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# INFERENCE IN ORDINARY LEAST SQUARES

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## 7.0 What We Need to Know When We Finish This Chapter

This chapter addresses the question of how accurately we can estimate the values of  $\beta$  and  $\alpha$  from  $b$  and  $a$ . Regression produces an estimate of the standard deviation of  $\varepsilon_i$ . This, in turn, serves as the basis for estimates of

the standard deviations of  $b$  and  $a$ . With these, we can construct confidence intervals for  $\beta$  and  $\alpha$  and test hypotheses about their values. Here are the essentials.

1. **Section 7.1:** We assume that the true distributions of  $b$  and  $a$  are the normal. Because we have to estimate their variances in order to standardize them, however, we have to treat their standardized versions as having  $t$ -distributions if our samples are small.
2. **Section 7.2:** *Degrees of freedom* count the number of independent observations that remain in the sample after accounting for the sample statistics that we've already calculated.
3. **Equation (7.3), section 7.2:** The ordinary least squares (OLS) estimator for  $\sigma^2$ , the variance of  $\varepsilon_i$ , is

$$s^2 = \frac{\sum_{i=1}^n e_i^2}{n-2}.$$

4. **Equation (7.9), section 7.3:** The  $(1 - \alpha)\%$  confidence interval for  $\beta$  is

$$1 - \alpha = \mathbb{P} \left( b - t_{\alpha/2}^{(n-2)} \sqrt{\frac{s^2}{\sum_{i=1}^n (x_i - \bar{x})^2}} < \beta < b + t_{\alpha/2}^{(n-2)} \sqrt{\frac{s^2}{\sum_{i=1}^n (x_i - \bar{x})^2}} \right).$$

5. **Section 7.3:** Larger samples and greater variation in  $x_i$  yield narrower confidence intervals. So does smaller  $\sigma^2$ , but we can't control that.
6. **Equation (7.16), section 7.4:** The two-tailed hypothesis test for  $H_0 : \beta = \beta_0$  is

$$1 - \alpha = \mathbb{P} \left( \beta_0 - t_{\alpha/2}^{(n-2)} \sqrt{\frac{s^2}{\sum_{i=1}^n (x_i - \bar{x})^2}} < b < \beta_0 + t_{\alpha/2}^{(n-2)} \sqrt{\frac{s^2}{\sum_{i=1}^n (x_i - \bar{x})^2}} \right).$$

The alternative hypothesis is  $H_1 : \beta \neq \beta_0$ .

7. **Section 7.4:** The test of the null hypothesis  $H_0 : \beta = 0$  is always interesting because, if true, it means that  $x_i$  doesn't affect  $y_i$ .

8. **Equation (7.26), section 7.4:** The upper-tailed hypothesis test for  $H_0 : \beta = \beta_0$  is

$$1 - \alpha = P \left( b < \beta_0 + t_{\alpha}^{(n-2)} \sqrt{\frac{s^2}{\sum_{i=1}^n (x_i - \bar{x})^2}} \right).$$

9. **Section 7.5:** The best linear unbiased estimator of  $E(y_0)$  is  $\hat{y}_0 = a + bx_0$ .
10. **Section 7.5:** Predictions are usually more reliable if they are based on larger samples and made for values of the explanatory variable that are similar to those that appear in the sample.