# LECTURE: CONFIDENCE INTERVALS (I)

## 1. Confidence Intervals

Suppose that we're trying to estimate a parameter  $\theta$  and let  $Y_1, \ldots, Y_n$  be iid samples from our population.

### **Definition:**

A confidence interval uses  $Y_1, \ldots, Y_n$  to get an interval  $[\hat{L}, \hat{U}]$ 

L and U means lower bound and upper bound, and we use hats to indicate estimators.

Ideally, we would like our interval to have the following properties:

- (1) It should contain  $\theta$
- (2) It should be relatively small
- (3) We should be able to calculate the the probability that  $\theta$  is in our interval

That probability is called the **confidence coefficient** 

### **Definition:**

The **confidence coefficient** for  $[\hat{L}, \hat{U}]$  is the number  $1 - \alpha$  with

 $P(\hat{L} \le \theta \le \hat{U}) = 1 - \alpha$ 

Note: The reason we use  $1 - \alpha$  instead of  $\alpha$  will be clear once we discuss hypothesis testing. Essentially,  $\alpha$  will be the probability of getting a false positive result

## 2. Confidence Intervals for Large Sample Sizes

In this section, suppose our sample size is large.

For example, for the sample mean  $\overline{Y}$  we take  $n \ge 30$ 

Let  $\theta$  be our parameter and  $\hat{\theta}$  be an (unbiased) estimator.

#### Goal:

Construct a confidence int  $[\hat{L}, \hat{U}]$  for  $\hat{\theta}$  with confidence coeff  $1 - \alpha$ 

**Upshot:** Since the sample size is large, the Central Limit Theorem says that  $\hat{\theta}$  is normally distributed, so it's enough to convert to the standard normal variable Z

**STEP 1:** Since  $\hat{\theta}$  is unbiased by assumption, we have  $E(\hat{\theta}) = \theta$ 

Let  $\hat{\sigma}$  be the standard deviation of  $\hat{\theta}$ . Then:

$$Z = \frac{\hat{\theta} - \theta}{\hat{\sigma}}$$

is (approximately) a standard normal random variable.

**STEP 2:** Converting to Z, our question is equivalent to finding numbers  $-z_{\alpha/2}$  and  $z_{\alpha/2}$  such that

$$P(-z_{\alpha/2} \le Z \le z_{\alpha/2}) = (1-\alpha)$$



This is done using a Z-table

**Example:** If  $(1 - \alpha) = 0.95$ , then  $\alpha/2 = 0.025$ . Consulting the Z table, we find that  $-z_{\alpha/2} = -1.96$ . By symmetry of the standard normal distribution about its mean of 0,  $z_{\alpha/2} = 1.96$ .

**STEP 3:** To find  $[\hat{L}, \hat{U}]$  just solve for  $\theta$ 

$$P\left(-z_{\alpha/2} \le \frac{\hat{\theta} - \theta}{\hat{\sigma}} \le z_{\alpha/2}\right) = 1 - \alpha$$
$$P\left(-\hat{\theta} - z_{\alpha/2}\hat{\sigma} \le -\theta \le -\hat{\theta} + z_{\alpha/2}\hat{\sigma}\right) = 1 - \alpha$$
$$P\left(\hat{\theta} - z_{\alpha/2}\hat{\sigma} \le \theta \le \hat{\theta} + z_{\alpha/2}\hat{\sigma}\right) = 1 - \alpha$$

**STEP 4:** Answer:

#### Fact:

Assuming n is large, the  $(1 - \alpha)$  confidence interval for  $\theta$  is:

$$[\hat{L}, \hat{U}] = [\hat{\theta} - z_{\alpha/2} \,\hat{\sigma}, \hat{\theta} + z_{\alpha/2} \,\hat{\sigma}]$$

**Note:** If you also know  $\sigma$  then you can use  $\hat{\sigma} = \frac{\sigma}{\sqrt{n}}$  to get

$$[\hat{L}, \hat{U}] = \left[\hat{\theta} - z_{\alpha/2}\left(\frac{\sigma}{\sqrt{n}}\right), \hat{\theta} + z_{\alpha/2}\left(\frac{\sigma}{\sqrt{n}}\right)\right]$$

## 3. EXAMPLES

# Example 1:

A ball bearing machine produces ball bearings whose diameters are normally distributed with mean  $\mu$  mm and standard deviation  $\sigma = 0.1$  mm.

To do this, we take n = 9 ball bearings and use  $\bar{Y} = 10$  mm as our estimator for  $\mu$ 

What is the 90% confidence interval for  $\mu$ ?

This does not require a large sample size because we know  $Y_i$  are normal  $\Rightarrow \bar{Y}$  is also normal

**STEP 1:** Since we know  $\sigma$  we use

$$\hat{\sigma} = \frac{\sigma}{\sqrt{n}} = \frac{0.1}{\sqrt{9}} = \frac{0.1}{3} = 0.0333$$

~ .

**STEP 2:** Z-table

$$1 - \alpha = 0.9 \Rightarrow \alpha = 0.1 \Rightarrow \frac{\alpha}{2} = 0.05$$

Looking at the Z table, we will choose  $z_{\alpha/2} = 1.65$  which gives a probability of 0.0495 (ok to choose a probability of 0.505 instead)

**STEP 3:** Thus our 90% confidence interval for  $\mu$  is given by:

$$\begin{split} [\hat{L}, \hat{U}] &= [\bar{Y} - z_{\alpha/2}\hat{\sigma}, \bar{Y} + z_{\alpha/2}\hat{\sigma}] \\ &= [\bar{Y} - (1.65)(0.0333), \bar{Y} + (1.65)(0.0333)] \\ &= [10 - (1.65)(0.0333), 10 + (1.65)(0.0333)] \\ &= [9.945, 10.055] \end{split}$$

Although we cannot say for certain that  $\mu$  falls within this range, we can say that the probability that it does is 0.90.

Note: In this example, we knew what  $\sigma$  was. If we don't know what  $\sigma$  is, then we would use the sample standard deviation S

Example 2:

The shopping times of n = 64 randomly selected customers at a local supermarket were recorded.

The sample mean and sample variance of the 64 shoppers were  $\bar{Y} = 33$  minutes and  $S^2 = 256$  minutes, respectively.

Find a 98% confidence interval for  $\mu$ 

The parameter of interest is  $\mu$  and our estimator is  $\bar{Y}$ 

Since the sample is large  $(n \ge 30)$ , by the Central Limit Theorem, we can assume that  $\bar{Y}$  is normally distributed.

**STEP 1:** We do not know  $\sigma$ , we will use the sample variance  $S^2$  hence for  $\hat{\sigma}$  we use

$$\hat{\sigma} = \frac{S}{\sqrt{n}} = \frac{\sqrt{256}}{\sqrt{64}} = \frac{16}{8} = 2$$

**STEP 2:** To find  $z_{\alpha/2}$ , we look at our Z table

$$(1 - \alpha) = 0.98 \Rightarrow \alpha = 0.02 \Rightarrow \frac{\alpha}{2} = 0.01$$

Looking at our Z table, the closest probability we have to 0.01 is 0.0099 which gives  $z_{\alpha/2} = 2.33$ 

**STEP 3:** Therefore our 98% confidence interval is

$$[\hat{L}, \hat{U}] = [\bar{Y} - z_{\alpha/2}\hat{\sigma}, \bar{Y} + z_{\alpha/2}\hat{\sigma}]$$
  
= [33 - (2.33)(2), 33 + (2.33)(2)]  
= [28.34, 37.66]