

## The Elements of a Statistical Test

1. Null hypothesis,  $H_0$
2. Alternative hypothesis,  $H_a$
3. Test statistic
4. Rejection region

### DEFINITION 10.1

A *type I error* is made if  $H_0$  is rejected when  $H_0$  is true. The *probability of a type I error* is denoted by  $\alpha$ . The value of  $\alpha$  is called the *level* of the test.

A *type II error* is made if  $H_0$  is accepted when  $H_a$  is true. The *probability of a type II error* is denoted by  $\beta$ .

## Large-Sample $\alpha$ -Level Hypothesis Tests

$$H_0 : \theta = \theta_0.$$

$$H_a : \begin{cases} \theta > \theta_0 & \text{(upper-tail alternative).} \\ \theta < \theta_0 & \text{(lower-tail alternative).} \\ \theta \neq \theta_0 & \text{(two-tailed alternative).} \end{cases}$$

$$\text{Test statistic: } Z = \frac{\hat{\theta} - \theta_0}{\sigma_{\hat{\theta}}}.$$

$$\text{Rejection region: } \begin{cases} \{z > z_\alpha\} & \text{(upper-tail RR).} \\ \{z < -z_\alpha\} & \text{(lower-tail RR).} \\ \{|z| > z_{\alpha/2}\} & \text{(two-tailed RR).} \end{cases}$$

the probability  $\beta$  of a type II error is

$$\beta = P(\hat{\theta} \text{ is not in RR when } H_a \text{ is true})$$

$$= P(\hat{\theta} \leq k \text{ when } \theta = \theta_a) = P\left(\frac{\hat{\theta} - \theta_a}{\sigma_{\hat{\theta}}} \leq \frac{k - \theta_a}{\sigma_{\hat{\theta}}} \text{ when } \theta = \theta_a\right).$$

## Sample Size for an Upper-Tail $\alpha$ -Level Test

$$n = \frac{(z_\alpha + z_\beta)^2 \sigma^2}{(\mu_a - \mu_0)^2}$$

### DEFINITION 10.2

If  $W$  is a test statistic, the *p-value*, or *attained significance level*, is the smallest level of significance  $\alpha$  for which the observed data indicate that the null hypothesis should be rejected.

RR:  $\{w \leq k\}$ —the  $p$ -value associated with an observed value  $w_0$  of  $W$  is given by

$$p\text{-value} = P(W \leq w_0, \text{ when } H_0 \text{ is true}).$$

Analogously, if we were to reject  $H_0$  in favor of  $H_a$  for large values of  $W$ —say, RR:  $\{w \geq k\}$ —the  $p$ -value associated with the observed value  $w_0$  is

$$p\text{-value} = P(W \geq w_0, \text{ when } H_0 \text{ is true}).$$

### A Small-Sample Test for $\mu$

Assumptions:  $Y_1, Y_2, \dots, Y_n$  constitute a random sample from a normal distribution with  $E(Y_i) = \mu$ .

$$H_0: \mu = \mu_0.$$

$$H_a: \begin{cases} \mu > \mu_0 & \text{(upper-tail alternative).} \\ \mu < \mu_0 & \text{(lower-tail alternative).} \\ \mu \neq \mu_0 & \text{(two-tailed alternative).} \end{cases}$$

$$\text{Test statistic: } T = \frac{\bar{Y} - \mu_0}{S/\sqrt{n}}.$$

$$\text{Rejection region: } \begin{cases} t > t_\alpha & \text{(upper-tail RR).} \\ t < -t_\alpha & \text{(lower-tail RR).} \\ |t| > t_{\alpha/2} & \text{(two-tailed RR).} \end{cases}$$

(See Table 5, Appendix 3, for values of  $t_\alpha$ , with  $\nu = n - 1$  df.)

### Small-Sample Tests for Comparing Two Population Means

Assumptions: Independent samples from normal distributions with  $\sigma_1^2 = \sigma_2^2$ .

$$H_0: \mu_1 - \mu_2 = D_0.$$

$$H_a: \begin{cases} \mu_1 - \mu_2 > D_0 & \text{(upper-tail alternative).} \\ \mu_1 - \mu_2 < D_0 & \text{(lower-tail alternative).} \\ \mu_1 - \mu_2 \neq D_0 & \text{(two-tailed alternative).} \end{cases}$$

$$\text{Test statistic: } T = \frac{\bar{Y}_1 - \bar{Y}_2 - D_0}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}, \text{ where } S_p = \sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}}.$$

$$\text{Rejection region: } \begin{cases} t > t_\alpha & \text{(upper-tail RR).} \\ t < -t_\alpha & \text{(lower-tail RR).} \\ |t| > t_{\alpha/2} & \text{(two-tailed RR).} \end{cases}$$

Here,  $P(T > t_\alpha) = \alpha$  and degrees of freedom  $\nu = n_1 + n_2 - 2$ . (See Table 5, Appendix 3.)

