

# STAT 102: Week 6

**Ricky's Section**

## Introductions and Attendance

**Introduction:** Name

**Question of the Week:** What is your favorite “thing” at the moment? Snack, activity, book, etc.

# Important Reminders

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## Midterm

- **Written Component:** Wed, 03/12 from 6 to 9 PM in Science Center 705 and 706
- **Oral Component:** Over Zoom afterwards on 03/13 and 03/14 (10 minute sessions)
- No class/section on Thur, Mar 13
- **You all got this!** 😊

# Review

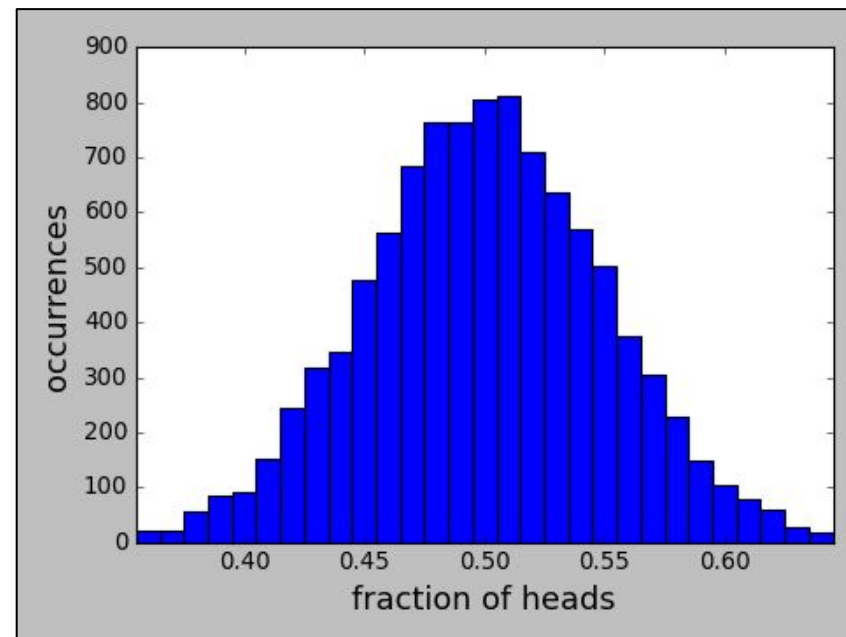
- **Review Session** with me and Sarah on Sunday, 03/09 from 7 to 9 PM in Science Center 316!
- Sign up for practice oral exams if you haven't already!
  - <https://canvas.harvard.edu/courses/143378/modules/items/1874820>

# **Content Review: Week 5**

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# “Theoretical” Distributions

- Theoretically, **Sample Mean** is approximately normally distributed with a **SD of  $\sqrt{p(1 - p)/n}$**
- Theoretically, **Sample Proportion** is approximately normally distributed with a **SD of  $\sqrt{\sigma^2/n}$**
- This is why we don't use **Sample Standard Deviation**  $\sigma$ -hat as our estimate of the **Sample Statistic's SD**
- Instead, we use the **SD of our Bootstrap Distribution**, which is theoretically a good approximation



