Lecture 16: Sample Size and Power

Chapter 4.6

Last Time: Reedie Sleep Example

Tested number of hours of sleep:

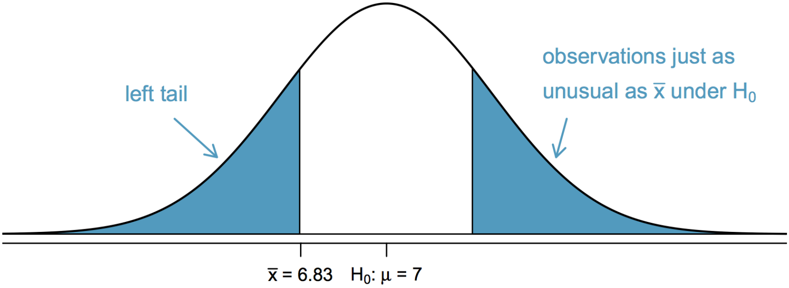
- $H_0 : \mu = 7$
- $H_A : \mu > 7$

Two-Sided Alternative Hypothesis

Say instead we had a two-sided alternative hypothesis:

- $H_0 : \mu = 7$
- $H_A : \mu \neq 7$

The the p-value would be double: $2 \times 0.007 = 0.014$. Picture:



Pre-specifying α

Say Dr. Q is conducting a hypothesis tests. They start with $\alpha = 0.05$.

They conduct the test and get p-value $= 0.09$. They then declare "having used an $\alpha = 0.10$, we reject the null hypothesis and declare our results to be significant."

What's not honest about this approach?

Ronald Fisher, the creator of p-values, never intended for them to be used this way: http://en.wikipedia.org/wiki/P-value#Criticisms

Goals for Today

- More in depth discussion of
  - 10% sampling rule
  - Skew condition to check to use the normal model
- How big a sample size do I need?
- Statistical power
- Statistical vs practical significance

10% Sampling Rule

Question: Why do we set $n \leq 10\%$ of the population size N?

Intuition: Shouldn't we always sample as many people as we can?

Answer: Yes, if we only care about the mean. If we also care about the SE, then we need to be careful.

Issue: Sampling without vs with replacement.

Finite Population Correction

The finite population correction (FPC) to the SE accounts for the sampling without replacement:

$$SE = \frac{\sigma}{\sqrt{n}} \times \sqrt{\frac{N-n}{N-1}} = \frac{\sigma}{\sqrt{n}} \times FPC$$

Say we have $N = 10000$.

- Let $n = 100$ (1%), then

$$FPC = \sqrt{\frac{10000 - 100}{10000 - 1}} = 0.995$$

- Let $n = 5000$ (50%), then

$$FPC = \sqrt{\frac{10000 - 5000}{10000 - 1}} = 0.707$$

Finite Population Correction

$$SE = \frac{\sigma}{\sqrt{n}} \times \sqrt{\frac{N-n}{N-1}} = \frac{\sigma}{\sqrt{n}} \times FPC$$

We've been ignoring the FPC. So when

- n is relatively small, the FPC ≈ 1, so not a problem.
- n is relatively large, the FPC $\longrightarrow 0$.
  i.e. $\frac{\sigma}{\sqrt{n}}$ is not the true SE.

Conclusion: By capping $n \leq 10\%$ of N, we have a rule of thumb for keeping the FPC "close" to 1.

Conceptual and Mathematical Notions of Sampling

Conceptual: If we sample everybody, we know the true μ.

and

Mathematical: If $n = N$ then $FPC = \sqrt{\frac{N-n}{N-1}} = 0$ then $SE = \frac{\sigma}{\sqrt{n}} \times FPC = 0$

i.e.

- the sampling distribution is just one point: the true μ.
- if we repeat this procedure many times, we get the same value each time: 0 variability.

Sampling and the SE

Question: Why do we care that our SE is correct?

