# Sullivan Section 8.1

Gene Quinn

# Confidence intervals about a Population Mean

**Definition:** A **point estimate** of a parameter is a value of a statistic that estimates the value of the parameter. two values known as **parameters**:

# Confidence intervals about a Population Mean

**Definition:** A **point estimate** of a parameter is a value of a statistic that estimates the value of the parameter. two values known as **parameters**:

**Example:** The sample mean  $\overline{x}$  is a *point estimate* of the **population** mean  $\mu$ .

# Confidence intervals about a Population Mean

**Definition:** A **point estimate** of a parameter is a value of a statistic that estimates the value of the parameter. two values known as **parameters**:

**Example:** The sample mean  $\overline{x}$  is a *point estimate* of the **population** mean  $\mu$ .

**Example:** The sample standard deviation s is a *point estimate* of the population standard deviation  $\sigma$ .

The number of statistics that can potentially be derived from a sample is very large.

The number of statistics that can potentially be derived from a sample is very large.

Because there are many potential point estimates for, say, the population mean  $\mu$ , the question that naturally arises is, which is the best?

The number of statistics that can potentially be derived from a sample is very large.

Because there are many potential point estimates for, say, the population mean  $\mu$ , the question that naturally arises is, which is the best?

There is no simple answer to this question, because it depends entirely on which criteria you choose to compare different estimates.

For example, the sample mean  $\overline{x}$ , the sample median M, and the sample mode m can all be considered point estimates of the population mean  $\mu$ .

For example, the sample mean  $\overline{x}$ , the sample median M, and the sample mode m can all be considered point estimates of the population mean  $\mu$ .

Do we choose the estimate with:

- The smallest sample variance?
- The smallest bias?

For example, the sample mean  $\overline{x}$ , the sample median M, and the sample mode m can all be considered point estimates of the population mean  $\mu$ .

Do we choose the estimate with:

- The smallest sample variance?
- The smallest bias?
- The best large sample properties?

For example, the sample mean  $\overline{x}$ , the sample median M, and the sample mode m can all be considered point estimates of the population mean  $\mu$ .

Do we choose the estimate with:

- The smallest sample variance?
- The smallest bias?
- The best large sample properties?

For example, the sample mean  $\overline{x}$ , the sample median M, and the sample mode m can all be considered point estimates of the population mean  $\mu$ .

Do we choose the estimate with:

- The smallest sample variance?
- The smallest bias?
- The best large sample properties?

Depending on the situation, any one of these may be the criterion of choice.

For example, the sample mean  $\overline{x}$ , the sample median M, and the sample mode m can all be considered point estimates of the population mean  $\mu$ .

Do we choose the estimate with:

- The smallest sample variance?
- The smallest bias?
- The best large sample properties?

Depending on the situation, any one of these may be the criterion of choice.

For example, the sample mean  $\overline{x}$ , the sample median M, and the sample mode m can all be considered point estimates of the population mean  $\mu$ .

Do we choose the estimate with:

- The smallest sample variance?
- The smallest bias?
- The best large sample properties?

Depending on the situation, any one of these may be the criterion of choice.

**Definition:** An **unbiased estimator** is an estimator whose expected value is equal to the population parameter being estimated.

**Definition:** An **unbiased estimator** is an estimator whose expected value is equal to the population parameter being estimated.

An estimator of the population mean  $\mu$  is unbiased if its expected value is  $\mu.$ 

**Definition:** An **unbiased estimator** is an estimator whose expected value is equal to the population parameter being estimated.

An estimator of the population mean  $\mu$  is unbiased if its expected value is  $\mu.$ 

The **expected value** of a statistic is the value that would be obtained if we calculated the statistic for all possible random samples from the population we are studying, and computed the mean of the statistic over all possible samples.

**Definition:** An **unbiased estimator** is an estimator whose expected value is equal to the population parameter being estimated.

An estimator of the population mean  $\mu$  is unbiased if its expected value is  $\mu.$ 

The **expected value** of a statistic is the value that would be obtained if we calculated the statistic for all possible random samples from the population we are studying, and computed the mean of the statistic over all possible samples.

An equivalent statement is that an **unbiased estimate** does not systematically underestimate or overestimate the population parameter.

**Definition:** A **consistent estimator** is an estimator whose expected value approaches the population parameter as the sample size increases.

**Definition:** A **consistent estimator** is an estimator whose expected value approaches the population parameter as the sample size increases.

Consistency is a "large sample" property of an estimator and is a desirable property.

**Definition:** The **efficiency** of an estimator is based on how its sample standard deviation compares to other possible estimators.

**Definition:** The **efficiency** of an estimator is based on how its sample standard deviation compares to other possible estimators.

If two different point estimates have different sample standard deviations, the estimate with the smaller sample standard deviation is said to be more efficient than the other estimate.

**Definition:** The **efficiency** of an estimator is based on how its sample standard deviation compares to other possible estimators.

If two different point estimates have different sample standard deviations, the estimate with the smaller sample standard deviation is said to be more efficient than the other estimate.

An estimator that has the smallest possible sample standard deviation among a class of estimators is described simply as **efficient**.

In any situation where we use sampling to estimate a population parameter, say, the population mean  $\mu$ , there will be a degree of uncertainty in the estimate.

In any situation where we use sampling to estimate a population parameter, say, the population mean  $\mu$ , there will be a degree of uncertainty in the estimate.

The point estimate  $\overline{x}$  of the population parameter  $\mu$  does not convey any information about this uncertainty.

In any situation where we use sampling to estimate a population parameter, say, the population mean  $\mu$ , there will be a degree of uncertainty in the estimate.