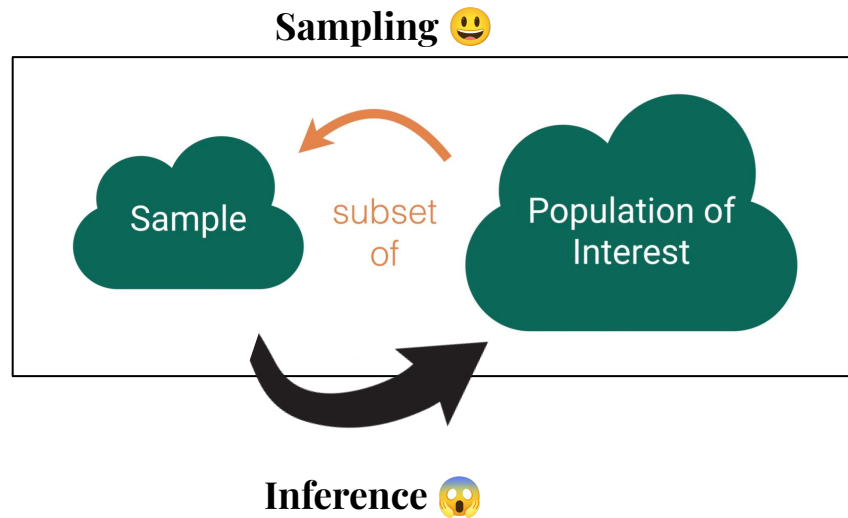
# **Content Review: Week 6**

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# Recap of Inference

- Last week, we started **inference** with **confidence intervals**
- Now, we'll continue with **hypothesis testing**
- Though complementary, they are different
  - **Confidence intervals** estimate the **parameter**
  - **Hypotheses** test a certain “conjecture” about the **parameter**



# A Tale of Two Hypotheses

- **Test statistic**: Numerical summary of the **sample data** (often, but not always, equal to our **observed sample statistic**)
- **Null hypothesis ( $H_o$ )**: World where **research conjecture is false** (“no change, status quo”)
  - Null distribution is sampling distribution of test statistic assuming null hypothesis is true
- **Alternative hypothesis ( $H_A$ )**: World where **research conjecture is true**
  - Alt. distribution is sampling distribution of test statistic assuming alt. hypothesis is true
- **P-value**: Probability of getting the **observed test statistic OR MORE EXTREME** if null hypothesis is true, represented by area under curve of null distribution

# A Note on Test Statistic

- **Test statistic**: Numerical summary of the **sample data** (often, but not always, equal to our **observed sample statistic**)
  - Last week, our **observed sample statistic** was  $\hat{p} = 0.5$  from a random sample of 600 viewers
  - We note this as “**observed**” because if we took a different sample of 600 viewers, we probably would’ve gotten a different sample statistic, such as  $\hat{p} = 0.4$  (i.e., **sampling variability**)
- As the name implies, this is the statistic we’ll be using in our **(hypothesis) test!**
  - More on this later, but there will be other test statistics

Can the null and  
alternative  
hypotheses both  
be true?

# Question:

Can the null and alternative hypotheses both be true?

No!

The **null hypothesis** and **alternative hypotheses** are mutually exclusive. That is, they **CANNOT** coexist.

Only 1 can be true. Either this drug works, or it doesn't. Either this coin is rigged, or it's not. And so on.

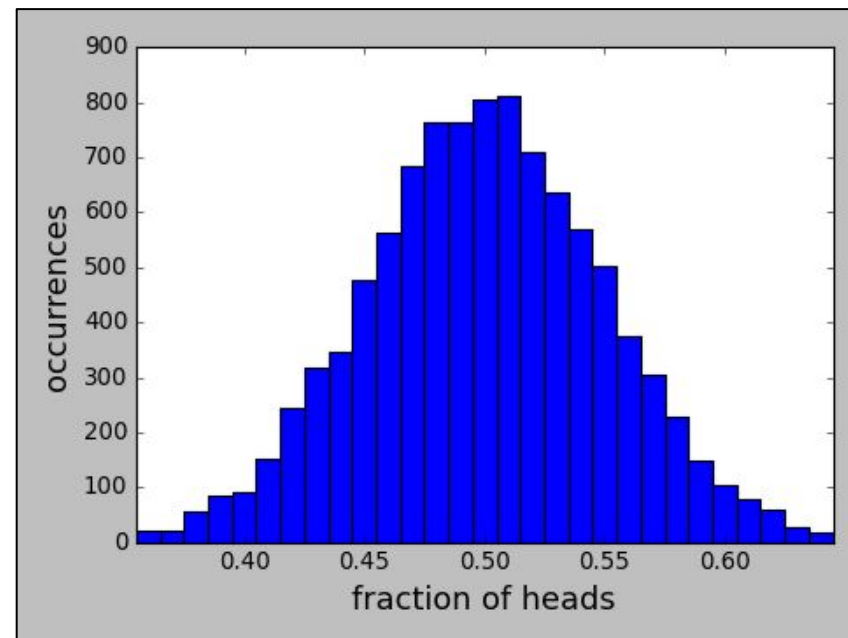
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# Essentials of Hypothesis Testing

