

## 37. Normal Mean Tests (variance known)

Simple Hypothesis Test

Example

$p$ -Value

Designing a Test

Example

Two-Sample Hypothesis Test

Example

## Simple Hypothesis Test

Suppose that  $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Nor}(\mu, \sigma^2)$ , where  $\sigma^2$  is somehow *known* (not very realistic).

Two-sided test:

$$H_0 : \mu = \mu_0$$

$$H_1 : \mu \neq \mu_0$$

We'll use  $\bar{X}$  to estimate  $\mu$ . If  $\bar{X}$  is “significantly different” than  $\mu_0$ , then we'll reject  $H_0$ . How much is “significantly different”?

Define

$$Z_0 \equiv \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}}.$$

If  $H_0$  is true, then  $Z_0 \sim \text{Nor}(0, 1)$ , in which case

$$\Pr(-z_{\alpha/2} \leq Z_0 \leq z_{\alpha/2}) = 1 - \alpha.$$

A value of  $Z_0$  outside the interval  $[-z_{\alpha/2}, z_{\alpha/2}]$  is highly unlikely if  $H_0$  is true. Therefore,

$$\text{Reject } H_0 \quad \text{iff} \quad |Z_0| > z_{\alpha/2}.$$

This assures us that

$$\Pr(\text{Type I error}) = \Pr(\text{Reject } H_0 \mid H_0 \text{ true}) = \alpha.$$

If  $|Z_0| > z_{\alpha/2}$ , then we're in the **rejection region**.  
(Also called **critical region**.)

If  $|Z_0| \leq z_{\alpha/2}$ , then we're in the **acceptance region**.

One-sided test:

$$H_0 : \mu \leq \mu_0$$

$$H_1 : \mu > \mu_0$$

A value of  $Z_0 = (\bar{X} - \mu_0)/(\sigma/\sqrt{n})$  outside the interval  $(-\infty, z_\alpha]$  is highly unlikely if  $H_0$  is true. Therefore,

$$\text{Reject } H_0 \quad \text{iff} \quad Z_0 > z_\alpha.$$

If  $Z_0 > z_\alpha$ , this suggests  $\mu > \mu_0$ .

The other one-sided test:

$$H_0 : \mu \geq \mu_0$$

$$H_1 : \mu < \mu_0$$

A value of  $Z_0$  outside the interval  $[-z_\alpha, \infty)$  is highly unlikely if  $H_0$  is true. Therefore,

$$\text{Reject } H_0 \quad \text{iff} \quad Z_0 < -z_\alpha.$$

If  $Z_0 < -z_\alpha$ , this suggests  $\mu < \mu_0$ .

**Example:** We examine the weights of 25 nine-year-old kids. Suppose we somehow know that the weights are normally distributed with  $\sigma = 4$ . The sample mean of the 25 weights is 42.

Test the hypothesis that the mean weight is 40. Keep the probability of Type I error = 0.05.

$$H_0 : \mu = \mu_0$$

$$H_1 : \mu \neq \mu_0$$

Here we have

$$Z_0 = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}} = \frac{42 - 40}{4/\sqrt{25}} = 2.5.$$

Since  $|Z_0| = 2.5 > z_{\alpha/2} = z_{.025} = 1.96$ , we *reject*  $H_0$ .

Notice that a lower  $\alpha$  results in a higher  $z_{\alpha/2}$ . Then it's "harder" to reject  $H_0$ .

Example: If  $\alpha = 0.01$ , then  $z_{.005} = 2.58$ , and we *fail to reject*  $H_0$  in the above example.

Definition: The ***p*-value** of a test is the smallest level of significance  $\alpha$  that would lead to rejection of  $H_0$ .

For the two-sided normal mean test with known variance, we reject  $H_0$  iff

$$|Z_0| > z_{\alpha/2} = \Phi^{-1}(1 - \alpha/2)$$

$$\text{iff } \Phi(|Z_0|) > 1 - \alpha/2$$

$$\text{iff } \alpha > 2(1 - \Phi(|Z_0|)).$$

Thus, for the two-sided test

$$H_0 : \mu = \mu_0$$

$$H_1 : \mu \neq \mu_0$$

the  $p$ -value is  $2(1 - \Phi(|Z_0|))$ .

