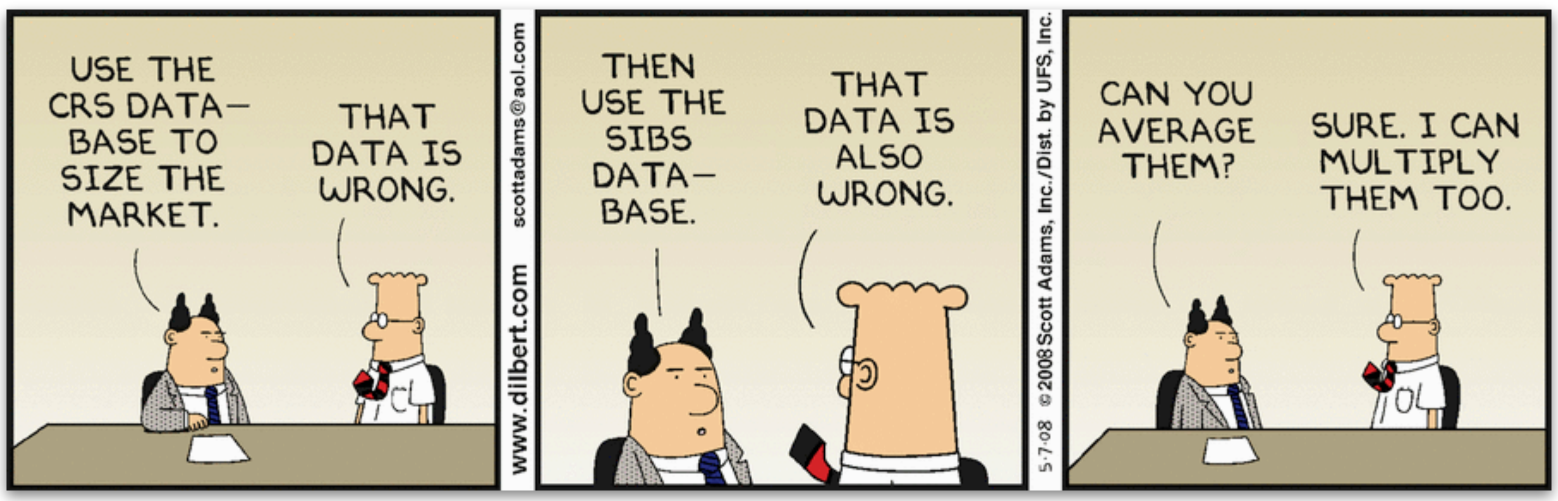
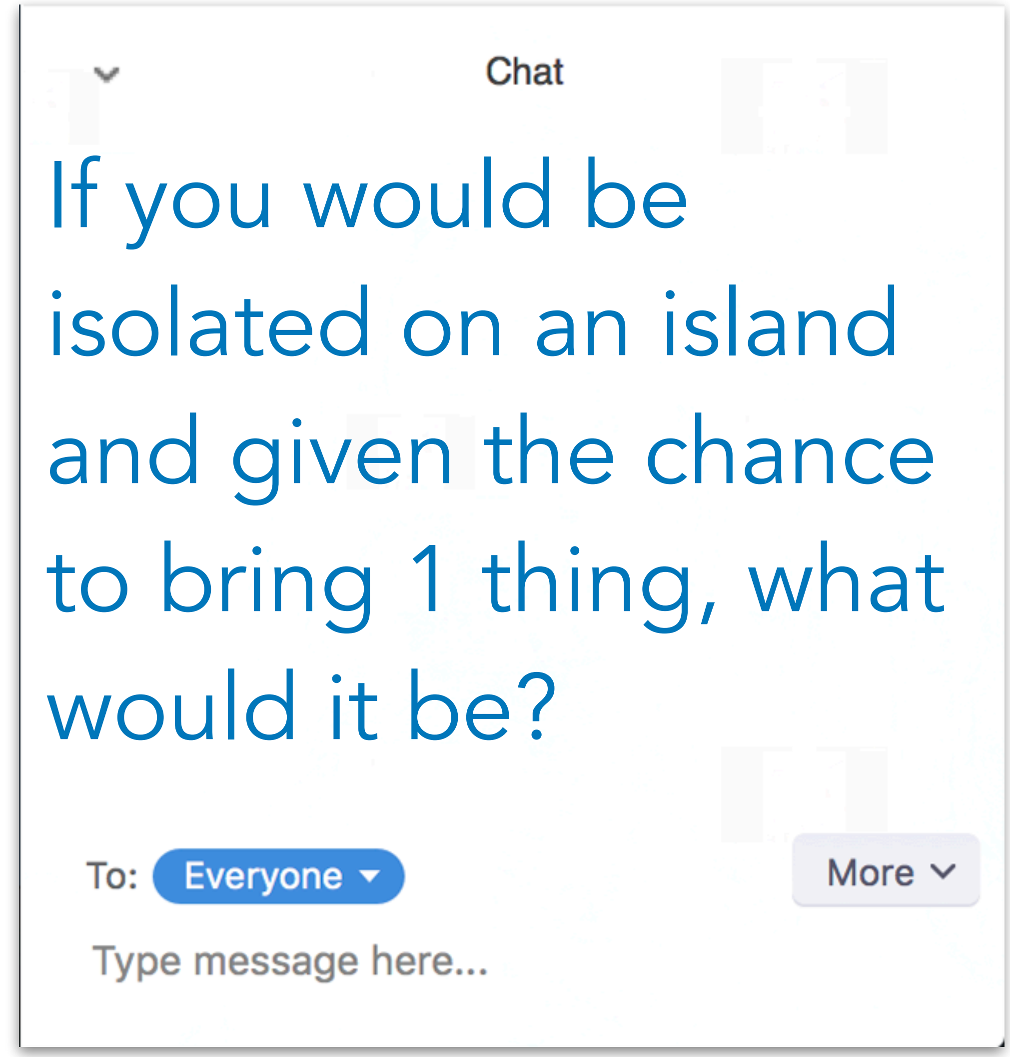
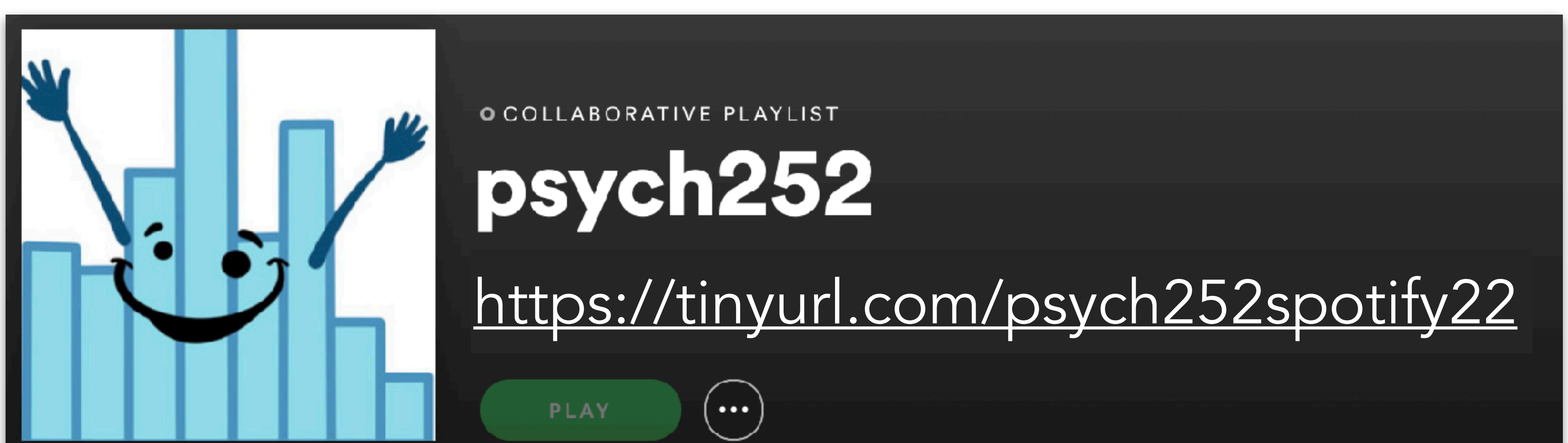
PSYCH 252: Statistical Methods for Behavioral and Social Sciences

