# Research Methods

### **MICHAEL BERNSTEIN CS 376**



### Respondent

### Theoretical

From McGrath, Methodology Matters

### Experiment

### Field





### Respondent

Sample Survey

> Formal Theory

### Theoreticar

From McGrath, Methodology Matters

Computer Simulation

### Laboratory Experiment

### Experiment

Experimental Simulation

### Field Experiment

Field

Field Study



# Method triangulation

- All methods are flawed
- Thus, your argument becomes far stronger if you can
  - Complement your statistics with semi-structured interviews
  - data

demonstrate the same phenomenon using multiple methods Complement qualitative work with primary source evidence or log



# Objectivity in reporting Readers are more cynical if that paper is presenting a one-sided

- argument
- Which argument do you buy?
  - "Ellipsoidal windows were better for all tasks." VS. users found them to be confusing."

"Ellipsoidal windows were better for all tasks we measured. However,



# Framing an evaluation

- trying to maximize
- number of clicks
- But, testing the easily quantifiable often misses the point.

• The difficulty: defining and isolating the construct that you are

• It is tempting to aim for something easy: time, task completion,



# Framing an evaluation

- good idea.
  - InForm is a good idea because...
  - Designing in parallel is a good idea because...
  - Soylent is a good idea because...
- (It may or may not be comparative in nature.)

Reflect on your implicit thesis about why your contribution is a

• This thesis can directly imply the claim that you need to test.



# Example theses

- Enable previously difficult/impossible tasks
- Improve task performance or outcome
- Modify/influence behavior
- Improve ease-of-use, user satisfaction
- User experience





# Hypothesis Testing

# Anatomy of a statistical test If your change had no effect, what would the world look like?

No difference in means

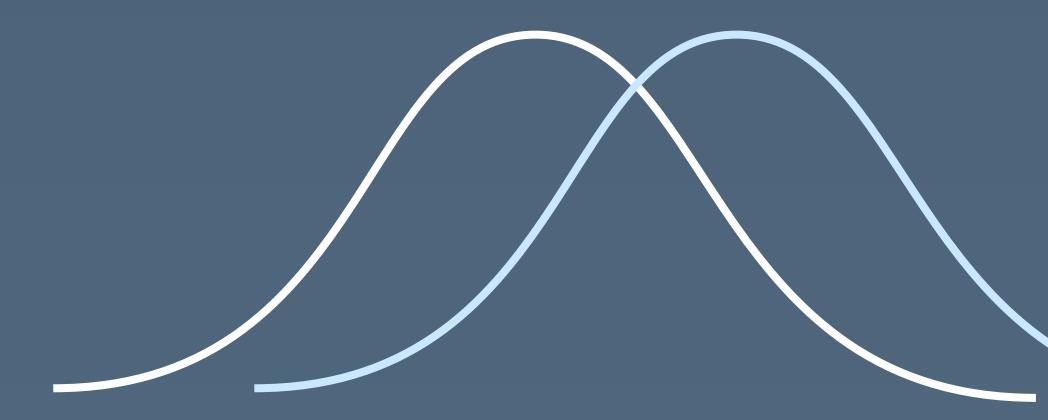
• This is known as the null hypothesis

No slope in relationship

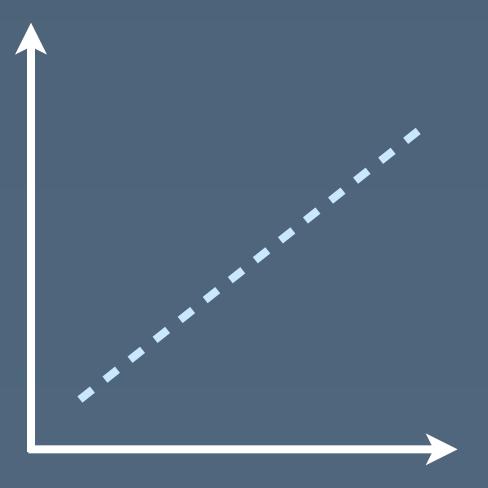
10

# Anatomy of a statistical test • Given the difference you observed, how likely is it to have

occurred by chance?