- **Step 1:** State **hypotheses** (in terms of **population parameter**)
  - Null hypothesis posits the coin is normal. Alternative hypothesis argues it's rigged.  $H_0: p = 0.5$ ,  $H_A: p > 0.5$
- **Step 2:** Specify a **significance level**,  $\alpha$  (usually  $\alpha = 0.05$ )
- **Step 3:** Generate **null distribution**
  - If I were to repeatedly sample under the null hypothesis (assuming the coin has a normal 50% chance of heads), what would my sampling distribution look like?
- **Step 4:** Compute **observed test statistic** and **compute p-value**
  - Let's say, with  $n = 50$ , I observe 30 heads, so  $\hat{p} = 0.6$ . Under our null distribution, this has a p-value of 0.103.
- **Step 5:** Draw conclusions **in the context of the problem**
  - The probability of seeing 30 or more heads when flipping a fair coin 50 times is equal to 0.103. Since our p-value is high ( $0.103 > 0.05$ ), we fail to reject the null hypothesis. There is little evidence the coin is rigged.

# Coin Flips: An Intuition behind Sampling Distributions

- Let's flip a FAIR coin 15 times and record the proportion of heads
- Will our sample statistic always be 0.5? No!
- The center is the “theoretical” population proportion ( $p = 0.5$ )
- We're graphing a bunch of sample proportions ( $\hat{p}_1 = 0.4$ ,  $\hat{p}_2 = 0.5$ ,  $\hat{p}_3 = 0.6$ , ...)



## The “P-Value Formula”

- “If {null hypothesis} were true, then the probability of observing {test statistic} or {more extreme} would be {p-value}.”
  - This is “interpreting the p-value”
- “Because {p-value} is a {high/low} probability compared to {alpha}, we reject {reject/fail to reject} the null hypothesis.”
  - This is “drawing a relevant conclusion”



If I want to see whether or not the majority of Harvard students agree with a new bill, what should my hypotheses be (in terms of my pop. parameters)?

# Other Parameters and Statistics

	Response Variable		Numeric Quantity	Sample Statistic	Population Parameter
1 variable	Numerical		Mean	$\bar{x}$	$\mu$
	Binary Categorical		Proportion	$\hat{p}$	$p$
	Response variable	Explanatory Variable	Numeric Quantity	Sample Statistic	Population Parameter
2 variables	Numerical	Binary Categorical	Difference in Means	$\bar{x}_1 - \bar{x}_2$	$\mu_1 - \mu_2$
	Binary Categorical	Binary Categorical	Difference in Proportions	$\hat{p}_1 - \hat{p}_2$	$p_1 - p_2$
	Numerical	Numerical	Correlation	$r$	$\rho$

# Question:

If I want to see whether or not the majority of Harvard students agree with a new bill, what should my hypotheses be (in terms of my pop. parameters)?

We have a **binary categorical response variable** (fraction of students that agree). This is a **one-tailed proportion**.

$H_0: p = \frac{1}{2}$  (There is no majority)

$H_A: p > \frac{1}{2}$  (The majority agree)

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If I want to see if Harvard students get less sleep than other college students, what should my hypotheses be (in terms of pop. parameters)?

# Question:

If I want to see if Harvard students get less sleep than other college students, what should my hypotheses be (in terms of pop. parameters)?

We have a **binary categorical explanatory variable** (Harvard or not) and **numerical response variable** (hours of sleep). This is a **one-tailed difference of means**.

$H_0: \mu_{\text{Harvard}} - \mu_{\text{Other}} = 0$  (Harvard students get same amount of sleep)

$H_A: \mu_{\text{Harvard}} - \mu_{\text{Other}} < 0$  (Harvard students get less sleep)

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If I observe a difference of means of  $-2.7$  hours (and a p-value of  $0.003$ ), what is an interpretation of the p-value and a conclusion? Assume  $\alpha = 5\%$ .

