

## 8.1: Confidence Intervals Using the z-Distribution

With confidence intervals we will make our first statistical inference. Confidence intervals give us a direct inference about the population from a sample. The probability statement is one about hypotheses about the mean  $\mu$  of the population based on the mean  $\bar{x}$  and standard deviation  $s$  of the sample. This is a fine point. The frequentist definition of probability gives no way to assign a probability to a hypothesis. How do you count hypotheses? The central limit theorem makes a statement about the sample means  $\bar{x}$  on the basis of a hypothesis about a population, about its mean  $\mu$  and standard deviation  $\sigma$ . If the population is fixed then the central limit theorem gives the results of counting sample means, frequentist probabilities. If we let  $H$  represent a hypothesis about a population (i.e. that it is described by  $\mu$  and  $\sigma$ ) and let  $D$  represent data (with mean  $\bar{x}$ ) then the central limit theorem gives the probability  $P(D | H) = P(\bar{x} | \mu, \sigma)$ . The confidence intervals that we'll look at first give  $P(H | D) = P(\mu | \bar{x}, \sigma)$ . We'll look at the recipe for computing confidence intervals for means first, then return to this discussion about probabilities for hypotheses.

Our goal is to define a symmetric interval about the population mean  $\mu$  that will contain all potentially measured values of  $\bar{x}$  with a probability<sup>[1]</sup> of  $\mathcal{C}$ .

Typically  $\mathcal{C}$  will be

$$\mathcal{C} = 0.90 \quad (90\% \text{ confidence}) \quad (8.1.1)$$

$$\mathcal{C} = 0.95 \quad (95\% \text{ confidence}) \quad (8.1.2)$$

$$\mathcal{C} = 0.99 \quad (99\% \text{ confidence}) \quad (8.1.3)$$

The assumptions that we need in order to use the  $z$ -distribution to compute confidence intervals for means are :

1. The population standard deviation,  $\sigma$ , is known (a somewhat artificial assumption since it is usually not known in an experimental situation) or
2. The sample size is greater than (or equal to) 30,  $n \geq 30$  and we use  $\sigma = s$ , the sample standard deviation in our confidence interval formula.

**Definition :** Let  $z_{\mathcal{C}} = z_{\alpha/2}$  where  $\mathcal{C} = 1 - \alpha$  be the  $z$ -value, from the **Standard Normal Distribution Table** that corresponds to an area, between 0 and  $z_{\mathcal{C}}$  of  $\mathcal{C}/2$  as shown in Figure 8.1.

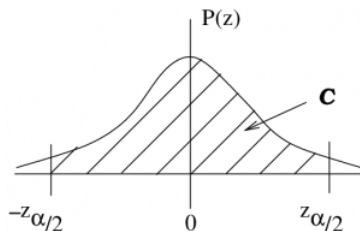


Figure 8.1 : The  $z$ -distribution areas of interest associated with  $z_{\mathcal{C}} = z_{\alpha/2}$ .

To get our confidence interval we simply inverse  $z$ -transform the picture of Figure 8.1, taking the mean of 0 to the sample mean  $\bar{x}$  and the standard deviation of 1 to the standard error  $\sigma/\sqrt{n}$  as shown in Figure 8.2.

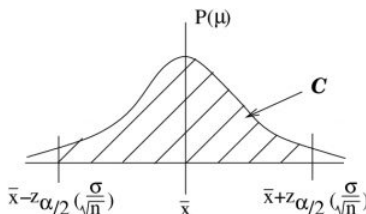


Figure 8.2 : The inverse  $z$ -transformation of Figure 8.1 gives the confidence interval for  $\mu$ .

So here is our recipe from Figure 8.2. The  $\mathcal{C}$ -confidence interval for the mean, under one of the two assumptions given above, is :

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or using notation that we will use as a standard way of denoting symmetric confidence intervals

$$\bar{x} - E < \mu < \bar{x} + E$$

where

$$E = z_C \left( \frac{\sigma}{\sqrt{n}} \right). \quad (8.1.4)$$

The notation  $z_C$  is more convenient for us than  $z_{\alpha/2}$  because we will use the **t Distribution Table** in the [Appendix](#) to find  $z_C$  very quickly. We could equally well write

$$\mu = \bar{x} \pm E \quad (8.1.5)$$

but we will use Equation (8.1) because it explicitly gives the bounds for the confidence interval.

Notice how the confidence interval is *backwards* from the picture that the central limit theorem gives, the picture shown in Figure 8.3. We actually had no business using the inverse  $z$ -transformation  $\mu = (z - \bar{x}) / (\sigma / \sqrt{n})$  to arrive at Figure 8.2. It reverses the roles of  $\mu$  and  $\bar{x}$ . We'll return to this point after we work through the mechanics of an example.

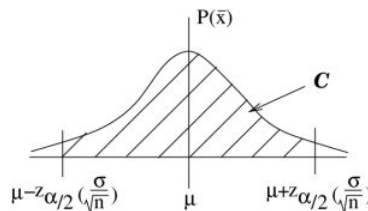


Figure 8.3 : The central limit theorem is about distributions of sample means.

**Example 8.2 :** What is the 95% confidence interval for student age if the population  $\sigma$  is 2 years, sample  $n = 50$ ,  $\bar{x} = 23.2$ ?

*Solution :* So  $C = 0.95$ . First write down the formula prescription so you can see with numbers you need:

$$\bar{x} - E < \mu < \bar{x} + E \text{ where } E = z_{95\%} \frac{\sigma}{\sqrt{n}}. \quad (8.1.6)$$

First determine  $z_C = z_{\alpha/2}$ . With the tables in the Appendices, there are two ways to do this. The first way is to use the **Standard Normal Distribution Table** noting that we need the  $z$  associated with a table area of  $0.95/2 = 0.475$ . Using the table backwards we find  $z_C = 1.96$ . The **second way**, the *recommended way* especially during exams, is to use the **t Distribution Table**. Simply find the column for the 95% confidence level and read the  $z$  from the last line of the table. We quickly find  $z_{95\%} = 1.960$ .

Either way we now find

$$E = 1.96 \left( \frac{2}{\sqrt{50}} \right) = 0.6 \quad (8.1.7)$$

so

$$\begin{aligned} \bar{x} - E &< \mu < \bar{x} + E \\ 23.2 - 0.6 &< \mu < 23.2 + 0.6 \\ 22.6 &< \mu < 23.8 \end{aligned}$$

with 95% confidence.

□

1. Because of this issue about probabilities of hypotheses, many prefer to say "confidence" and not probability. But we will learn enough about Bayesian probability to say "probability". ←

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