The point estimate  $\overline{x}$  of the population parameter  $\mu$  does not convey any information about this uncertainty.

If anything, quoting a single value creates a false impression of absolute precision: That the population mean is exactly equal to  $\overline{x}$ 

It would make more sense to report  $\overline{x}$  together with an interval containing  $\overline{x}$  and with some measure of our confidence that the population mean  $\mu$  lies somewhere in this interval.

It would make more sense to report  $\overline{x}$  together with an interval containing  $\overline{x}$  and with some measure of our confidence that the population mean  $\mu$  lies somewhere in this interval.

This serves two purposes:

- It makes it clear that  $\overline{x}$  does not have absolute precision.
- It provides a quantitative measure of the precision of the estimate.

It would make more sense to report  $\overline{x}$  together with an interval containing  $\overline{x}$  and with some measure of our confidence that the population mean  $\mu$  lies somewhere in this interval.

This serves two purposes:

- It makes it clear that  $\overline{x}$  does not have absolute precision.
- It provides a quantitative measure of the precision of the estimate.

It would make more sense to report  $\overline{x}$  together with an interval containing  $\overline{x}$  and with some measure of our confidence that the population mean  $\mu$  lies somewhere in this interval.

This serves two purposes:

- It makes it clear that  $\overline{x}$  does not have absolute precision.
- It provides a quantitative measure of the precision of the estimate.

For a specific estimate  $\overline{x}$ , the length of this interval will depend on the level of confidence:

- A greater level of confidence will require a relatively wide interval.
- A narrower interval can be used, but at the expense of lower confidence that it contains  $\mu$ .

For a specific estimate  $\overline{x}$ , the length of this interval will depend on the level of confidence:

- A greater level of confidence will require a relatively wide interval.
- A narrower interval can be used, but at the expense of lower confidence that it contains  $\mu$ .

In practice, it is more common to report  $\overline{x}$  together with information that allows the computation of an interval with any desired level of confidence.

**Definition:** A confidence interval estimate of a parameter consists of an interval together with a measure of the likelihood that the interval contains the (unknown) population parameter  $\mu$ .

**Definition:** A confidence interval estimate of a parameter consists of an interval together with a measure of the likelihood that the interval contains the (unknown) population parameter  $\mu$ .

The **level of confidence** in a confidence interval is the proportion of time that the interval will contain  $\mu$  if a large number of samples are taken.

A common convention in statistics is to use the letter  $\alpha$  to denote the proportion of time an outcome corresponding to some kind of false positive is obtained.

A common convention in statistics is to use the letter  $\alpha$  to denote the proportion of time an outcome corresponding to some kind of false positive is obtained.

Small values of  $\alpha$  are associated with small probabilities of a false positive.

A common convention in statistics is to use the letter  $\alpha$  to denote the proportion of time an outcome corresponding to some kind of false positive is obtained.

Small values of  $\alpha$  are associated with small probabilities of a false positive.

Typical values for  $\alpha$  are .05 and .01, sometimes described as 5 percent and 1 percent.

A common convention in statistics is to use the letter  $\alpha$  to denote the proportion of time an outcome corresponding to some kind of false positive is obtained.

A common convention in statistics is to use the letter  $\alpha$  to denote the proportion of time an outcome corresponding to some kind of false positive is obtained.

Small values of  $\alpha$  are associated with small probabilities of a false positive.

A common convention in statistics is to use the letter  $\alpha$  to denote the proportion of time an outcome corresponding to some kind of false positive is obtained.

Small values of  $\alpha$  are associated with small probabilities of a false positive.

Typical values for  $\alpha$  are .05 and .01, sometimes described as 5 percent and 1 percent.

A common convention in statistics is to use the letter  $\alpha$  to denote the proportion of time an outcome corresponding to some kind of false positive is obtained.

Small values of  $\alpha$  are associated with small probabilities of a false positive.

Typical values for  $\alpha$  are .05 and .01, sometimes described as 5 percent and 1 percent.

Somewhat confusingly, a confidence interval associated with a 5% chance of a false positive is referred to as a 95 percent confidence interval.

The formula for computing a confidence interval is as follows: Lower bound:

lower bound = 
$$\overline{x} - z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

Upper bound:

upper bound = 
$$\overline{x} + z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

The formula for computing a confidence interval is as follows:

Lower bound:

lower bound = 
$$\overline{x} - z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

Upper bound:

upper bound 
$$= \overline{x} + z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

The value  $z_{\alpha/2}$  represents the value from the *z* table corresponding to  $\alpha/2$ , where  $1 - \alpha$  is the level of confidence.

The formula for computing a confidence interval if both the mean and standard deviation have been estimated from the sample uses the t-distribution instead of the z distribution:

Lower bound:

lower bound 
$$= \overline{x} - t_{\alpha/2} \cdot rac{s}{\sqrt{n}}$$

Upper bound:

upper bound 
$$= \overline{x} + t_{lpha/2} \cdot rac{s}{\sqrt{n}}$$

The formula for computing a confidence interval if both the mean and standard deviation have been estimated from the sample uses the t-distribution instead of the z distribution:

Lower bound:

ower bound 
$$= \overline{x} - t_{\alpha/2} \cdot \frac{s}{\sqrt{n}}$$

Upper bound:

upper bound 
$$= \overline{x} + t_{lpha/2} \cdot rac{s}{\sqrt{n}}$$

The value  $z_{\alpha/2}$  represents the value from the *z* table corresponding to  $\alpha/2$ , where  $1 - \alpha$  is the level of confidence.