Topic 5: Confidence Intervals

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Outline

1. Confidence Intervals

2. Normal Confidence Intervals

Leadup

- Let's go on a fishing trip!

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- Say we saw a fish in a specific spot in a lake.

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- But... is that really the most efficient way to catch a fish?

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- Let's go on a fishing trip!
- Say we saw a fish in a specific spot in a lake.
- To catch a fish, we could simply throw a spear right where we saw our last fish.
- But... is that really the most efficient way to catch a fish?
- Wouldn't it be better to cast a *net*, somewhere around where we saw our last fish, to try and increase our odds of catching at least one fish?

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Leadup

- In many ways, estimation is like fishing.
- The true value of the population parameter is analogous to our fish.
- Constructing a single estimate from a single estimator (constructed from a single sample) is like throwing a spear - our estimate is a single value, which we hope is pretty close to the true value of the population parameter.
- So, what's the analog of casting a net in estimation?

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Confidence Intervals

Interval Estimators

- To make things more mathematical, suppose we have an i.i.d. sample $\vec{\boldsymbol{Y}} := \{Y_i\}_{i=1}^{n}$ from a population with parameter θ.

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Interval Estimators

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Interval Estimators

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- Previously, we constructed **point estimators** $\widehat{\theta}_n$ which, in the language of our textbook, are rules we can use to generate numerical estimates of θ.
- We'll now turn our attention to **interval estimators** (often referred to as **confidence intervals**), which we hope will cover the true value of θ.

Interval Estimators

- As the name suggests, an interval estimator is a random interval. That is, it is an interval of the form

$$\left[\widehat{\theta}_L \ , \ \widehat{\theta}_U \right]$$

where $\widehat{\theta}_L$ and $\widehat{\theta}_U$ are random variables.

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  where $\widehat{\theta}_L$ and $\widehat{\theta}_U$ are random variables.
- Note that the *endpoints* of a confidence interval are random.
  - The lower endpoint, $\widehat{\theta}_L$, is often referred to as the **lower confidence limit** and the upper endpoint, $\widehat{\theta}_u$, is often referred to as the **upper confidence limit**.

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Interval Estimators

- As I mentioned at the start of this discussion, we want to have some degree of certainty that the interval $[\widehat{\theta}_L\ ,\ \widehat{\theta}_U]$ covers the true value of θ.

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Interval Estimators

- As I mentioned at the start of this discussion, we want to have some degree of certainty that the interval $[\widehat{\theta}_L \ , \ \widehat{\theta}_U]$ covers the true value of θ.
- Since our interval is random, it makes sense to talk about the **coverage probability** (aka **confidence coefficient**), defined to be

$$\mathbb{P}(\widehat{\theta}_L \leq \theta \leq \widehat{\theta}_U)$$

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- Since our interval is random, it makes sense to talk about the **coverage probability** (aka **confidence coefficient**), defined to be

$$\mathbb{P}(\widehat{\theta}_L \leq \theta \leq \widehat{\theta}_U)$$

- So, for example, a **95% confidence interval** (i.e. a confidence interval with 95% coverage probability) is one such that

$$\mathbb{P}(\widehat{\theta}_L \leq \theta \leq \widehat{\theta}_U) = 0.95$$

  i.e. an interval $[\widehat{\theta}_L \ , \ \widehat{\theta}_U]$ that we are 95% certain covers the true value of θ.

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Example: Population Mean

- As a somewhat more concrete example, let's return to our problem of trying to estimate the true average weight of a randomly-selected DSH cat.

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Example: Population Mean

- As a somewhat more concrete example, let's return to our problem of trying to estimate the true average weight of a randomly-selected DSH cat.
- Assuming $Y_1, \cdots, Y_n$ denotes an i.i.d. sample of cat weights following some distribution with unknown parameter μ, a $(1-\alpha) \times 100\%$ confidence interval for μ is an interval $[\widehat{\mu}_L\ ,\ \widehat{\mu}_U]$ such that

$$\mathbb{P}(\widehat{\mu}_L \leq \mu \leq \widehat{\mu}_U) = 1 - \alpha$$

where $1-\alpha$ denotes the coverage probability. (The reason why we use $(1-\alpha)$ will become clear next week, after we discuss Hypothesis Testing.)