# Question:

If I observe a difference of means of -2.7 hours (and a p-value of 0.003), what is an interpretation of the p-value and a conclusion?

Assume  $\alpha = 5\%$ .

Using the p-value formula...

If there was no difference in mean hours of sleep between Harvard and non-Harvard students, then the probability of observing our test statistic, a difference of -2.7 hours, or less would be 0.3%.

Because 0.3% is a **low** probability ( $0.3\% < 5\%$ ), we **reject** the null hypothesis.

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# Decisions, Decisions

- There are 4 potential outcomes of a **hypothesis test** (shown below), depending on what we do and what's actually true
- **$\alpha$**  - Probability of Type I Error (rejecting  $H_0$  when it's true)
- **$\beta$**  - Probability of Type II Error (failing to reject  $H_0$  when  $H_A$  is true)
  - As  $\alpha$  decreases,  $\beta$  increases (but they DON'T add up to 1)
- **Power**: Probability of rejecting  $H_0$  when  $H_A$  is true (best outcome 😊)
  - **Power** =  $1 - \beta$

	We Reject $H_0$	We Fail to Reject $H_0$
$H_0$ is true	Type I Error	Correct Decision 😊
$H_A$ is true	Correct Decision 😊	Type II Error



If we reject the null hypothesis, is it possible we committed a Type I Error? A Type II Error?

## Question:

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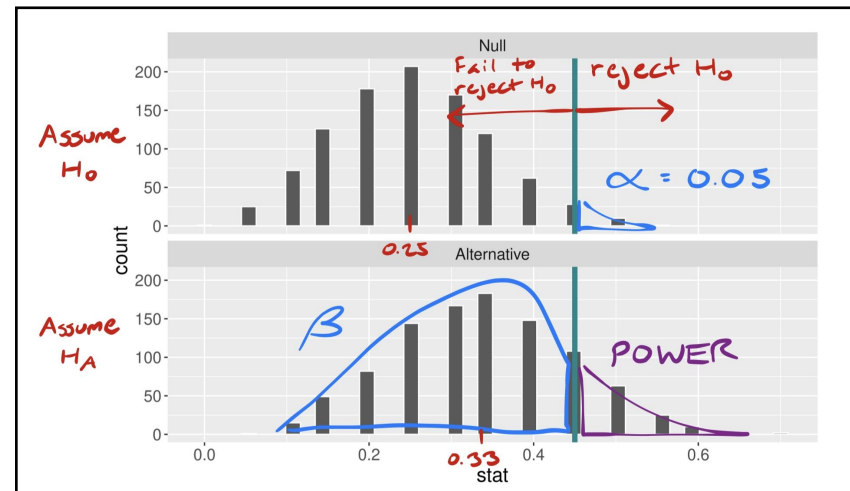
I remember Type I Error as a “delusional scientist” and Type II Error as a “missed opportunity.”

If we reject the null hypothesis, there's a possibility we committed a Type I Error but no possibility we committed a Type II Error (by definition, this would require FAILING to reject the null hypothesis).

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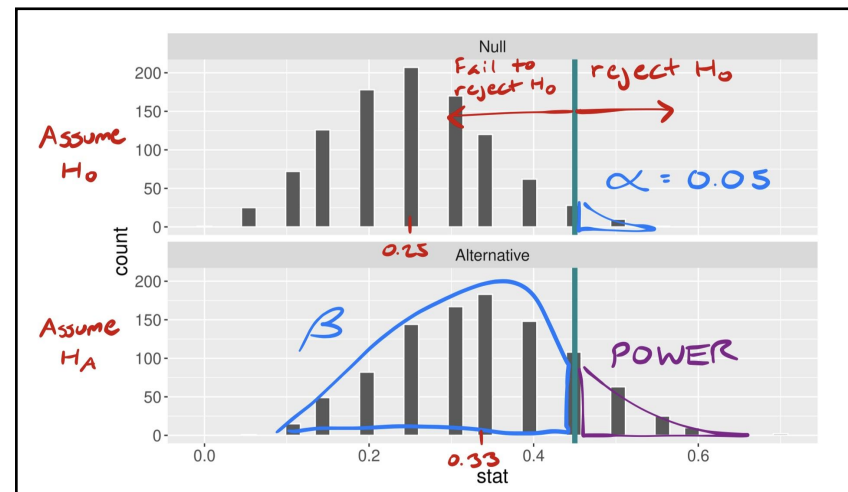
## More on Power...