Simulation 2





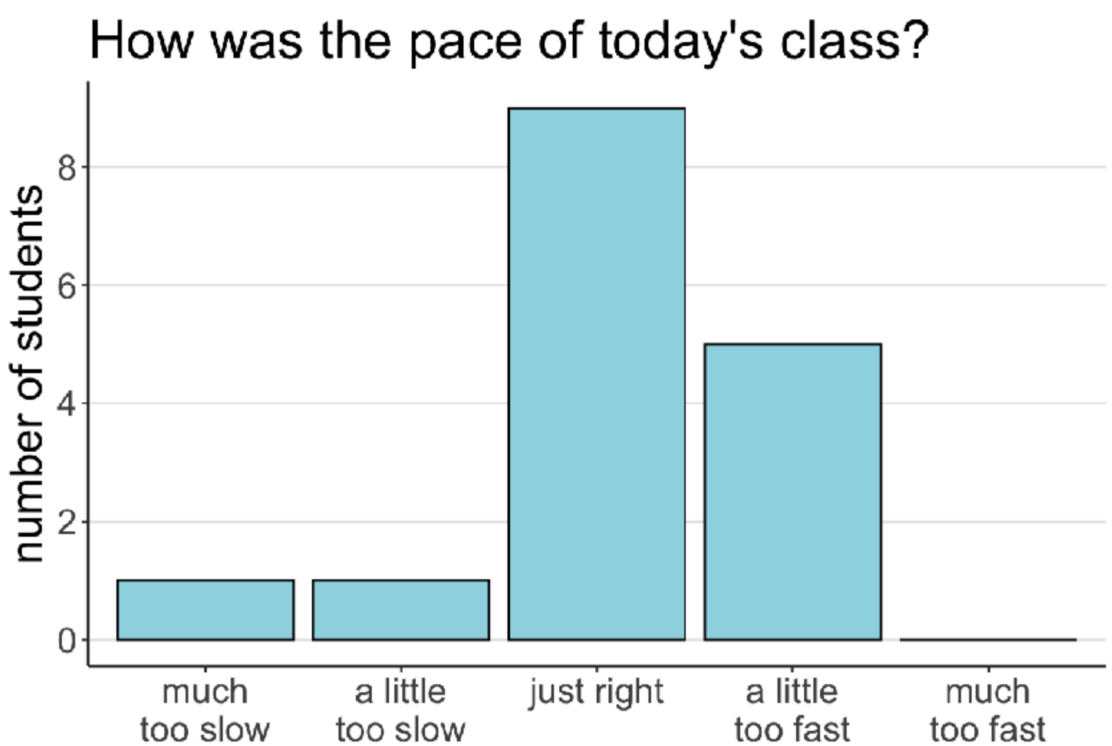


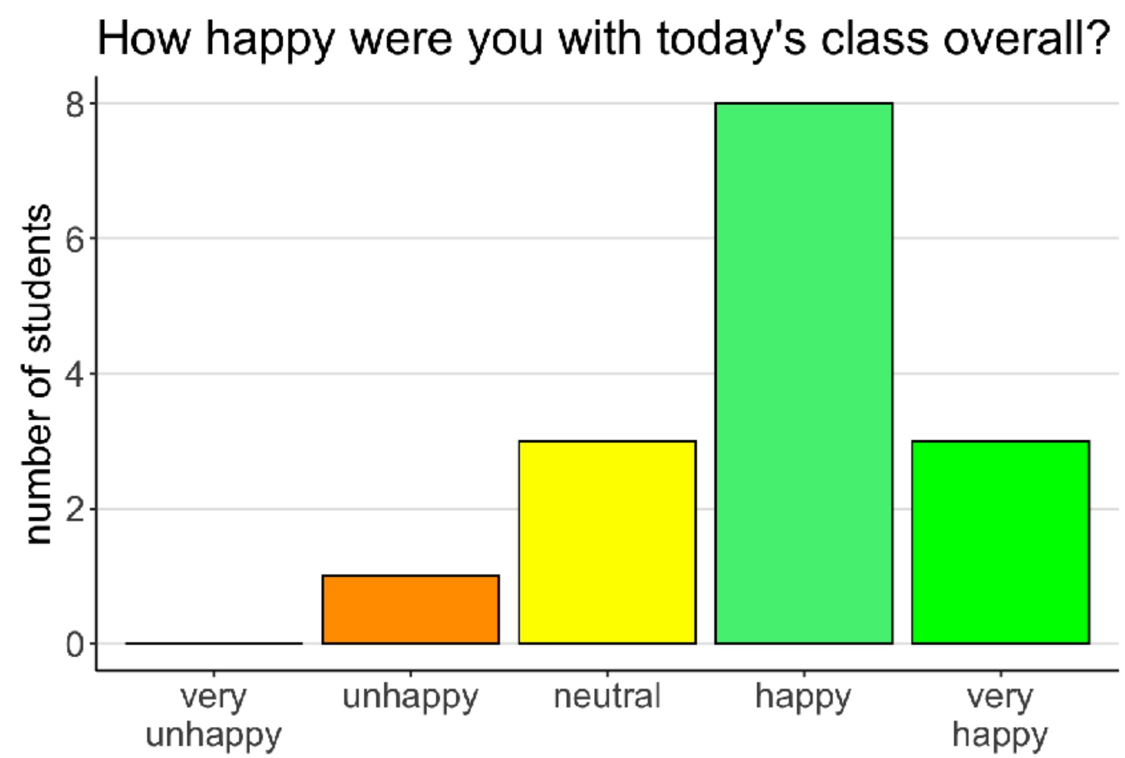
We're listening to "Chemicals" by "The Notwist"