Example: Population Mean

- Can anyone give me a 100% confidence interval for μ?

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- Can anyone give me a 100% confidence interval for μ?
- Sure: $(-\infty, \infty)$. I am 100% sure that the true average weight of a randomly-selected DSH cat lies somewhere between $-\infty$ and ∞.

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  - Indeed, even $[0, \infty)$ would be a 100% confidence interval for μ, based on the physical constraints of our problem but we can ignore that for now.
- Alright, but this is an (effectively) useless interval! But, this highlights something important: there is a tradeoff between coverage probability and the *width* of our confidence interval. Higher coverage probabilities necessitate larger and larger confidence intervals - this is why it's not really practical to construct a 100% confidence interval.

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Confidence Intervals

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- I'm going to break our considerations into two: first we'll talk about constructing confidence intervals assuming a normally-distributed population, and then we'll relax the normality assumption and discuss ways to construct confidence intervals for more general distributions.

Normal Confidence Intervals

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First Goal

Goal

Given $Y_1, \cdots, Y_n \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$ for an unknown $\mu \in \mathbb{R}$ but a known $\sigma^2 > 0$, we want to construct a $(1 - \alpha) \times 100\%$ confidence interval for μ.

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Sample Mean

- Now, again, we know that the sample mean $\overline{Y}_n$ is a very good point estimator for μ.

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- Of course, there's no guarantee that for any *particlar* sample, $\overline{Y}_n$ will be exactly equal to μ (hence why we're trying to construct *intervals* now!)

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  - Again, it's an unbiased and consistent estimator for μ, as well as a sufficient statistic for μ.
- Of course, there's no guarantee that for any *particlar* sample, $\overline{Y}_n$ will be exactly equal to μ (hence why we're trying to construct *intervals* now!)
- But, consistency more or less tells us that $\overline{Y}_n$ will probably be quite *close* to the true value of μ.

Sample Mean

- So, it makes sense to construct our interval by taking $\overline{Y}_n$ (which, again, will likely be very close to the true value of μ), and adding and subtracting some **margin of error** (think of it like padding).

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Sample Mean

- So, it makes sense to construct our interval by taking $\overline{Y}_n$ (which, again, will likely be very close to the true value of μ), and adding and subtracting some **margin of error** (think of it like padding).
- In other words, we'll take our interval to be

$$\overline{Y}_n \pm \text{m.e.} = \left[\overline{Y}_n - \text{m.e.}\ ,\ \overline{Y}_n + \text{m.e}\right]$$

where "m.e." stands for margin of error (i.e. the half-width of our confidence interval).

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  where "m.e." stands for margin of error (i.e. the half-width of our confidence interval).
- Since we're constructing a $(1 - \alpha) \times 100\%$ confidence interval, we want

$$\mathbb{P}(\overline{Y}_n - \text{m.e.} \leq \mu \leq \overline{Y}_n + \text{m.e.}) = 1 - \alpha$$

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Sample Mean

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- $\mathbb{P}(\mu \leq \overline{Y}_n + \text{m.e.}) = \mathbb{P}(\overline{Y}_n \geq \mu - \text{m.e.})$

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- $\mathbb{P}(\mu \leq \overline{Y}_n + \text{m.e.}) = \mathbb{P}(\overline{Y}_n \geq \mu - \text{m.e.})$
- So, what we have is

$$\mathbb{P}(\overline{Y}_n - \text{m.e.} \leq \mu \leq \overline{Y}_n + \text{m.e.}) = \mathbb{P}(\mu - \text{m.e.} \leq \overline{Y}_n \leq \mu + \text{m.e.})$$

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Sample Mean

- Again, we are trying to select m.e. such that this whole probability equals $1 - \alpha$:

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- Now, we know that $\overline{Y}_n \sim \mathcal{N}(\mu, \sigma^2/n)$. So, it seems tempting to standardize the RHS!

