# **Confidence Intervals**

Ryan Miller



#### Introduction

Lately, we've discussed Normal probability models, and we've seen how these can be applied to two different distributions:



Image credit: https://www.researchgate.net/publication/383141443\_Introducing\_prediction\_intervals\_for\_sample\_means



In an attempt to make their terminology less confusing/overloaded, statisticians use the following terms:

- Standard deviation describes the variability of *data-points* around an expected value (mean)
- Standard error describes the variability of *estimates* around an expected value (population parameter)
- **Sampling distribution** the distribution of *sample estimates*

Standard error is the standard deviation of the sampling, but it is given a distinct name because standard error formulas often involve the standard deviation of the cases in a sample



### Statistical Inference

Statistical analyses attempt to generalize a statistic, such as the sample mean, to a broader population.



Because sampling is a random process, any statistic calculated from a sample contains uncertainty

In any practical application, we never see the population, and we only get to see one sample, making Central Limit theorem a powerful tool in understanding this uncertainty



Statisticians consider two types of estimates for an unknown population parameter:

- 1) **Point estimate** a *single number* that is the *best guess* for what the population parameter is. For example, the sample mean  $\overline{x}$  is a point estimate for the population's mean,  $\mu$
- Interval estimate a range of numbers that represent plausible values of the population parameter. Interval estimates usually have the form: Point Estimate ± Margin of Error



- 1. What are the chances that a point estimate, such as the sample mean, *exactly matches* the corresponding parameter in the population? *Hint*: think about the probability of a continuous random variable taking on any particular value.
- 2. For a given sample, how could you create an interval estimate that will *always* contain the population parameter of interest?



- A confidence interval is an interval estimate whose margin of error is calculated using procedure with a long-run "success rate" known as a *confidence level* 
  - A 95% confidence interval uses a procedure that will succeed in containing the true population parameter in 95% of different random samples (or study replications)



Confidence intervals have the following properties:

- They are made with the intention of giving a plausible range of values for a population parameter
- They are the observed result of a random process (ie: sampling)
- Before that random process has been observed (ie: before we've collected a sample) the procedure used to calculate the interval has a chance of containing population parameter defined as the confidence level
  - After the random process has unfolded (ie: after we've collected our sample) the interval is no longer random, it is either correct (contains the truth) or incorrect (doesn't contain the truth)



## **Confidence Intervals**

Shown below are 95% CI estimates from 100 different random samples (n = 20) drawn from a population with correlation of  $\rho = 0$ 



Notice that 95 of 100 samples produced a 95% CI estimate containing the true population-level correlation. This suggests the method used to form these intervals is a *valid* 95% confidence



### Not Confidence Intervals

Suppose we use a different method to calculate interval estimates for the same set of 100 randomly selected samples (of size n = 20):



Why isn't this a valid 95% confidence interval procedure?



## Finding Confidence Interval Estimates

The challenge in calculating a confidence interval is properly calibrating the interval's margin of error to achieve the stated confidence level:

Point Estimate ± Margin of Error

If we calculate margins of error that are too small, the intervals will not contain the true population parameter often enough to achieve the desired confidence level

This increases the chances of false positive findings

- If we calculate margins of error that are too large, we are expressing an unnecessary amount of uncertainty
  - This increases the chances of *false negative* findings



## Central Limit Theorem and Confidence Intervals

- We know that the sample mean follows a Normal distribution given by the Central Limit theorem
  - This distribution tells us how much sampling variability to expect when using the sample mean as an estimate
- For example, if we know that 95% of sample means are within a distance of 1.4 units from the center of the distribution, we can use 1.4 as the margin of error for a 95% confidence interval





### Two Ways to use CLT

Approach #1 - Use the sample data to directly estimate the distribution of sample means and take the middle P% as the P% confidence interval estimate of the population mean:

```
## Standard error (based upon CLT)
std_error = sample_sd/sqrt(n)
## Lower endpoint
lower = qnorm(0.025, mean = sample_mean, sd = std_error)
## Upper endpoint
upper = qnorm(0.975, mean = sample_mean, sd = std_error)
## Interval
c(lower, upper)
```



### Two Ways to use CLT

Approach #2 - Rather than using a specific Normal distribution, use a generic formula with an appropriate quantile from N(0,1):

```
## Quantile for the middle 95% of N(0,1)
key_quantile = qnorm(0.975, mean = 0, sd = 1)
## Standard error (based upon CLT)
std_error = sample_sd/sqrt(n)
## Lower endpoint
lower = sample_mean - key_quantile*std_error
## Upper endpoint
upper = sample mean + key quantile*std error
## Interval
c(lower, upper)
```



### Conclusions

There are three major takeaways from this presentation:

- 1. Interval estimates use sample data to provide a range of plausible values for an unknown characteristic of a population.
- 2. Confidence intervals are interval estimates whose margin of error is determined by a procedure with a long-run success rate, known as the confidence level.
- You can calculate a P% confidence interval by taking the middle P% of the distribution of sample estimates, or by applying a generic formula involving the point estimate, a quantile from the N(0,1) distribution, and the standard error.