01/21/2022

Your feedback

Your feedback





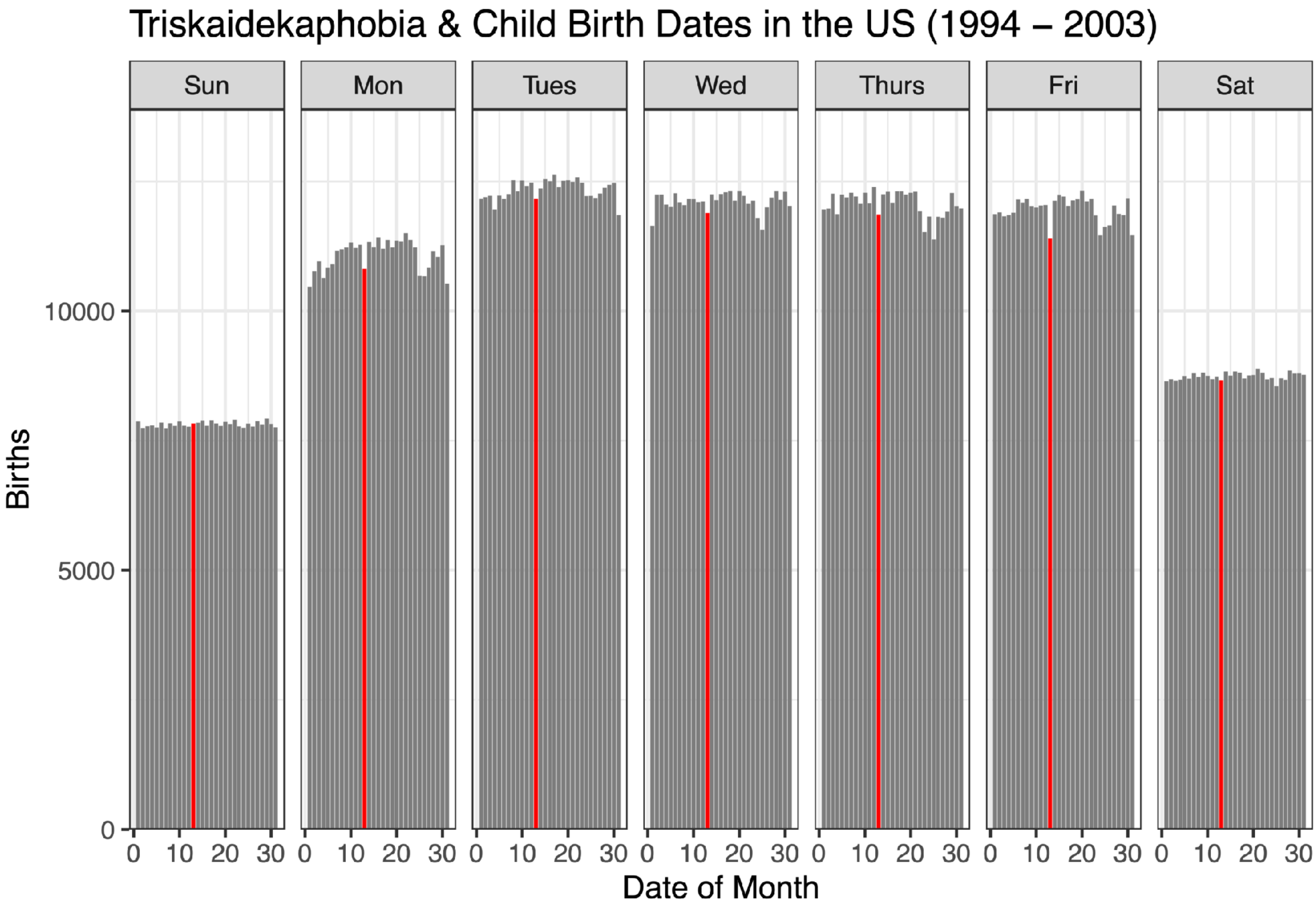
The class was interesting but it wasn't clear what we were supposed to takeaway from the lecture. For example, are we expected to know how to do power analysis based on the lecture today?

for me ... (also, help me slow down by asking questions)