Probability of seeing a mean difference at least this large, by chance, is 0.012



Probability of seeing a slope at least this large, by chance, is 0.012



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### Difference detected?

True positive

Y

Ν

Y

Type 2 errorget more data?

### Difference exists? N

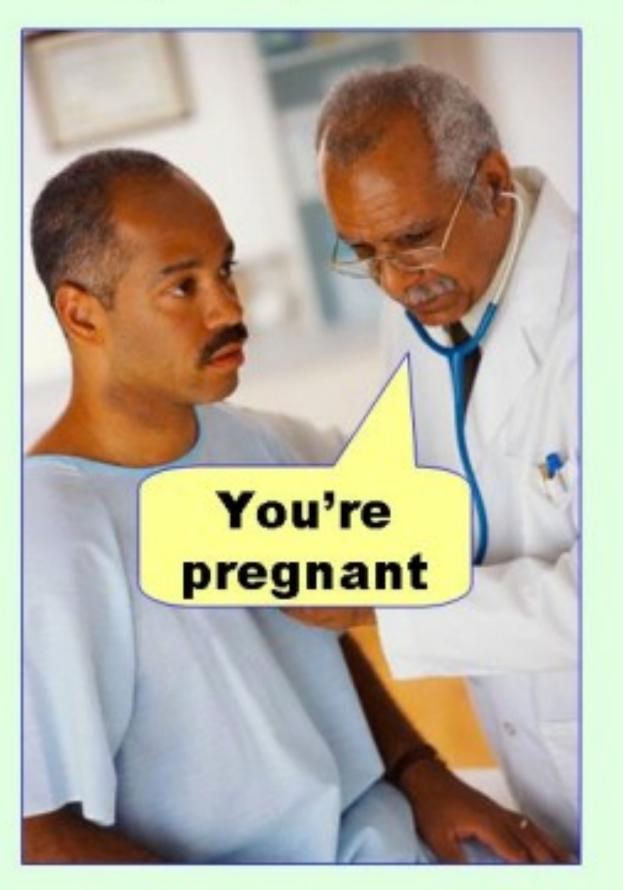


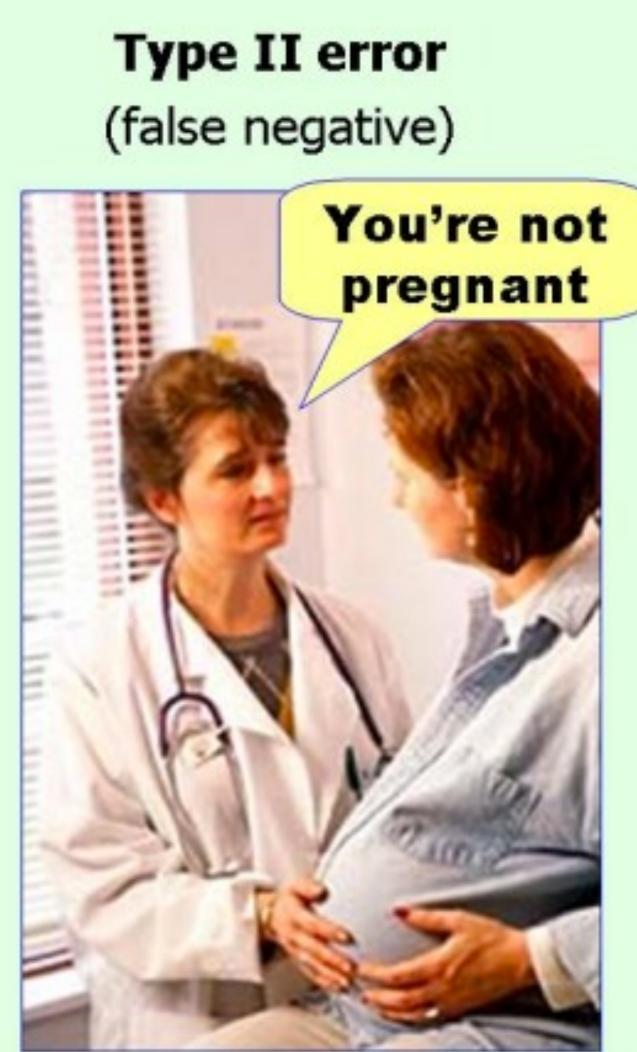
### True negative

12



### **Type I error** (false positive)





13

## p-value

- The probability of seeing the observed difference by chance In other words, P(Type I error)
- Typically accepted levels: 0.05, 0.01, 0.001