- **Power**: Assuming  $H_A$ , what is the probability we reject  $H_0$ ?
- Think of **power** as a thought experiment—it helps us better understand **hypothesis testing**
  - In real life, we don't know if  $H_A$  is true... or where it's centered at!
  - There is an infinite number of alternative distributions that could exist... let's pick just one



# Intuition behind Power

- **Power**: Assuming  $H_A$ , what is the probability we reject  $H_0$ ?
  - Given  $H_A$  is true, we look at the **alternative distribution** (which, now, is the true state of the world)
  - The **alpha level** is the probability of rejecting  $H_0$  in the **null distribution**
    - The **critical region** (to the right of  $\alpha$ ) is where we reject  $H_0$
  - Thus, in the **alternative distribution**, the region to the right of the **alpha level** is **power**

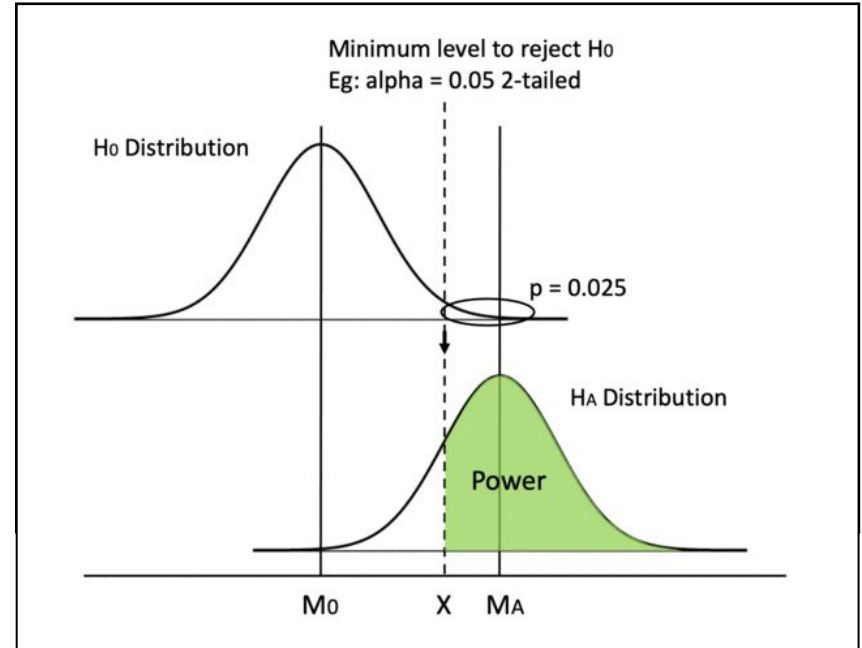


## Example: Baseball

- Ricky, an avid baseball player, has been a **0.250** career hitter, but, magically, he improves to be a **0.333** hitter
- He wants a raise, but he has to convince his manager he genuinely improved
- The manager offers to examine his performance in **20 trials**
- **$H_0: p = 0.250$ ,  $H_A: p > 0.250$  ( $p \neq 0.333$ )**
  - Because the **alternative hypothesis** is  $p > 0.250$ , there is an infinite amount of **alternative distributions** that could exist... specifically, I'm interested in the one centered at 0.333
- He wants his test to be “powerful”
  - When  $\alpha = 0.05$ , he needs to get **9 or more hits** to get a small enough **p-value** to reject  $H_0$
  - Unfortunately, at  $\alpha = 0.05$ , the **power of this test** is **0.211** (only a 21% probability of being in the best outcome), so how can we improve the **power of this test**?

