \frac{\hat{\sigma}^2}{\sigma^2} \sim \chi_{n-k}^2$$

where $\hat{\sigma}^2 = yM_X y / (n - k)$ is the unbiased error variance estimator.

Proof. Define the residuals as,

$$\hat{\epsilon} = y - X\beta'$$

Note we can define these with the residual maker matrix,

$$\hat{\epsilon} = M_X y = M_x (X\beta + \epsilon) = M_x \epsilon \equiv (I - X(X'X)^{-1}) \epsilon$$

Notice that,

$$\text{tr}(M_x) = n - k$$

This is obvious because of the diagonalization,

$$D = Q^T M_x Q = \text{diag}(1, \dots, 1, 0, \dots, 0)$$

Using the fact that,

$$\hat{\epsilon} \sim N(0, \sigma^2 M_x)$$

we have that by delta method,

$$Q\hat{\epsilon} \sim N(0, \sigma^2 D)$$

So clearly,

$$\frac{\|Q\hat{\epsilon}\|^2}{\sigma^2} \sim \chi_{n-k}^2$$

And to complete the proof notice that

$$\hat{\sigma}^2 = \frac{1}{n - k} \sum_i (y_i - x_i \hat{\beta})^2 = \hat{\epsilon}' M_X \hat{\epsilon} = [Q\hat{\epsilon}]^2$$

So we have,

$$\frac{\|Q\hat{\epsilon}\|^2}{\sigma^2} = \frac{\hat{\sigma}^2}{\sigma^2}$$

where we know that χ^2 has $n - k$ degree because $\text{tr}(M_x) = n - k$ as the trace is equal to the rank of the matrix. \square

Now we can put this all together to get the **F-Statistic**,

$$F = \frac{A'A/q}{B/(n - k)} = \frac{R'(\hat{\beta}_{OLS} - \beta_0) \left[R'(X'X)^{-1} R \right]^{-1} R'(\hat{\beta}_{OLS} - \beta_0) / q}{\hat{\sigma}^2} \sim F_{q, n-k}$$

By definition of the F-distribution.

The F-statistic is often written as,

$$F = \frac{(TSS - RSS) / q}{RSS / (n - k)}$$

It is easy to see the equivalence in the denominator as,

$$RSS = yM_x y$$

Also define,

$$\begin{aligned} TSS &= y^T \left(I - \frac{1}{n} \right) y \\ ESS &= y^T \left(X'(X'X)^{-1} X^T - \frac{1}{n} \right) y \end{aligned}$$

We know that if $\theta_0 = 0$ we have,

$$\frac{ESS}{\sigma^2} = \frac{y^T \left(X' (X'X)^{-1} X^T - \frac{1}{n} \right) y}{\sigma^2} \sim \chi_{q-1}^2$$

and,

$$\frac{ESS}{\sigma^2} = TSS - RSS$$

so it is easy to see that the usual formulation satisfies the F-distribution.

2.1 Asymptotic Power