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# Comparing two populations:

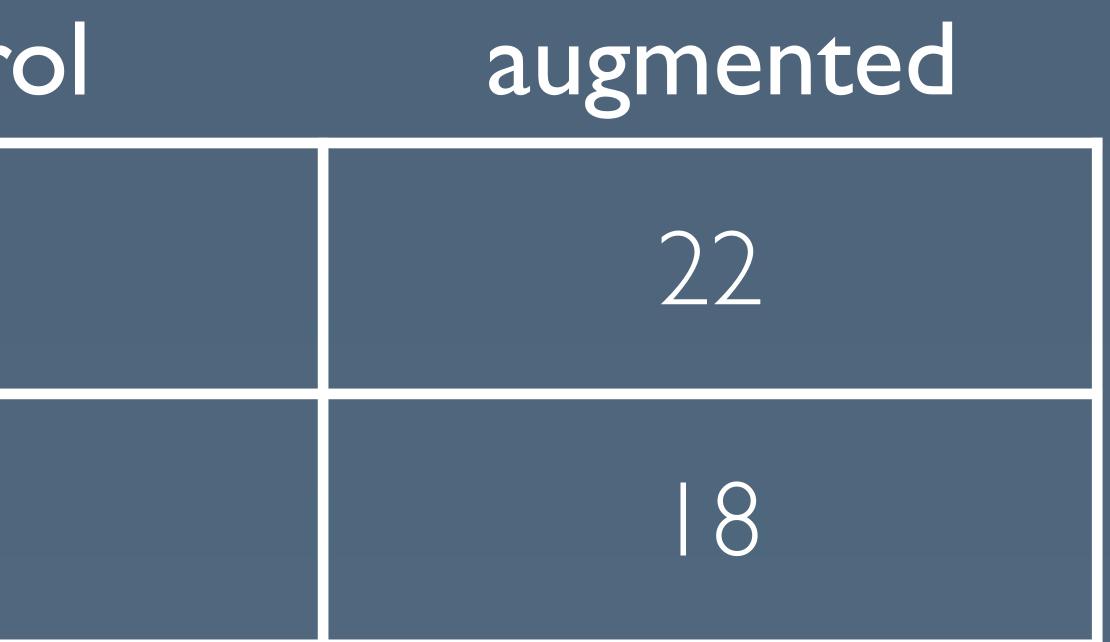
## Count or occurrence data

### control

### success

failure

• "Fifteen people completed the trial with the control interface, and twenty two completed it with the augmented interface."



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### Pearson's chi-square test for independence

control



Expected is (row total)\*(column total) / overall total. • Upper left: expected is 27\*40/80 = 13.5

### Determine the expected number of outcomes for each cell augmented total

22	27
8	53
40	80



# Calculating a chi-square statistic $\chi^2 = \frac{(observed - expected)^2}{expected}$

e.g.,  $(5-13.5)^2 / 13.5 = 5.35$ Sum this value over all possible outcomes

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# How many degrees of freedom? If we know there are a total of 40 participants...