Homework

Homework 1
Show case

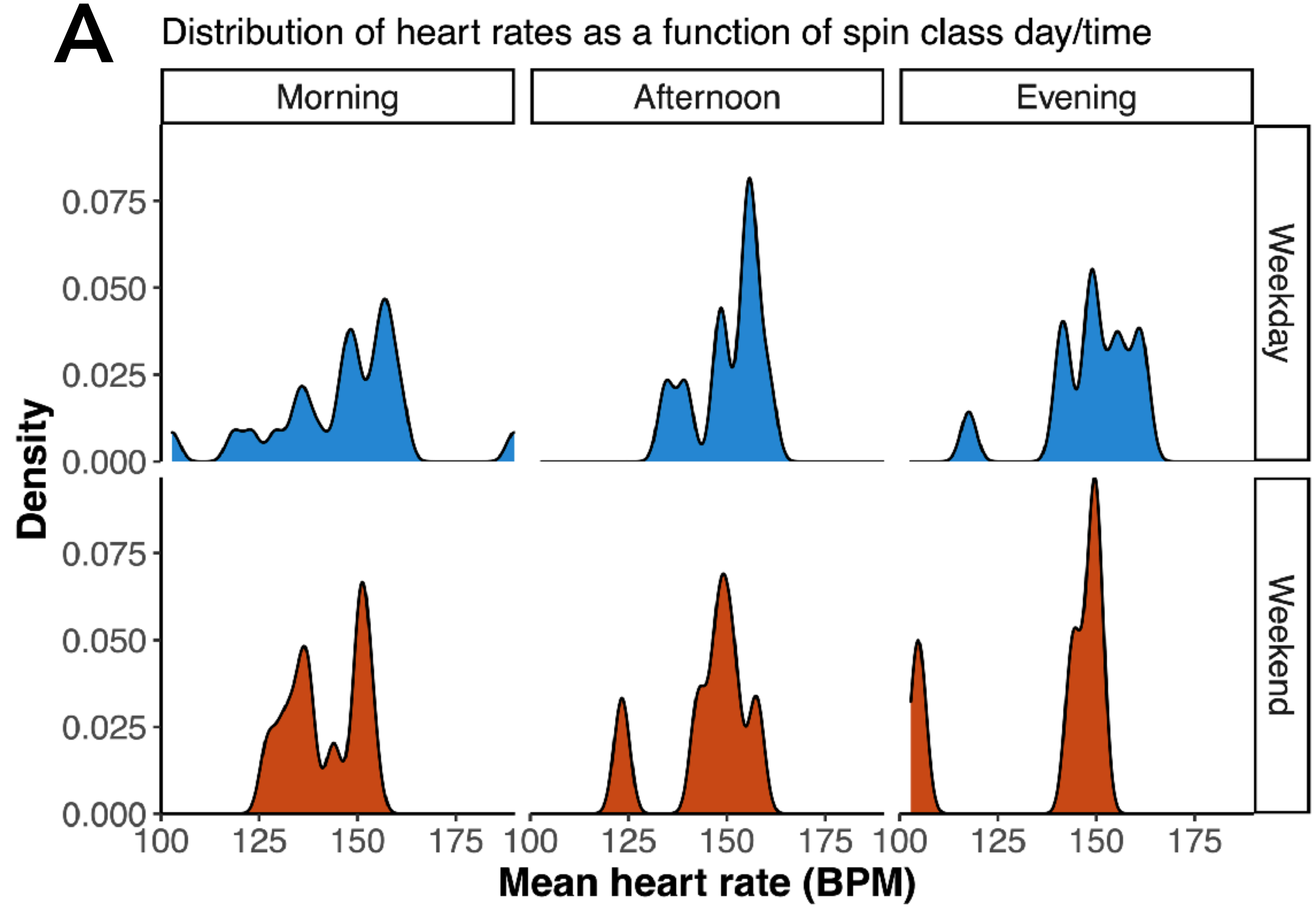
Stacia King



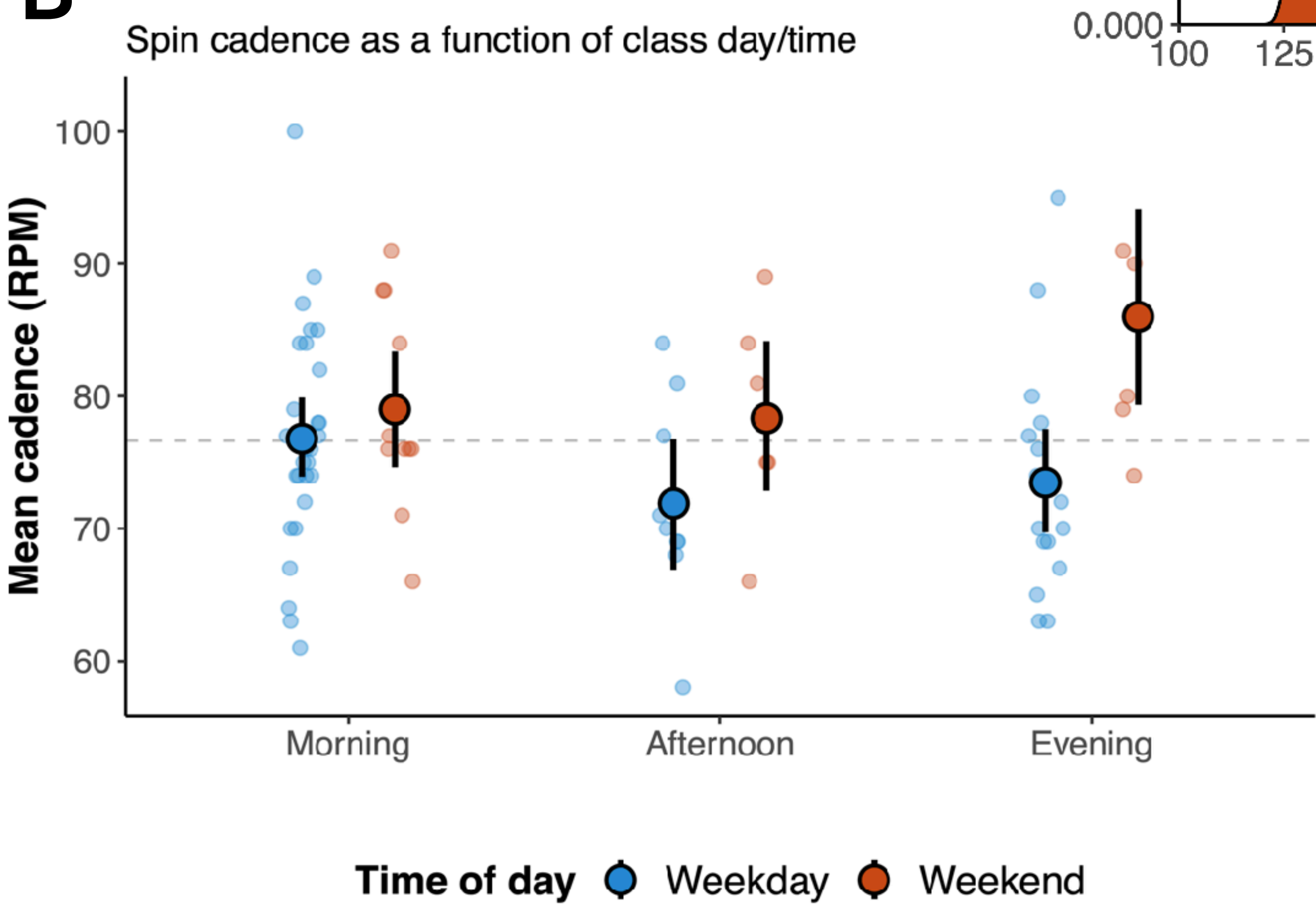
Triskaidekaphobia & Child Birth Dates in the US (1994 – 2003)
Sun
Mon
Tues
Wed
Thurs
Fri
Sat
Births
10000
5000
0
0 10 20 30
Date of Month