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Sample Mean

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$$\mathbb{P}(\mu - \text{m.e.} \leq \overline{Y}_n \leq \mu + \text{m.e.})$$

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Sample Mean

- That is:

$$\mathbb{P}(\mu - \text{m.e.} \leq \overline{Y}_n \leq \mu + \text{m.e.}) = \mathbb{P}\left(-\frac{\text{m.e.}}{\sigma/\sqrt{n}} \leq \frac{\overline{Y}_n - \mu}{\sigma/\sqrt{n}} \leq \frac{\text{m.e.}}{\sigma/\sqrt{n}} \right)$$

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Sample Mean

- That is:

$$\begin{aligned}\mathbb{P}(\mu - \text{m.e.} \leq \overline{Y}_n \leq \mu + \text{m.e.}) &= \mathbb{P}\left(-\frac{\text{m.e.}}{\sigma/\sqrt{n}} \leq \frac{\overline{Y}_n - \mu}{\sigma/\sqrt{n}} \leq \frac{\text{m.e.}}{\sigma/\sqrt{n}} \right) \\ &= \Phi\left(\frac{\text{m.e.}}{\sigma/\sqrt{n}} \right) - \Phi\left(-\frac{\text{m.e.}}{\sigma/\sqrt{n}} \right)\end{aligned}$$

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$$
\begin{aligned}
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&= \Phi\left(\frac{\text{m.e.}}{\sigma/\sqrt{n}} \right) - \Phi\left(-\frac{\text{m.e.}}{\sigma/\sqrt{n}} \right) \\
&= 2\Phi\left(\frac{\text{m.e.}}{\sigma/\sqrt{n}} \right) - 1
\end{aligned}
$$

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&= \Phi\left(\frac{\text{m.e.}}{\sigma/\sqrt{n}} \right) - \Phi\left(-\frac{\text{m.e.}}{\sigma/\sqrt{n}} \right) \\
&= 2\Phi\left(\frac{\text{m.e.}}{\sigma/\sqrt{n}} \right) - 1
\end{aligned}$$

- So, our margin of error must satisfy

$$2\Phi\left(\frac{\text{m.e.}}{\sigma/\sqrt{n}} \right) - 1 = 1 - \alpha \implies \boxed{\text{m.e.} = \Phi^{-1}\left(1 - \frac{\alpha}{2}\right) \cdot \frac{\sigma}{\sqrt{n}}}$$

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Confidence Interval for the Mean; Known Variance

Theorem (CI for μ; Known Variance)

Given $Y_1, \cdots, Y_n \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$ where $\mu \in \mathbb{R}$ is unknown but $\sigma^2 > 0$ is known, a $(1-\alpha) \times 100\%$ confidence interval for μ is given by

$$\begin{aligned} &\overline{Y}_n \pm \Phi^{-1}\left(1 - \frac{\alpha}{2}\right) \cdot \frac{\sigma}{\sqrt{n}} \\ &\qquad = \left[\overline{Y}_n - \Phi^{-1}\left(1 - \frac{\alpha}{2}\right) \cdot \frac{\sigma}{\sqrt{n}} \, , \, \overline{Y}_n + \Phi^{-1}\left(1 - \frac{\alpha}{2}\right) \cdot \frac{\sigma}{\sqrt{n}}\right] \end{aligned}$$

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Example

The weight of a croissant from *Le Gaucho* (in grams) is normally distributed about some unknown mean μ and known standard deviation 2 grams. An i.i.d. sample of 8 croissants from *Le Gaucho* is taken, and their weights (in grams) are as follows:

$$63.5,\ 64.5,\ 65.1,\ 68.9,\ 69.9,\ 70.1,\ 72.3,\ 72.4$$

(a) Construct a 90% confidence interval for μ, based on the data that was collected. You may leave your answer in terms of $\Phi^{-}(\cdot)$, the inverse of the standard normal CDF.

(b) Would a 80% confidence interval for μ be wider or narrower than the interval you constructed in part (a)?

Solutions

- We only need to plug into our formula from above!

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- Firstly, the sample mean is easily computed to be $\overline{y}_8 = 68.3375$ g.

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Solutions

- We only need to plug into our formula from above!
- Firstly, the sample mean is easily computed to be $\overline{y}_8 = 68.3375$ g.
- Now, a 90% confidence interval is equivalent to a $(1 - 0.1) \times 100\%$ confidence interval, meaning we plug $\alpha = 0.1$ into our CI formula from above:

$$\overline{y}_n \pm \Phi^{-1}\left(1 - \frac{\alpha}{2}\right) \cdot \frac{\sigma}{\sqrt{n}} = \boxed{68.3375 \pm \Phi^{-1}(0.95) \cdot \frac{2}{\sqrt{8}}}$$

Solutions

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- With a computer software, we can compute this to be $[67.17441 \ , \ 69.50059]$ - that is, we are 95% confident that the true averag weight of a *Le Gaucho* croissant is between 67.17441 grams and 69.50059 grams (**notice the wording of our conclusion!**)

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Solutions

- For part (b), we need only to remember our discussion from earlier, about the relationship between the width of a CI and our coverage probability.