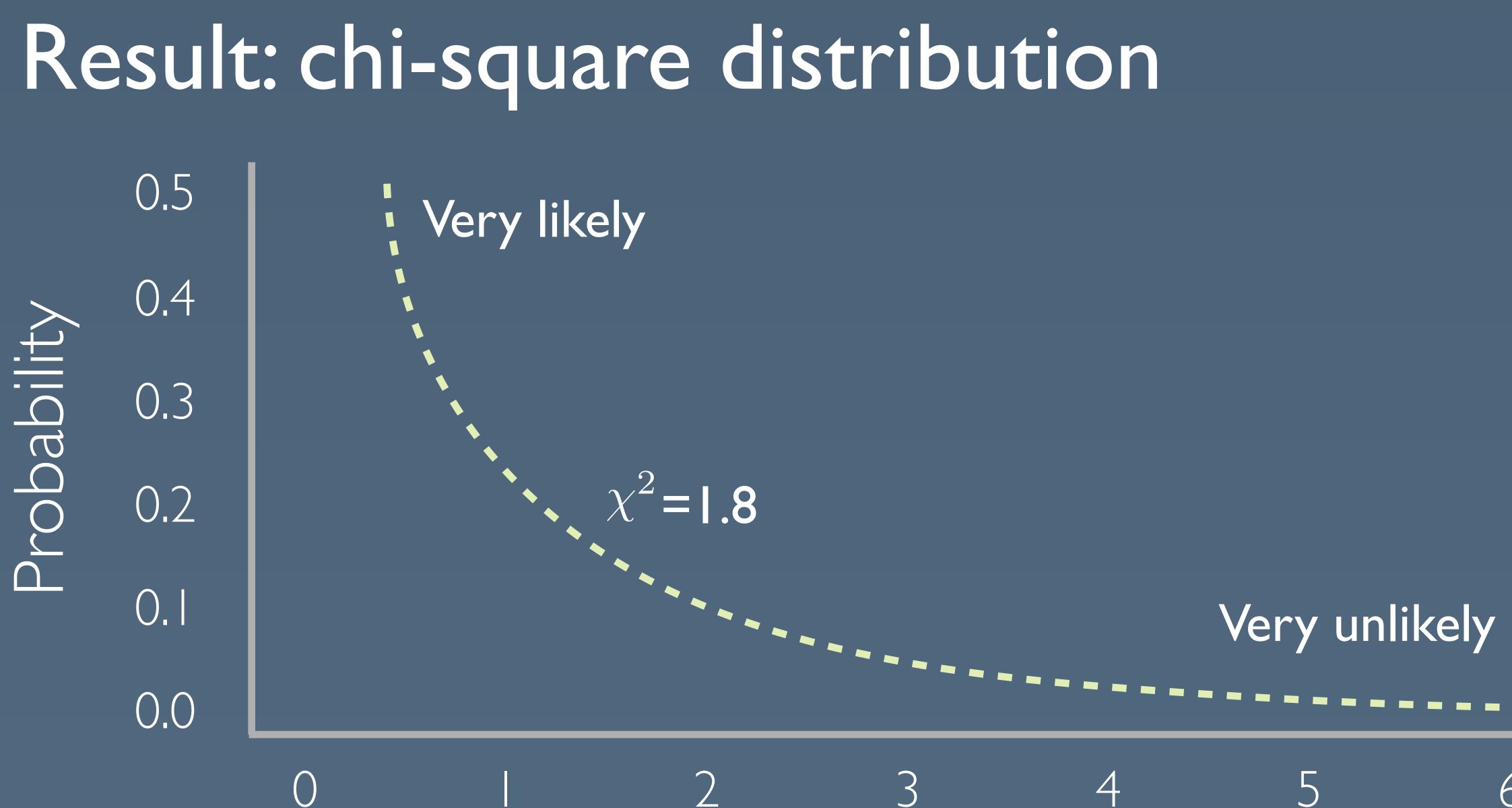


• We get (rows - I) \* (columns - I) degrees of freedom. So, if it's a two-by-two design, one degree of freedom.