## Test of Hypotheses Concerning a Population Variance ← equivalent for $\sigma$

Assumptions:  $Y_1, Y_2, \dots, Y_n$  constitute a random sample from a normal distribution with

$$E(Y_i) = \mu \quad \text{and} \quad V(Y_i) = \sigma^2.$$

$$H_0: \sigma^2 = \sigma_0^2$$

$$H_a: \begin{cases} \sigma^2 > \sigma_0^2 & \text{(upper-tail alternative).} \\ \sigma^2 < \sigma_0^2 & \text{(lower-tail alternative).} \\ \sigma^2 \neq \sigma_0^2 & \text{(two-tailed alternative).} \end{cases}$$

$$H_0: \sigma = \sigma_0$$

$$\Leftrightarrow H_0: \sigma^2 = \sigma_0^2$$

$$\text{Test statistic: } \chi^2 = \frac{(n-1)S^2}{\sigma_0^2}.$$

$$\text{Rejection region: } \begin{cases} \chi^2 > \chi_{\alpha}^2 & \text{(upper-tail RR).} \\ \chi^2 < \chi_{1-\alpha}^2 & \text{(lower-tail RR).} \\ \chi^2 > \chi_{\alpha/2}^2 \text{ or } \chi^2 < \chi_{1-\alpha/2}^2 & \text{(two-tailed RR).} \end{cases}$$

Notice that  $\chi_{\alpha}^2$  is chosen so that, for  $\nu = n - 1$  df,  $P(\chi^2 > \chi_{\alpha}^2) = \alpha$ .  
(See Table 6, Appendix 3.)

### DEFINITION 10.3

Suppose that  $W$  is the test statistic and RR is the rejection region for a test of a hypothesis involving the value of a parameter  $\theta$ . Then the *power* of the test, denoted by  $\text{power}(\theta)$ , is the probability that the test will lead to rejection of  $H_0$  when the actual parameter value is  $\theta$ . That is,

$$\text{power}(\theta) = P(W \text{ in RR when the parameter value is } \theta).$$

$$\text{Power}(\theta_0) = \alpha = P(W \text{ in RR when } \theta = \theta_0)$$

### Relationship Between Power and $\beta$

If  $\theta_a$  is a value of  $\theta$  in the alternative hypothesis  $H_a$ , then

$$\text{power}(\theta_a) = 1 - \beta(\theta_a).$$

### DEFINITION 10.4

If a random sample is taken from a distribution with parameter  $\theta$ , a hypothesis is said to be a *simple hypothesis* if that hypothesis *uniquely specifies* the distribution of the population from which the sample is taken. Any hypothesis that is not a simple hypothesis is called a *composite hypothesis*.

**THEOREM 10.1**

**The Neyman–Pearson Lemma** Suppose that we wish to test the simple null hypothesis  $H_0 : \theta = \theta_0$  versus the simple alternative hypothesis  $H_a : \theta = \theta_a$ , based on a random sample  $Y_1, Y_2, \dots, Y_n$  from a distribution with parameter  $\theta$ . Let  $L(\theta)$  denote the likelihood of the sample when the value of the parameter is  $\theta$ . Then, for a given  $\alpha$ , the test that maximizes the power at  $\theta_a$  has a rejection region, RR, determined by

$$\frac{L(\theta_0)}{L(\theta_a)} < k.$$

The value of  $k$  is chosen so that the test has the desired value for  $\alpha$ . Such a test is a most powerful  $\alpha$ -level test for  $H_0$  versus  $H_a$ .

**A Likelihood Ratio Test**

Define  $\lambda$  by

$$\lambda = \frac{L(\hat{\Omega}_0)}{L(\hat{\Omega})} = \frac{\max_{\Theta \in \Omega_0} L(\Theta)}{\max_{\Theta \in \Omega} L(\Theta)}.$$

A likelihood ratio test of  $H_0 : \Theta \in \Omega_0$  versus  $H_a : \Theta \in \Omega_a$  employs  $\lambda$  as a test statistic, and the rejection region is determined by  $\lambda \leq k$ .