Shawn Schwartz

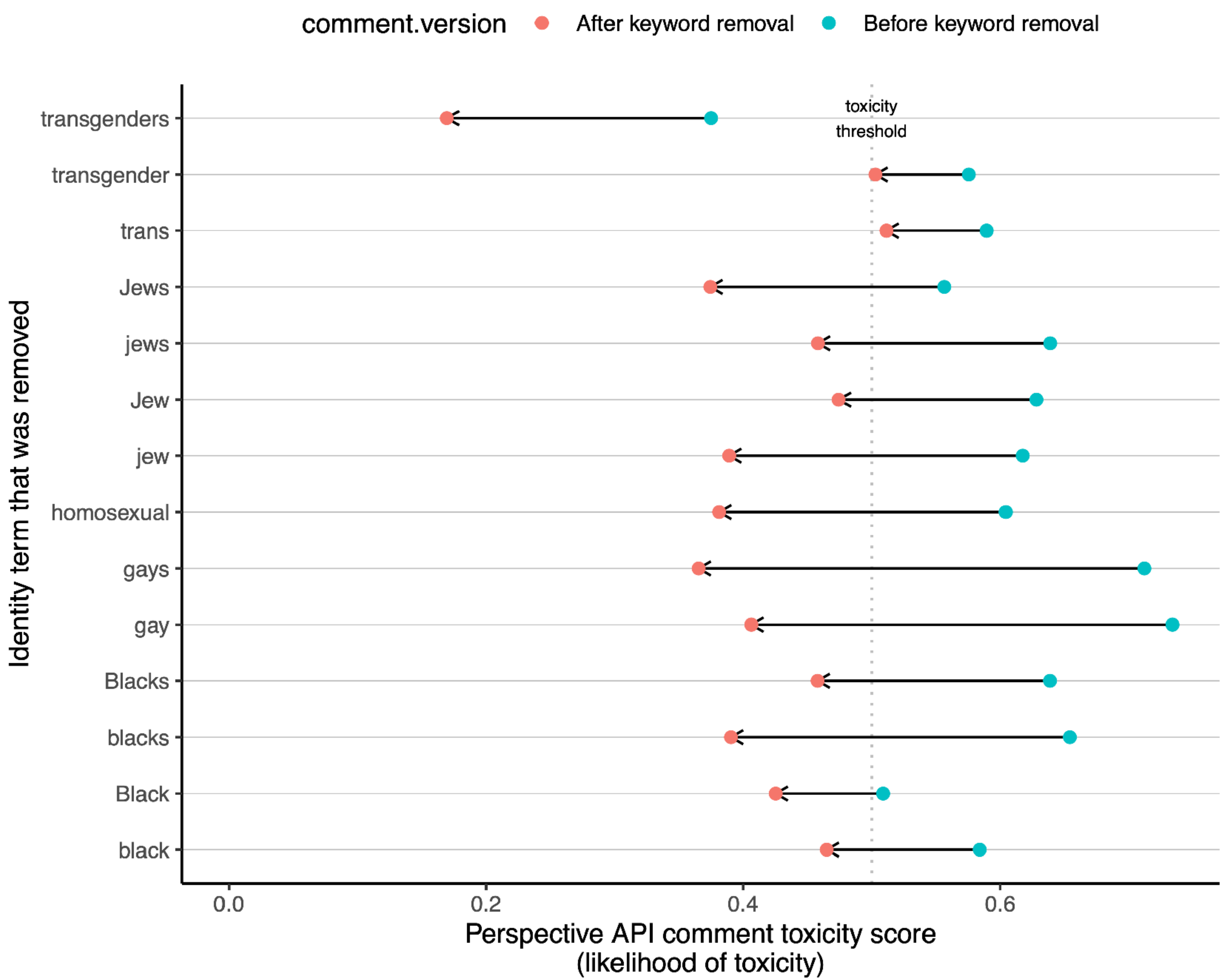
A



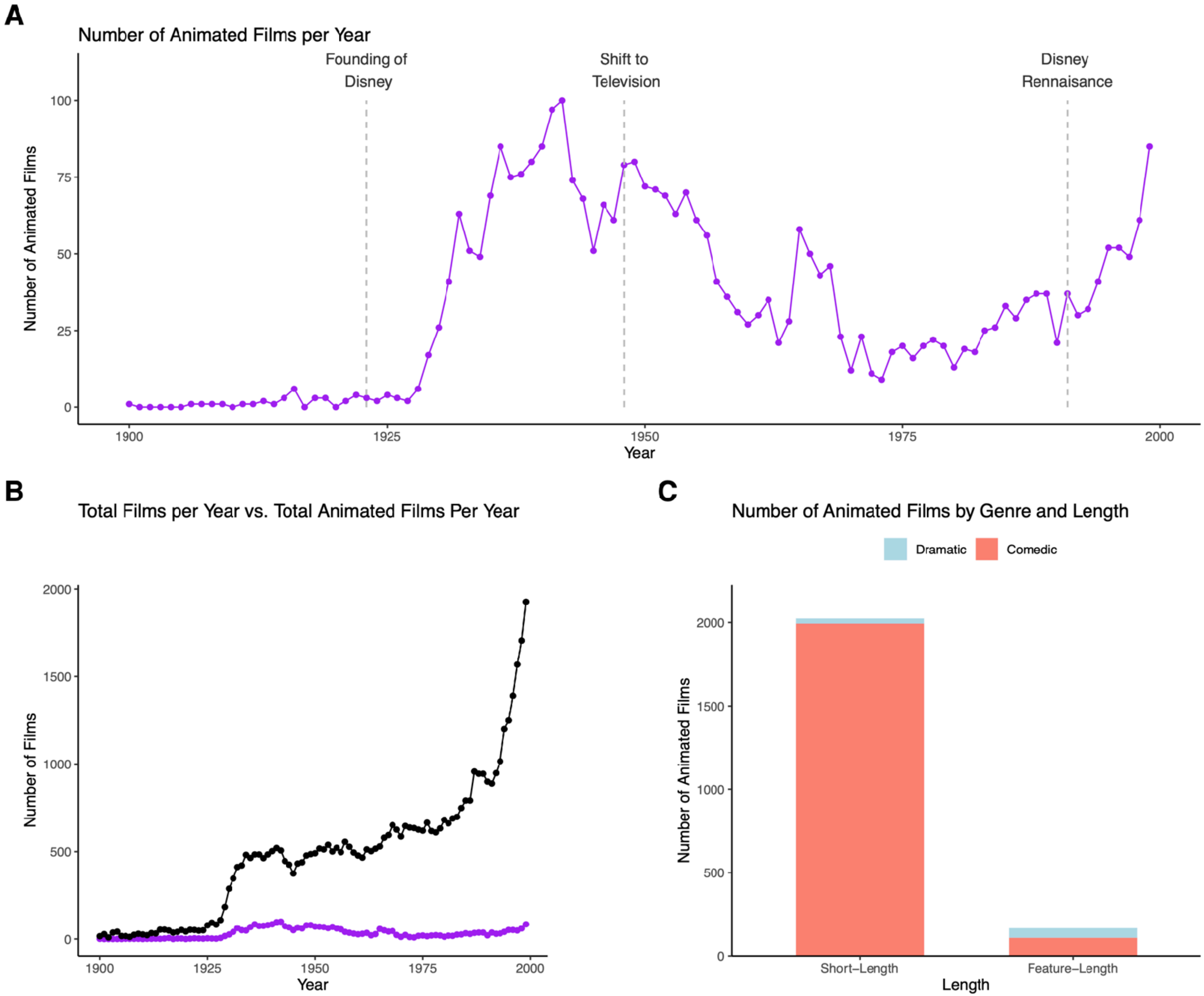
B



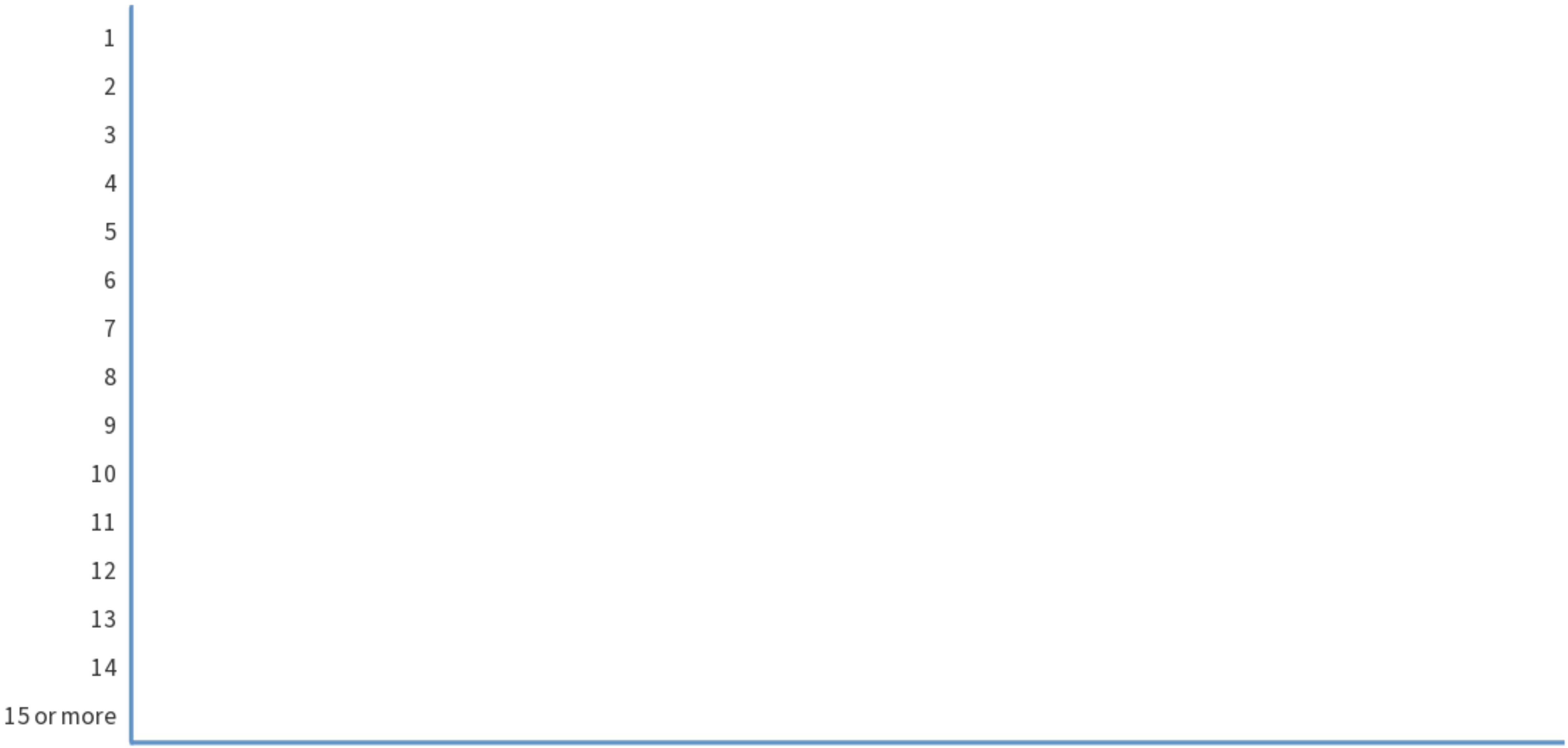
Michelle Lam



Peter Zhu


A
Number of Animated Films per Year
Founding of Disney
Shift to Television
Disney Rennaisance
Number of Animated Films
100
75
50
25
0
1900
1925
1950
1975
2000
Year
B
Total Films per Year vs. Total Animated Films Per Year
Number of Films
2000
1500
1000
500
0
1900
1925
1950
1975
2000
Year
C
Number of Animated Films by Genre and Length
Dramatic
Comedic
Number of Animated Films
2000
1500
1000
500
0
Short–Length
Feature–Length
Length

How many hours did it take you to complete Homework 2?



Homework 3

1 Distributions (1 point)

When we have empirical data, we can compute cumulative probabilities and create probability density functions using `quantile()` and `density()`, respectively. Take a look at the help files for both of these functions to better understand what they're doing.

Consider the following data set:

```
df.p1 = tibble(observation = 1:20,
               rating = c(0.3775909, 0.5908214, 0.07285336, 0.06989763, 0.2180343,
                          1.447484, 0.614781, 0.2698414, 0.4782837, 0.073523,
                          0.6953676, 0.3810149, 0.6188018, 2.211967, 0.5272716,
                          0.517622, 0.9380176, 0.3273733, 0.1684667, 0.2942399))
```

1.1 Quantile (0.5 points)

What's the 60% percentile of the `rating` vari
60% of the values are lower than that value?)

```
### YOUR CODE HERE ###

######################
```

1.2 Density (0.5 points)

Plot the density of the `rating` variable. Use

```
### YOUR CODE HERE ###

######################
```

2 Sampling distribution (7 points)

The sample standard deviation $s = \sqrt{\frac{\sum_{i=1}^{n}(Y_i-\overline{Y})^2}{n-1}}$ is an unbiased estimator of the population standard deviation.In this exercise, we will run a simulation to compare s with another estimator $s' = \sqrt{\frac{\sum_{i=1}^{n}(Y_i-\overline{Y})^2}{n}}$ and show that s' is biased. Note that the only difference between s and s' is in the denominator.