### |8|

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6 chi-square statistic with one degree of freedom



# Pearson's chi-square test for independence chisq.test (HCI R tutorial at <u>http://yatani.jp/HCIstats/ChiSquare</u>)

> data [,1] [,2] [1,] 5 22 [2,] 35 18 > chisq.test(data)

correction

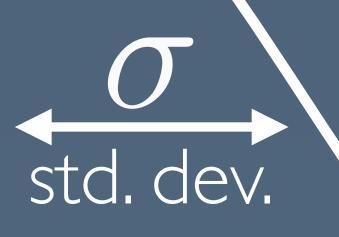
data: data X-squared = 14.3117, df = 1, p-value = 0.0001549

### Pearson's Chi-squared test with Yates' continuity



# Comparing two populations: means

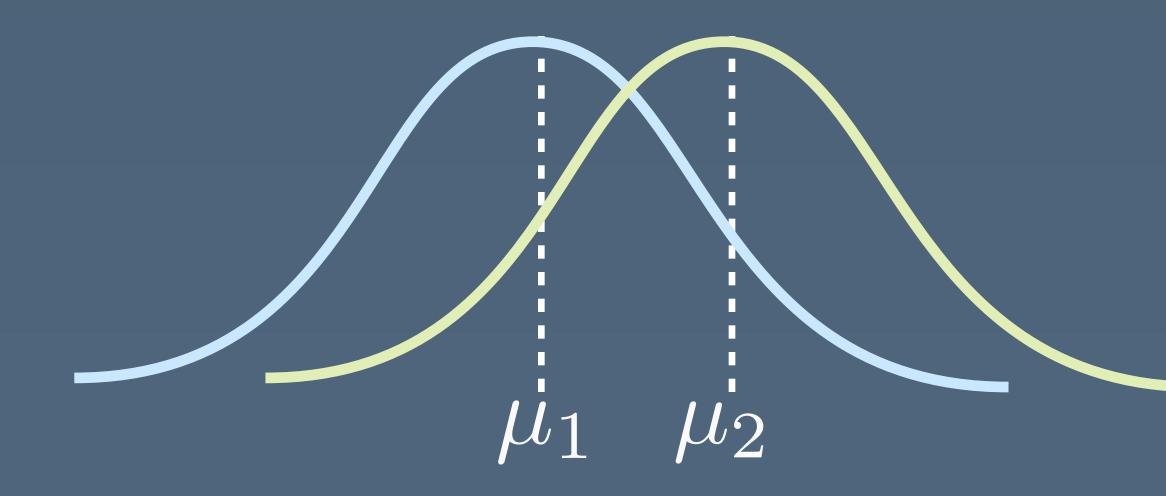