Answer: If not

- the *SE* in confidence intervals is off
- the z-scores of $\overline{x}$ have the wrong denominator

Skew Condition to Check to Use Normal Model

Throughout the book, they talk about the condition for $\overline{x}$ being nearly normal and using s in place of σ in $SE = \frac{\sigma}{\sqrt{n}}$:

- On page 164: the population distribution is not strongly skewed
- On page 167: the data are not strongly skewed
- On page 168: the distribution of sample observations is not strongly skewed
- On page 185: the population data are not strongly skewed

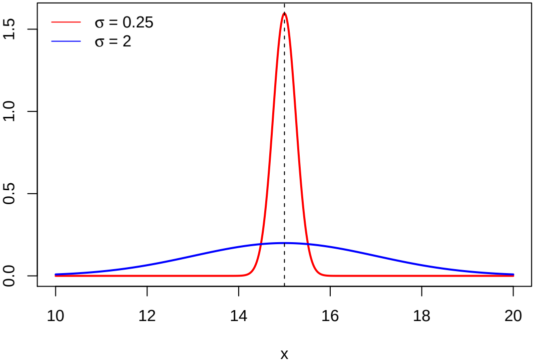
Skew Condition to Check to Use Normal Model

However, they all mean the same thing:

1. The true population distribution from which you are drawing your sample observations/data $x_1, \ldots, x_n$ is not too skewed.
2. The histogram (visual estimate) of the sample observations/data $x_1, \ldots, x_n$ is not too skewed.

Sample Size: Thought Experiment

Say you have two distributions with $\mu = 15$ but different σ.



Which of the two distributions do you think will require a bigger *n* to estimate μ "well"?

Margin of Error

Recall our formula for a 95% confidence interval:

$$\left[\overline{x} - 1.96\frac{s}{\sqrt{n}},\ \overline{x} + 1.96\frac{s}{\sqrt{n}}\right]$$

The margin of error is half the width of the CI.

Say we knew the true standard deviation σ, then

$$\text{Margin of Error} = 1.96\frac{\sigma}{\sqrt{n}}$$

Identify n for a Desired Margin of Error

To estimate the necessary sample size n for a maximum desired margin of error m, we set

$$m \geq z^* \frac{\sigma}{\sqrt{n}}$$

and solve for n.

Identify n for a Desired Margin of Error

Since

$$m \geq z^* \frac{\sigma}{\sqrt{n}}$$

$$\sqrt{n} \geq z^* \frac{\sigma}{m}$$

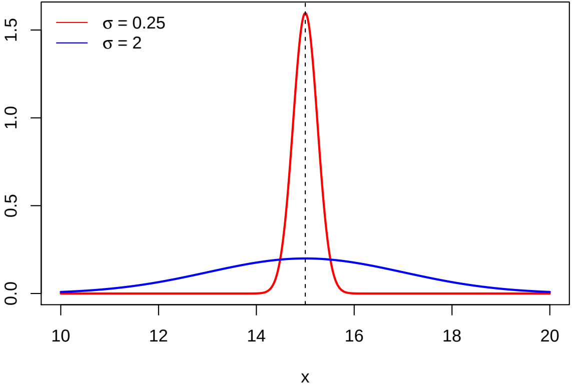
$$n \geq \left(z^* \frac{\sigma}{m}\right)^2$$

So

- As σ goes up, you need more n
- As z^* goes up, i.e. higher confidence level, you need more n
- As the desired margin of error goes down, you need more n

Back to Thought Experiment

For the same desired maximal margin of error m and same confidence level, we need a larger n to estimate the mean of the blue curve:



Type II Error Rate and Power

For a hypothesis test:

- The significance level α is the type I error rate: the rate at which we reject H_0 when it is true.
- The type II error rate β is the rate at which we fail to reject H_0 when H_A is true.
- $1 - \beta$ is called the statistical power: the rate at which we reject H_0 when H_A is true.

Type II Error Rate and Power

Say we are conducting $N = A + B + C + D$ hypothesis tests.

		Test conclusion	
		do not reject H_0	reject H_0 in favor of H_A
Truth	H_0 true	A	B
	H_A true	C	D

- The Type I Error rate is $\alpha = \frac{B}{A+B}$: rate at which B occurs given H_0 is true.
- The Type II Error is $\beta = \frac{C}{C+D}$: rate at which C occurs given H_A is true.
- The power is $1 - \beta = 1 - \frac{C}{C+D} = \frac{D}{C+D}$: rate at which D occurs given H_A is true.