1

2.1 Generate the sample distributions (2 poi

Let's simulate drawing 10,000 samples from a population distril
sample should be 40. To start off, create a new data frame `df.`
3 columns:

- **sim**: index for the simulation (from 1 to 10,000)
- **sample**: index for the sample in each simulation (from 1
- **x**: sample values drawn from the population distribution

For the population distribution assume a normal distribution

3 Permutation test (7 points)

Imagine that you collected data about people's heights from three different places and you are interested whether there are any differences in people's height between the three places.

By visualizing the data, we can see that the variances between the three groups differ considerably, which is troublesome for parametric tests (e.g. a t-test). However, we can perform a permutation test, which is non-parametric. In this case, we are interested in whether the maximal difference between each of the pairs of group means, is greater than we would expect to see by chance.

```
set.seed(1)

df.heights = read_csv("data/df_heights.csv")

df.heights %>%
  ggplot(data = .,
         mapping = aes(x = group,
                       y = height)) +
  geom_point(position = position_jitter(height = 0,
                                        width = 0.1),
             alpha = 0.5) +
  stat_summary(fun.data = "mean_cl_boot",
               shape = 21,
               fill = "lightblue",
               size = 1)
```

Homework 3

remember to set `eval = T`
when knitting the file

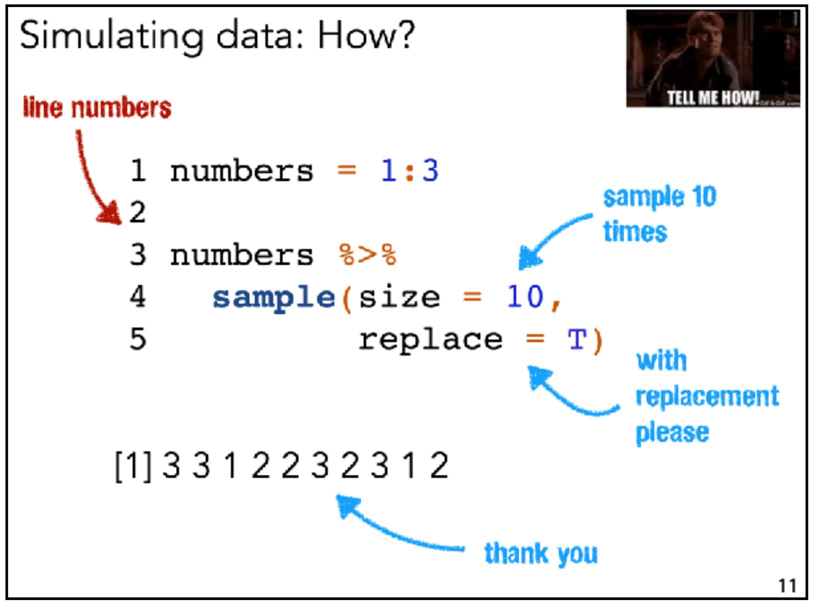
```{r p2.1, eval = F}
set.seed(1)

n_simulations = 10000 # number of simulations
n_samples = 40 # number of samples in each simulation
population_mean = 0 # ground truth mean
population_sd = 1 # ground truth standard deviation

### YOUR CODE HERE ###
df.samples =
######################

df.samples %>%
  head(5)

df.samples %>%
  summary()
```