Similarly, for the one-sided test

$$H_0 : \mu \leq \mu_0$$

$$H_1 : \mu > \mu_0$$

$$p = 1 - \Phi(Z_0).$$

Finally, for the one-sided test

$$H_0 : \mu \geq \mu_0$$

$$H_1 : \mu < \mu_0$$

we have  $p = \Phi(Z_0)$ .

Example: For the previous example,

$$p = 2(1 - \Phi(|Z_0|)) = 2(1 - \Phi(2.5)) = 0.0124.$$

Now we'll discuss how to design a test under constraints involving Type I and Type II errors....

## Test Design

Can we design a two-sided test such that

$$\Pr(\text{Type I error}) = \alpha \quad \text{and}$$

$$\Pr(\text{Type II error} \mid \mu = \mu_1 > \mu_0) = \beta?$$

I.e., can we design a two-sided test that will work when we require a Type I error bound  $\alpha$ , and a Type II prob  $\beta$  (in the special case that the true mean  $\mu$  happens to equal a user-specified value  $\mu_1 > \mu_0$ )?

Suppose the difference between the actual and hypothesized means is

$$\delta \equiv \mu - \mu_0 = \mu_1 - \mu_0.$$

(Without loss of generality, we'll assume  $\mu_1 > \mu_0$ .)

Then it can be shown that the  $\alpha$  and  $\beta$  design requirements can be achieved by taking a sample of size

$$n \approx \sigma^2(z_{\alpha/2} + z_{\beta})^2 / \delta^2.$$

Proof:

$$\begin{aligned}
 \beta &= \Pr(\text{Type II error} \mid \mu = \mu_1 > \mu_0) \\
 &= \Pr(\text{Fail to Reject } H_0 \mid H_0 \text{ false } (\mu = \mu_1 > \mu_0)) \\
 &= \Pr(|Z_0| \leq z_{\alpha/2} \mid \mu = \mu_1) \\
 &= \Pr(-z_{\alpha/2} \leq Z_0 \leq z_{\alpha/2} \mid \mu = \mu_1) \\
 &= \Pr\left(-z_{\alpha/2} \leq \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}} \leq z_{\alpha/2} \mid \mu = \mu_1\right) \\
 &= \Pr\left(-z_{\alpha/2} \leq \frac{\bar{X} - \mu_1}{\sigma/\sqrt{n}} + \frac{\mu_1 - \mu_0}{\sigma/\sqrt{n}} \leq z_{\alpha/2} \mid \mu = \mu_1\right)
 \end{aligned}$$

Notice that

$$Z \equiv \frac{\bar{X} - \mu_1}{\sigma/\sqrt{n}} \sim \text{Nor}(0, 1).$$

This gives

$$\begin{aligned} \beta &= \Pr\left(-z_{\alpha/2} \leq Z + \frac{\sqrt{n}\delta}{\sigma} \leq z_{\alpha/2}\right) \\ &= \Pr\left(-z_{\alpha/2} - \frac{\sqrt{n}\delta}{\sigma} \leq Z \leq z_{\alpha/2} - \frac{\sqrt{n}\delta}{\sigma}\right) \\ &= \Phi\left(z_{\alpha/2} - \frac{\sqrt{n}\delta}{\sigma}\right) - \Phi\left(-z_{\alpha/2} - \frac{\sqrt{n}\delta}{\sigma}\right) \end{aligned}$$

Consider the second term in the previous expression, i.e.,

$$\Phi\left(-z_{\alpha/2} - \frac{\sqrt{n}\delta}{\sigma}\right). \quad (*)$$

First, notice that  $-z_{\alpha/2} \ll 0$ .

Second, since  $\delta > 0$ , we see that  $\sqrt{n}\delta/\sigma < 0$ .

These two facts imply that  $(*) \approx 0$ .

Thus, we only need to use the first term in the previous expression for  $\beta$ :

$$\beta \approx \Phi\left(z_{\alpha/2} - \frac{\sqrt{n}\delta}{\sigma}\right)$$

iff

$$\Phi^{-1}(\beta) = -z_{\beta} \approx z_{\alpha/2} - \frac{\sqrt{n}\delta}{\sigma}$$

iff

$$\frac{\sqrt{n}\delta}{\sigma} \approx z_{\alpha/2} + z_{\beta}$$

iff

$$n \approx \sigma^2(z_{\alpha/2} + z_{\beta})^2/\delta^2.$$

### 9.37 Normal Mean Tests (var known)

Recap: If you want to test  $H_0 : \mu = \mu_0$  vs.  $H_1 : \mu \neq \mu_0$ , and

(1) You know  $\sigma^2$ ,

(2) You want  $\Pr(\text{Type I error}) = \alpha$ , and

(3) You want  $\Pr(\text{Type II error}) = \beta$  if  $\mu = \mu_1 (\neq \mu_0)$ ,

then you have to take  $n \approx \sigma^2(z_{\alpha/2} + z_{\beta})^2 / \delta^2$  observations.