# How to Increase Power: Increase Alpha

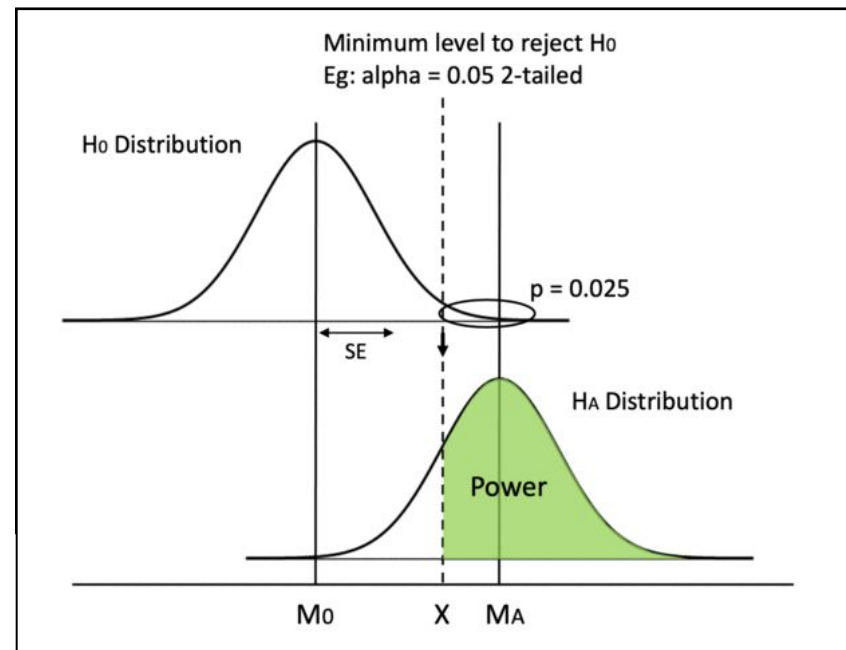
- This makes it easier to reject  $H_0$
- Also, this “shifts” the **critical line** to the left, leading to more area in the “**power region**” of the **alternative distribution**
- Intuitively, we now have a higher probability of rejecting  $H_0$ , and **power** is probability of rejecting  $H_0$  when  $H_A$  is true



<https://towardsdatascience.com/5-ways-to-increase-statistical-power-377c00dd0214>

# How to Increase Power: Increase Sample Size

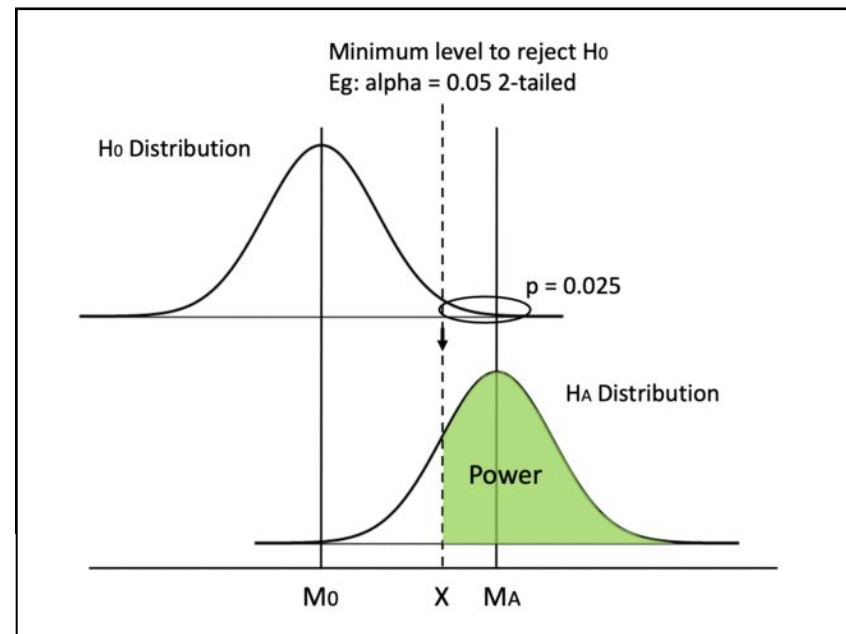
- This decreases **spread** of **histograms**, leading to less overlap between **null distribution** and **alternative distribution**



