

A multiple linear regression that describes the variation in the variable y in terms of the k (explanatory) variables x_1, x_2, \dots, x_k has the form

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \varepsilon.$$

- $\beta_0, \beta_1, \dots, \beta_k$ are population parameters.
- Assumptions about the model include
 - (i) The error ε has a normal distribution with mean 0 for each fixed set of values $x_1 = \xi_1, x_2 = \xi_2, \dots, x_k = \xi_k$.
 - (ii) The error is independent of the x_j s, so the standard deviation of ε is fixed. I.e., $\varepsilon \sim N(0, \sigma^2)$. (Homoskedasticity)
- These assumptions imply that

$$E(y|x_1 = \xi_1, x_2 = \xi_2, \dots, x_k = \xi_k) = \beta_0 + \beta_1 \xi_1 + \beta_2 \xi_2 + \dots + \beta_k \xi_k,$$

where $E(y|x_1 = \xi_1, x_2 = \xi_2, \dots, x_k = \xi_k)$ is the *expected (mean) y value* for all observations satisfying $x_1 = \xi_1, x_2 = \xi_2, \dots, x_k = \xi_k$.

Using sample data, we compute the estimated regression equation

$$\hat{y}_i = b_0 + b_1x_1 + b_2x_2 + \cdots + b_kx_k.$$

- The sample coefficients b_0, b_1, \dots, b_k are sample statistics (that estimate the population coefficients β_0, \dots, β_k). As such, b_0, \dots, b_k are all random variables, and the assumptions above imply that they all have *normal* distributions. In particular...

... for each i between 0 and k :

$$\frac{b_i - \beta_i}{SE(b_i)} \sim t\text{-distribution, with } n - (k + 1) \text{ d.f.}$$

We can use this to test individual coefficients for statistical significance:

$$H_0 : \beta_i = 0 \quad \text{vs.} \quad H_a : \beta_i \neq 0.$$

Rejecting H_0 means that there is significant linear correlation between x_i and y , and b_i is a reliable measure of the *marginal change* in y for a one-unit change in x_i , assuming that all other variables are held fixed.

We can also test the *overall significance* of the regression:

$$H_0 : \beta_1 = \beta_2 = \cdots = \beta_k = 0$$

$H_a : \beta_j \neq 0$, for at least one j between 1 and k .

The test statistic is

$$F^* = \frac{MSS_m}{MSS_e} = \frac{(\sum(\hat{y}_i - \bar{y})^2)/k}{(\sum(y_i - \hat{y}_i)^2)/(n - k + 1)}$$

which follows the ***F-distribution with k numerator d.f. and $n - k + 1$ denominator d.f.***

H_0 is rejected at the α level of significance if $F^* > F_\alpha$ (the critical F -value). Alternatively, reject H_0 if the P -value, $Prob(F > F^*)$, is smaller than α .

Comments:

1. For a *simple regression* $\bar{y}(x) = \beta_0 + \beta_1 x$, testing $H_0 : \beta_1 = 0$ (*t*-test) yields the same conclusion as the *F*-test for overall significance.
2. Most software packages (including JMP) compute the *t*-scores for all of the regression coefficients and their *p*-values, as well as the *F*-score of overall significance and its *p*-value.
3. One can also test other hypotheses about individual coefficients, e.g.,

$$H_0 : \beta_3 = 2 \text{ vs. } H_a : \beta_3 < 2.$$

With this null hypothesis,

$$\frac{b_3 - 2}{SE(b_3)} \sim t\text{-distribution, with } n - (k + 1) \text{ d.f.,}$$

and the mechanics of the test are the same as any other *t*-test.

Example: Estimating weight with a measuring tape.

Response variable: weight (lbs). Effect variables: waist circumference (cm), height (inches), age (years), arm circumference (cm).