Outline Goal: Revisit and understand key statistical concepts

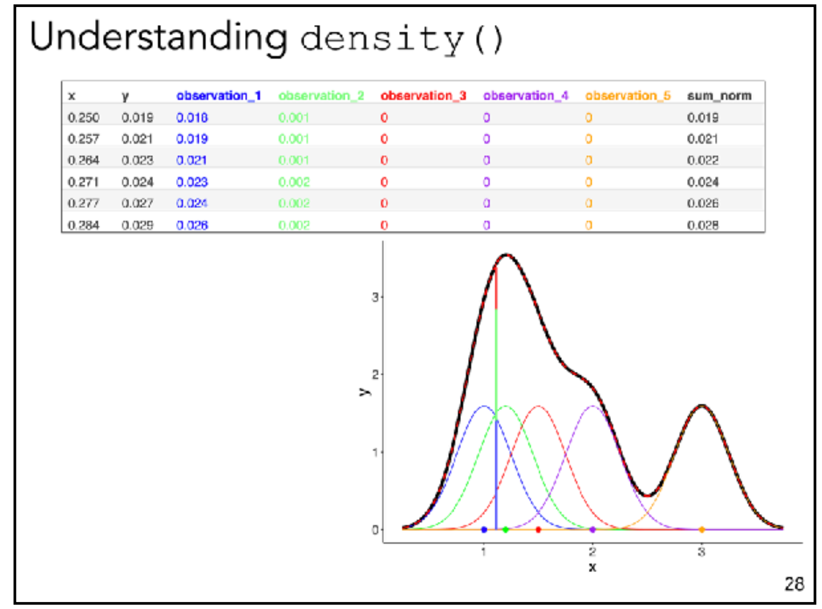
- Quick recap
- Doing Bayesian Analysis
- Inference in frequentist statistics
- Sampling distributions
- What is a p-value?
    - Permutation test
- Confidence intervals
- Bootstrapping