<https://towardsdatascience.com/5-ways-to-increase-statistical-power-377c00dd0214>

# How to Increase Power: Increase Effect Size

- **Effect Size**: Difference between true value of parameter and null value
- This makes it easier for us to notice a difference
- Also, this “shifts” the **center of the alternative distribution** to the right, leading to more area in the “**power region**”



<https://towardsdatascience.com/5-ways-to-increase-statistical-power-377c00dd0214>



## More on Effect Size...

- **Statistical Significance  $\neq$  Practical Significance**
  - *Ex: A study concluded couples who met online are more likely to be satisfied ( $p\text{-value} < 0.001$ ), but their happiness value of 5.64 isn't much more than the happiness value of 5.48 for couples who met in-person*
- Let's say, magically, Ricky actually improved to **0.400**
- Now, the **effect size (0.400 - 0.250)** is larger than before
  - Intuitively, it should now be more noticeable if he actually improved from before, so our **hypothesis test** is more “powerful”

What is the  
problem with  
increasing the  
alpha level?

# Question:

What is the problem with increasing the alpha level?

Though increasing the **alpha level** leads to higher **power**, it also leads to more **false positives** (a higher probability of a **Type I Error**).

There are a lot of trade offs, so these important choices depend on the context of the study.

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# When Should I Know to Calculate Power?

- **Hint 1:** The problem is about a hypothesis test
  - Ex: “Consider a scenario where at least 55% of voters must approve”
  - Here, we’re interested in the population proportion of voters
- **Hint 2:** The problem gives you a SPECIFIC value for the alternative hypothesis (in addition to a null value)
  - Ex: “If 60% of U.S. adults actually think marijuana should be legal...”
  - $H_0: p = 55\%$ ,  $H_A: p > 55\%$  ( $p \neq 60\%$ )
- **Hint 3:** You want to “test” something about your hypothesis test (e.g., if there is a sufficient sample size)
  - Ex: “Would  $n = 400$  be a reasonable sample size to demonstrate, with a one-sided test, that more than 55% of U.S. adults are in favor of legalization?”

## Important Code for Week 6

[https://drive.google.com/file/d/1SD1xhBFjU2Kxp  
bW\\_cXUNsOSrw74HCcr7/view?usp=drive link](https://drive.google.com/file/d/1SD1xhBFjU2Kxp<br/>bW_cXUNsOSrw74HCcr7/view?usp=drive_link)

# Questions?

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# Midterm Review (Weeks 1-6)

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## Week 2: Data Visualization

- **Grammar of graphics**: Dataset, geom, aesthetic
- **Color palettes**: Sequential, diverging, qualitative
- **Choosing the right graph**



## Week 3: Data Wrangling

- **Data joins**: Left, (right), inner, full
- **Creating/modifying variables**
- **Grouping/filtering/selecting data**
- **Summary statistics**: Mean, median, SD, IQR
- **Handling missing values (NA)**
- **Interpreting code in English**

## Week 4: Data Collection

- **Groups**: Sample, census, population
- **Observational study vs. experiment**
- **Two types of bias**: Sampling, nonresponse
- **Four sampling methods**: Simple, systematic, cluster, stratified

## Week 5: Simulation-Based Inference

- **Parameter vs. statistic**
- **Distributions**: Sampling, bootstrap
- **Confidence intervals**: Constructing, interpreting

## Week 6: Simulation-Based Hypothesis Testing

- **Hypotheses and Distributions**: Null and alternative
- **Hypothesis tests**: Constructing, interpreting
- **Pitfalls**: Power, p-value

## Midterm Tips

- **PLEASE SET A TIMER FOR THE ORAL!** There should be 3 questions in 10 minutes, so try not to “ramble”
- If you haven’t already, make a **study guide**
- **Partial credit** counts (so don’t delete all your code)
- Remember to **load all relevant libraries**
- **Pace yourself**—if a question is taking too long, move on
- Sign up for **practice oral exams** (usually not 3 questions)

# Debugging Practice

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**Let's Practice Debugging!**

<https://posit.cloud/spaces/599255/content/99046>

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Have a great rest  
of your week!