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Solutions

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- Higher coverage probabilities necessitate wider intervals.

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Solutions

- For part (b), we need only to remember our discussion from earlier, about the relationship between the width of a CI and our coverage probability.
- Higher coverage probabilities necessitate wider intervals.
- Since an 80% coverage probability is *less* than a 95% coverage probability, we expect an 80% confidence interval to be narrower than a 95% confidence interval.

Solutions

- For part (b), we need only to remember our discussion from earlier, about the relationship between the width of a CI and our coverage probability.
- Higher coverage probabilities necessitate wider intervals.
- Since an 80% coverage probability is *less* than a 95% coverage probability, we expect an 80% confidence interval to be narrower than a 95% confidence interval.
- If you're curious, you can construct an 80% confidence interval which you should find to be around $[67.43131\ ,\ 69.24369]$, which is indeed narrower than our interval from part (a).

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Second Goal

Goal

Given $Y_1, \cdots, Y_n \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$ for an unknown $\mu \in \mathbb{R}$ and an unknown $\sigma^2 > 0$, we want to construct a $(1 - \alpha) \times 100\%$ confidence interval for μ.

Second Goal

- Let's still consider an interval for the form

$$\overline{Y}_n \pm \text{m.e.}$$

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- Re-using some of the work we did in the previous case (where σ^2 was known), we have

$$\mathbb{P}\left(\mu - \text{m.e.} \leq \overline{Y}_n \leq \mu + \text{m.e.}\right) = 1 - \alpha$$

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- Before, we standardized because we knew that $\overline{Y}_n \sim \mathcal{N}(\mu, \sigma^2/n)$.

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- Before, we standardized because we knew that $\overline{Y}_n \sim \mathcal{N}(\mu, \sigma^2/n)$.
- But, even though this is true, this fact doesn't really help us in practice since the value of σ is unknown!
- So, here's our clever idea - let's replace σ with a "good" estimator for it - namely, S_n (the sample standard deviation).

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Second Goal

- This works out well, because

$$\left(\frac{\overline{Y}_n - \mu}{S_n / \sqrt{n}} \right) \sim t_{n-1}$$

by our "Modified Standardization Result" from our lecture on multivariate transformations involving the normal distribution.

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Second Goal

- So:

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$$\mathbb{P}(\mu - \text{m.e.} \leq \overline{Y}_n \leq \mu + \text{m.e.})$$

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Second Goal

- So:

$$\mathbb{P}(\mu - \text{m.e.} \leq \overline{Y}_n \leq \mu + \text{m.e.}) = \mathbb{P}\left(-\frac{\text{m.e.}}{S_n/\sqrt{n}} \leq \frac{\overline{Y}_n - \mu}{S_n/\sqrt{n}} \leq \frac{\text{m.e.}}{S_n/\sqrt{n}} \right)$$

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$$= F_{t_{n-1}}^{-1}\left(\frac{\text{m.e.}}{S_n/\sqrt{n}} \right) - F_{t_{n-1}}^{-1}\left(-\frac{\text{m.e.}}{S_n/\sqrt{n}} \right)$$

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\mathbb{P}(\mu - \text{m.e.} \leq \overline{Y}_n \leq \mu + \text{m.e.}) &= \mathbb{P}\left(-\frac{\text{m.e.}}{S_n/\sqrt{n}} \leq \frac{\overline{Y}_n - \mu}{S_n/\sqrt{n}} \leq \frac{\text{m.e.}}{S_n/\sqrt{n}} \right) \\
&= F_{t_{n-1}}^{-1}\left(\frac{\text{m.e.}}{S_n/\sqrt{n}} \right) - F_{t_{n-1}}^{-1}\left(-\frac{\text{m.e.}}{S_n/\sqrt{n}} \right) \\
&= 2F_{t_{n-1}}^{-1}\left(\frac{\text{m.e.}}{S_n/\sqrt{n}} \right) - 1
\end{aligned}$$

