Central Limit Theorem

Grinnell College

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Bootstrapping involves the process of *resampling with replacement* from our original sample

When we compute a statistic on our bootstrapped sample (i.e., sample mean), we have a *bootstrapped sample statistic*

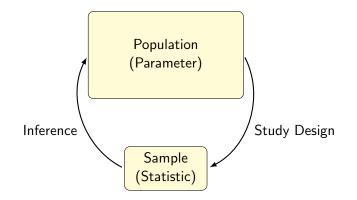
Repeating this process many many times gives us an estimate of the *sampling distribution*

Percentiles can be used on this bootstrapped sampling distribution without needing any further assumptions

Questions

- 1. Why are we constructing confidence intervals? What purpose do they serve?
- 2. Explain how the Point Estimate \pm Margin of Error method works
- 3. What is the bootstrapping process? How is it used to compute confidence intervals?
- 4. Could I use Point Estimate \pm Margin of Error on my bootstrapped sample means?
- 5. Explain how to create an 80% confidence interval using:
 - Point Estimate \pm Margin of Error method
 - Bootstrapping
- 6. What determines the width of our confidence intervals?
- 7. What determines how frequently they contain the true parameter value, on average?

The Statistical Framework



Consider a *sequence* of numbers:

$$1, \frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \ldots, \frac{1}{n}, \ldots$$

Where are they going?

In what sense are these numbers going to zero?

$$1, \ \frac{1}{2}, \ \frac{1}{3}, \ \frac{1}{4}, \ \dots, \ \frac{1}{n} \to 0$$

- Will they ever reach zero?
- Is there a value of n in which it is "close enough?"
- Why would this be useful to know?

Sequences and Limits

What about these sequences?

 $\frac{10,000}{n}$ $\frac{1}{n^2}$ $\frac{n}{1+n^3}$

If our variable X is normally distributed, with $X \sim N(\mu, \sigma^2)$, we have the curve:

$$f(x|\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Normal Distribution

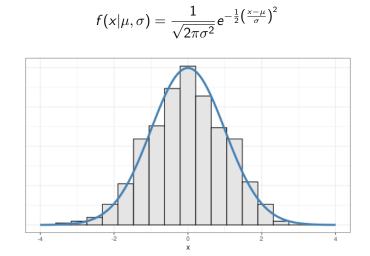
$$f(x|\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Note the standardized variable, $Z = \frac{x-\mu}{\sigma}$. Making this replacement gives a standard normal distribution,

$$f(z)=\frac{1}{\sqrt{2\pi}}e^{-\frac{z^2}{2}}$$

which has a mean value of $\mu=$ 0 and a standard deviation of $\sigma=1$

Normal Distribution



The particulars of our sample may change

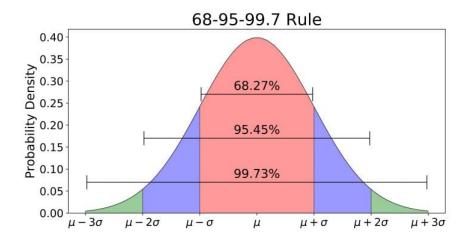
But we *assume* they are generated by normal, then we only need to know two things

And just make statements about the general form rather than pertaining to specifics of sample

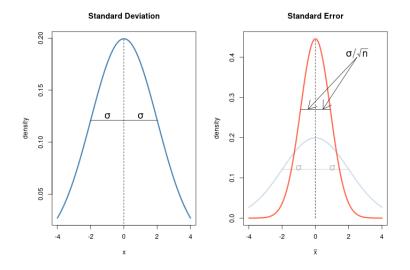
The **Central Limit Theorem (CLT)** is perhaps the most significant result in all of statistics:

- 1. A variable X has mean μ and standard deviation σ
- 2. The number of observations in our sample is n
- 3. The sample mean has a sampling distribution with mean μ and standard error σ/\sqrt{n}

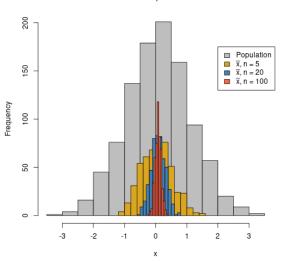
$$\overline{X} \sim N\left(\mu, \ \frac{\sigma^2}{n}\right)$$



Standard Deviation and Standard Error



Sample Mean Distribution



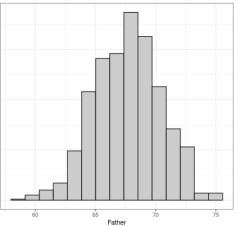
500 Samples of X

Father Height Data

From our sample of n = 1,078, we find:

- ▶ <u>x</u> = 67.68
- ▶ σ̂ = 2.74





Father Height Data

From our sample of n = 1,078, we find:

▶ ô = 2.74

To determine sampling distribution, we have

- Best prediction for mean is $\overline{x} = 67.68$
- Standard error of

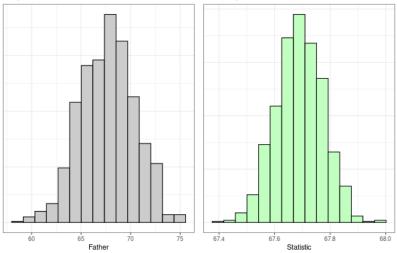
Std. Error
$$=\frac{\hat{\sigma}}{\sqrt{n}}=2.74/\sqrt{1,078}=0.084$$

A 95% confidence interval would then look like:

$$67.69 \pm 2 \times 0.084 = (67.512, 67.848)$$

Father Height Data

Height of Father Data

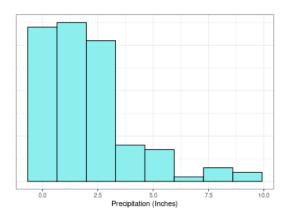


Sampling Distribution of Mean

Non-normal Populations

What about our Grinnell rain data?

- ▶ *n* = 121
- ► <u>x</u> = 2.07

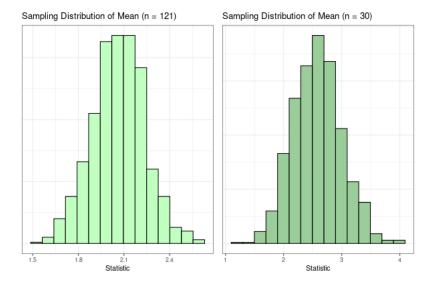


Rain Mean Sampling Distribution

1.5 1.8 2.4 2.1 Statistic

Sampling Distribution of Mean (n = 121)

Changing sample size



Limits and Approximations

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The Central Limit Theorem only applies to sampling distribution of the mean

It does not require that the population follow a normal distribution