# Normally distributed data







## t-test: do they have the same mean?

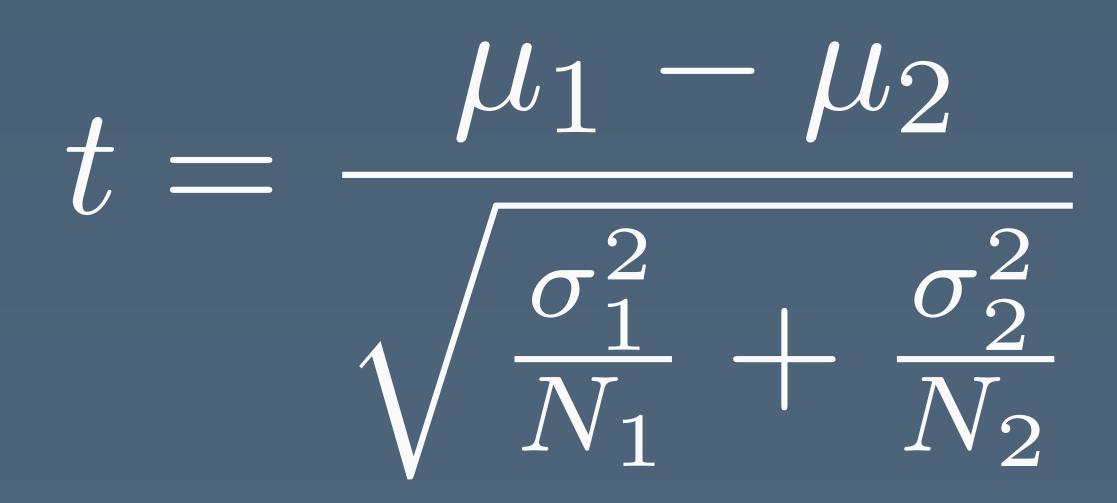


### likely have different means



### likely have the same mean (null hypothesis)

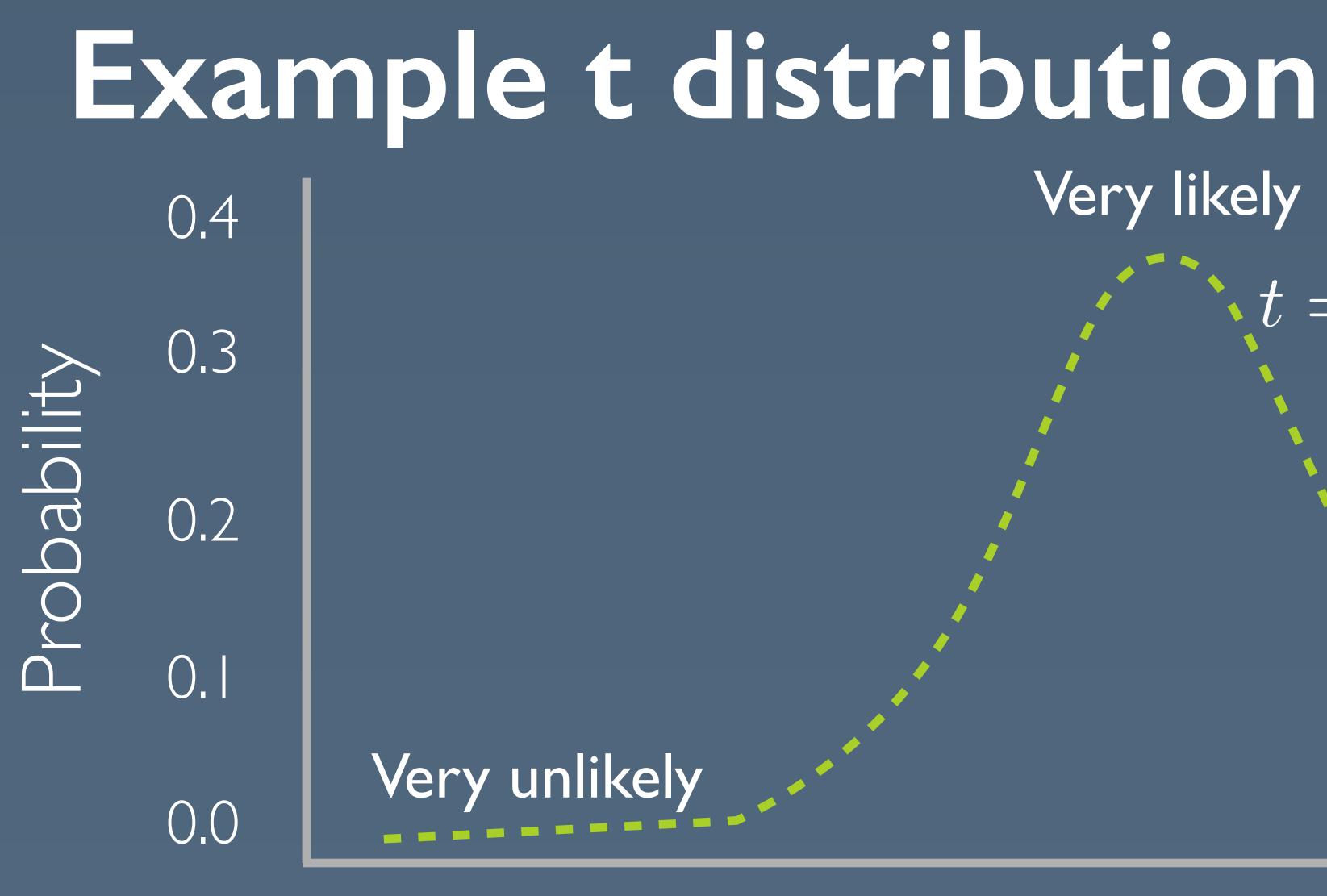




Numbers that matter:
Difference in means
larger means more significant
Variance in each group
larger means less significant
Number of samples

larger means more significant





 $\left( \right)$ -2 t statistic with 18 degrees of freedom

# Very likely

t = .92

### Very unlikely





# How many degrees of freedom? If we know the mean of N numbers, then only N-1 of those

- numbers can change.