Similarly, if you're doing a *one-sided* test, it turns out that you need to take  $n \approx \sigma^2(z_\alpha + z_\beta)^2/\delta^2$  obsns.

Example: Weights of 9-yr-old kids are normal with  $\sigma = 4$ . How many obsns should we take if we wish to test  $H_0 : \mu = 40$  vs.  $H_1 : \mu \neq 40$ , and we want  $\alpha = 0.05$ , and  $\beta = 0.05$  if  $\mu$  happens to actually equal  $\mu_1 = 42$ ?

$$n \approx \frac{\sigma^2}{\delta^2}(z_{\alpha/2} + z_\beta)^2 = \frac{16}{4}(1.96 + 1.645)^2 = 51.98.$$

In other words, you need about 52 observations.

## Two-Sample Normal Means Test when Variances are Known

Suppose we have the following set-up:

$$X_1, X_2, \dots, X_{n_x} \stackrel{\text{iid}}{\sim} \text{Nor}(\mu_x, \sigma_x^2) \quad \text{and}$$

$$Y_1, Y_2, \dots, Y_{n_y} \stackrel{\text{iid}}{\sim} \text{Nor}(\mu_y, \sigma_y^2),$$

where the samples are indep of each other, and  $\sigma_x^2$  and  $\sigma_y^2$  are somehow *known*.

Which population has the larger mean?

### 9.37 Normal Mean Tests (var known)

Here's the two-sided test to see if the means are different.

$$H_0 : \mu_x = \mu_y$$

$$H_1 : \mu_x \neq \mu_y$$

Define the test statistic

$$Z_0 = \frac{\bar{X} - \bar{Y} - (\mu_x - \mu_y)}{\sqrt{\frac{\sigma_x^2}{n_x} + \frac{\sigma_y^2}{n_y}}}.$$

If  $H_0$  is true (i.e., the means are equal), then

$$Z_0 = \frac{\bar{X} - \bar{Y}}{\sqrt{\frac{\sigma_x^2}{n_x} + \frac{\sigma_y^2}{n_y}}} \sim \text{Nor}(0, 1).$$

Thus, as before,

$$\text{Reject } H_0 \quad \text{iff} \quad |Z_0| > z_{\alpha/2}.$$

Using more of the same reasoning as before, we get the following one-sided tests.

9.37 Normal Mean Tests (var known)

$$H_0 : \mu_x \leq \mu_y \quad \text{vs.} \quad H_1 : \mu_x > \mu_y$$

$$\text{Reject } H_0 \quad \text{iff} \quad Z_0 = \frac{\bar{X} - \bar{Y}}{\sqrt{\frac{\sigma_x^2}{n_x} + \frac{\sigma_y^2}{n_y}}} > z_\alpha.$$

---

$$H_0 : \mu_x \geq \mu_y \quad \text{vs.} \quad H_1 : \mu_x < \mu_y$$

$$\text{Reject } H_0 \quad \text{iff} \quad Z_0 = \frac{\bar{X} - \bar{Y}}{\sqrt{\frac{\sigma_x^2}{n_x} + \frac{\sigma_y^2}{n_y}}} < -z_\alpha.$$

**Example:** Suppose we want to test  $H_0 : \mu_x = \mu_y$  vs.  $H_1 : \mu_x \neq \mu_y$ , and we have the following data:

$$n_x = 10, \bar{X} = 824.9, \sigma_x^2 = 40$$

$$n_y = 10, \bar{Y} = 818.6, \sigma_y^2 = 50$$

Then

$$Z_0 = \frac{824.9 - 818.6}{\sqrt{\frac{40}{10} + \frac{50}{10}}} = 2.10.$$

If  $\alpha = 0.05$ , then  $|Z_0| = 2.10 > z_{\alpha/2} = 1.96$ , and so we *reject*  $H_0$ .