Second Goal

- So:

$$\mathbb{P}(\mu - \text{m.e.} \leq \overline{Y}_n \leq \mu + \text{m.e.}) = \mathbb{P}\left(-\frac{\text{m.e.}}{S_n/\sqrt{n}} \leq \frac{\overline{Y}_n - \mu}{S_n/\sqrt{n}} \leq \frac{\text{m.e.}}{S_n/\sqrt{n}} \right)$$

$$= F_{t_{n-1}}^{-1}\left(\frac{\text{m.e.}}{S_n/\sqrt{n}} \right) - F_{t_{n-1}}^{-1}\left(-\frac{\text{m.e.}}{S_n/\sqrt{n}} \right)$$

$$= 2F_{t_{n-1}}^{-1}\left(\frac{\text{m.e.}}{S_n/\sqrt{n}} \right) - 1$$

- Thus, our margin of error must satisfy

$$2F_{t_{n-1}}\left(\frac{\text{m.e.}}{\sigma/\sqrt{n}} \right) - 1 = 1 - \alpha \implies \boxed{\text{m.e.} = F_{t_{n-1}}^{-1}\left(1 - \frac{\alpha}{2}\right) \cdot \frac{\sigma}{\sqrt{n}}}$$

Confidence Interval for the Mean; Unknown Variance

Theorem (CI for μ; Unknown Variance)

Given $Y_1, \cdots, Y_n \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$ where both $\mu \in \mathbb{R}$ and $\sigma^2 > 0$ are unknown, a $(1-\alpha) \times 100\%$ confidence interval for μ is given by

$$\overline{Y}_n \pm F^{-1}_{t_{n-1}}\left(1 - \frac{\alpha}{2}\right) \cdot \frac{S_n}{\sqrt{n}}$$

$$= \left[\overline{Y}_n - F_{t_{n-1}}\left(1 - \frac{\alpha}{2}\right) \cdot \frac{S_n}{\sqrt{n}} , \overline{Y}_n + F_{t_{n-1}}\left(1 - \frac{\alpha}{2}\right) \cdot \frac{S_n}{\sqrt{n}}\right]$$

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Example

Assume the same setup as the previous croissant example, except now assume that σ^2 is unknown. Construct a 95% CI for μ, the true average weight of a *Le Gaucho* croissant.

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- We still have $\overline{y}_n = 68.3375$ g. We also have $s_8 = 3.518903$. Therefore, plugging into our formula from the previous slide, our CI is

$$68.3375 \pm F_{t_7}^{-1}(0.95) \cdot \frac{3.518903}{\sqrt{8}}$$

which, using a computer software, amounts to around $[65.98042\ ,\ 70.69458]$.

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Asymptotic Confidence Intervals for the Mean

- Note that the CLT enables us to relatively easily construct *large-sample* (i.e. *asymptotic*) confidence intervals for the mean.

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Asymptotic Confidence Intervals for the Mean

- Note that the CLT enables us to relatively easily construct *large-sample* (i.e. *asymptotic*) confidence intervals for the mean.
- That is, we know that regardless of our population distribution (assuming finite mean and variance),

$$\frac{\sqrt{n}(\overline{Y}_n - \mu)}{\sigma} \rightsquigarrow \mathcal{N}(0, 1)$$

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- You'll work through some problems relating to this on the next (and final!) homework.

Interpreting Confidence Intervals

- One interpretation of an $(1 - \alpha) \times 100\%$ confidence interval $[a, b]$ is: "we are $(1 - \alpha) \times 100\%$ certain that the interval $[a, b]$ contains the true value of θ."

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- One interpretation of an $(1-\alpha) \times 100\%$ confidence interval $[a, b]$ is: "we are $(1-\alpha) \times 100\%$ certain that the interval $[a, b]$ contains the true value of θ."
  - So, for example, a 95% CI for a population mean μ can be interpreted as an interval that we are 95% certain covers the true value of μ.
- There is another interesting way to interpret CIs: If the same procedure was used many times, each individual interval would either contain or fail to contain the true value of θ, but the percentage of all intervals that capture θ would be very close to $(1-\alpha) \times 100\%$. (This is the wording taken from the textbook.) Let's see this in action by way of a live demo.

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