• We have two means, so a t-test has N-2 degrees of freedom.



# Running the test in R

### Use t.test (HCI R tutorial at <u>http://yatani.jp/HClstats/TTest</u>)

> data		
	group	result
1	control	1
2	control	1
3	control	2
4	control	3
5	control	1
6	control	3
7	control	2
8	control	4
9	control	1
10	control	2
11	augmented	6
12	augmented	5
13	augmented	1
14	augmented	3

> t.test(data[data["group"] == "control", 2], data[data["group"] == "augmented", 2], var.equal=T)

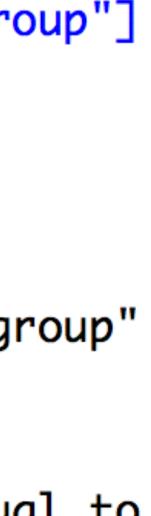
1 == "auamented". 21 0 95 percent confidence interval: -2.73610126 -0.06389874 sample estimates: mean of x mean of y 2.0 3.4

Two Sample t-test

data: data[data["group"] == "control", 2] and data[data["group"

t = -2.2014, df = 18, p-value = 0.04099

alternative hypothesis: true difference in means is not equal to



# Presenting the result

• "A t-test comparing the expert-rated scores of designs with the control (mean=2.0, std. dev=0.5) to the designs with the augmented condition (mean=3.4, std. dev=0.4) is significant (t(|8)=2.2, p<.05)."



## Within-subjects study designs • It can be easier to statistically detect a difference if the participants try both alternatives.

- Why?



## Paired t-test Control Augmented 6 5 2 3 3 2

A paired test controls for individual-level differences.





# Paired t-test $t = \frac{\mu - 0}{\sqrt{\frac{\sigma^2}{N}}}$

• Is the mean of that difference significantly different from zero?



# Running a paired t-test in R

> t.test(data[data["group"] == "control", 2], data[data["group"] == "augmented", 2], paired=T)

Paired t-test

data[data["group"] == "control", 2] and data[data["group" data: ] == "augmented", 2]t = -1.7685, df = 9, p-value = 0.1108 alternative hypothesis: true difference in means is not equal to 0 95 percent confidence interval: -3.1907752 0.3907752 sample estimates: mean of the differences -1.4

Why no longer significant? (Hint: look at the degrees of freedom "df")

Ten participants. If we had twenty rows like before, much more likely.













# Comparing two populations: nonparametrics

## What if the data isn't normally distributed?

- Skewed data
- Timing data
- Rankings or any ordinal data
- Likert scales with too few options (e.g., only 1-3)

Parametric tests assume normally-distributed data. Nonparametric tests do not.



# Transform the data into ranks





Intuition — Control: average rank is 13 Augmented: average rank is 7.7



## Mann-Whitney U Also known as the Wilcoxon rank sum test (Tutorial at <u>http://yatani.jp/HClstats/MannWhitney</u>) > wilcox.test(data[data["group"] == "control", 2], data[data["gr

oup"] == "augmented", 2])

Wilcoxon rank sum test with continuity correction

data: ] == "augmented", 2]W = 23.5, p-value = 0.04911 alternative hypothesis: true location shift is not equal to 0

Also available: Wilcoxon signed rank test (for paired data)

- data[data["group"] == "control", 2] and data[data["group"



# Summary

- p-values encode our desired probability of a false positive
- Chi-square test compares count or rate data
- t-test compares means
- Paired t-test compares means within subjects
- Mann-Whitney U compares ranks for non-normal data

probability of a false positive unt or rate data

s within subjects ranks for non-normal data