Quick recap

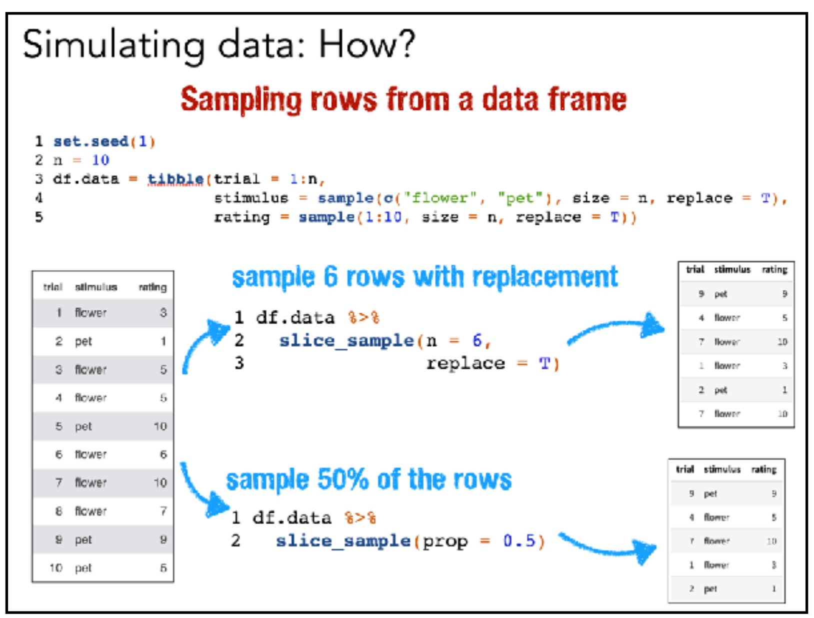
Quick recap from Simulation 1



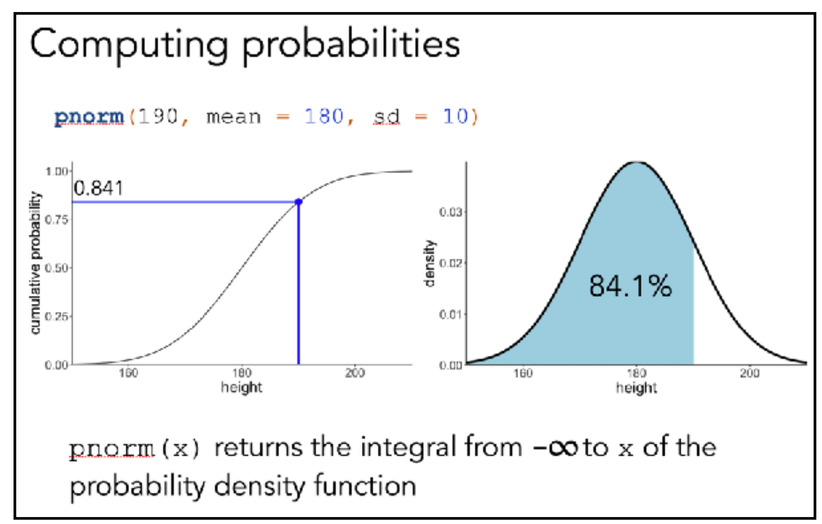
sampling values from a vector



understanding `density()`



sampling rows from a data frame



answering questions with probability distributions

or via drawing samples
`rnorm()` + wrangling

Doing Bayesian Analysis

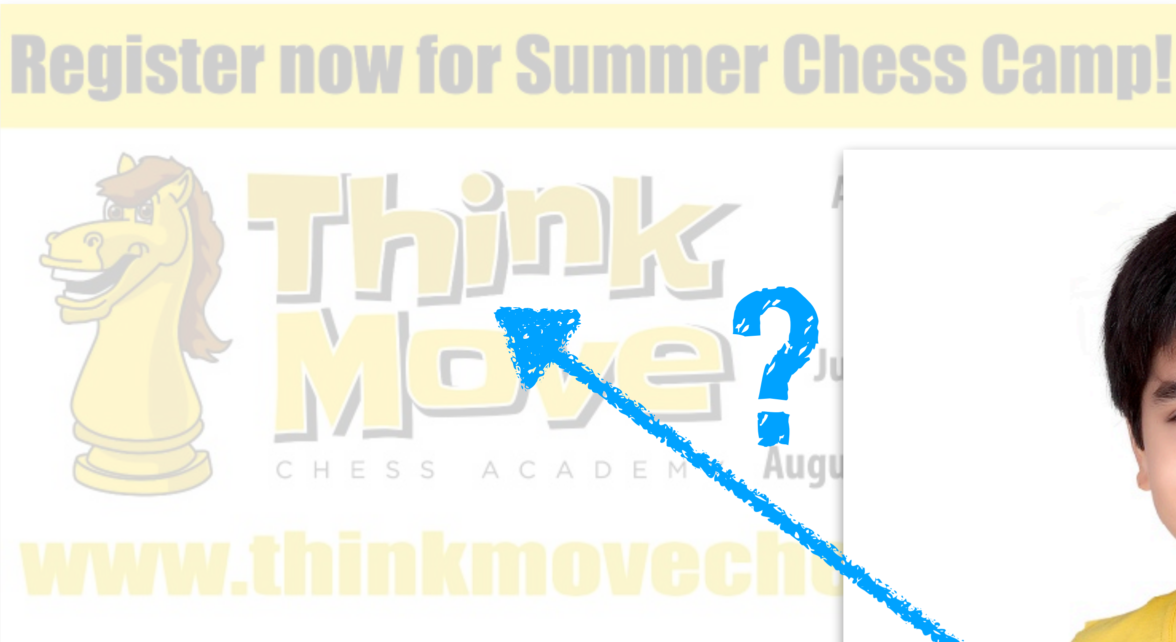
Summer camp

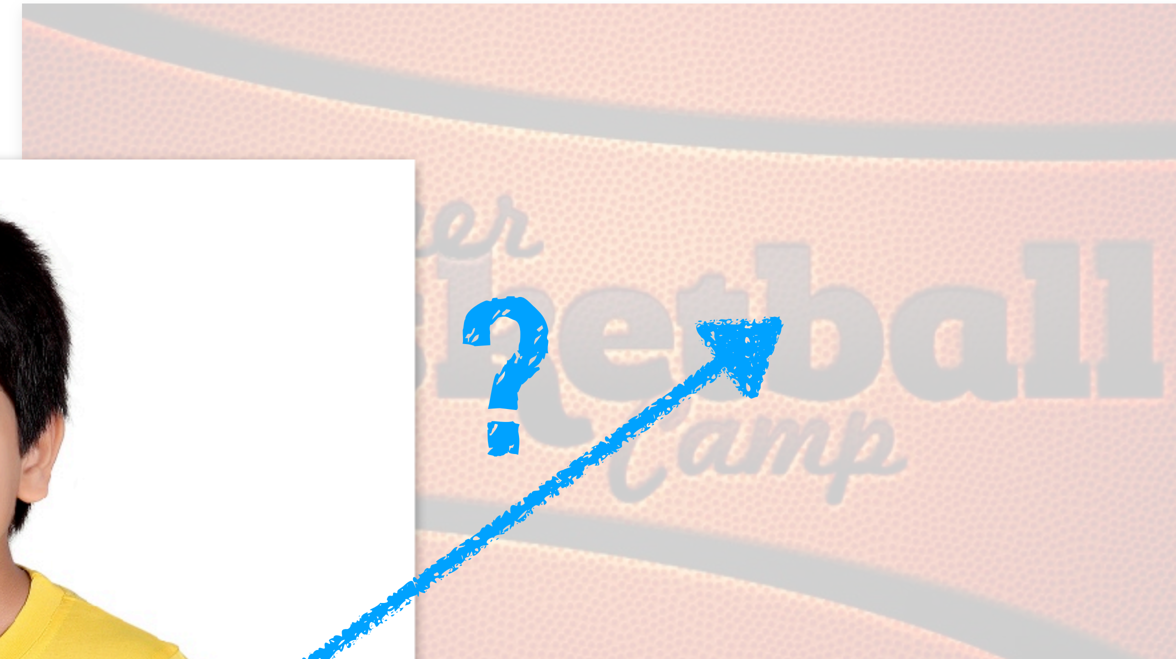
twice as many kids go to the basketball camp

$X \sim$ Normal$(\mu = 170,\ \sigma = 8)$

$X \sim$ Normal$(\mu = 180,\ \sigma = 10)$

Summer camp





twice as ma

etball camp

$X \sim$ Normal($\mu = 170$

al($\mu = 180$, $\sigma = 10$)

Analytic solution

Can you feel the Bayes?

H = {basketball, chess}

D = 175 cm

$$\underbrace{p(H|D)}_{\text{posterior}} = \frac{\overbrace{p(D|H)}^{\text{likelihood}} \cdot \overbrace{p(H)}^{\text{prior}}}{\underbrace{p(D)}_{\text{probability of the data?!}}}$$

$H =$ Hypothesis

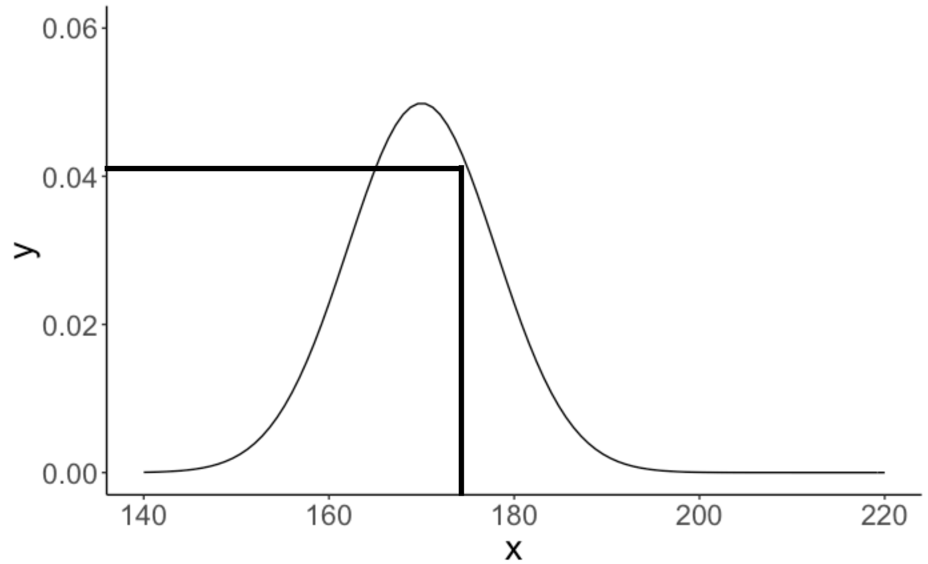
$D =$ Data

Summer camp

prior

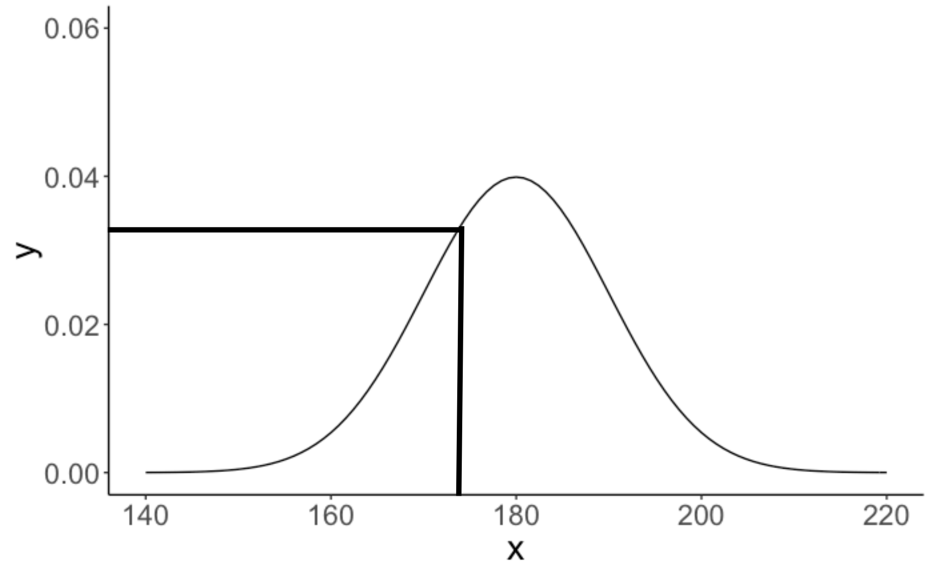
$$p(\text{chess}) = \frac{1}{3} \qquad p(\text{basketball}) = \frac{2}{3}$$

likelihood



`dnorm(175, mean = 170, sd = 8)`

= 0.041



`dnorm(175, mean = 180, sd = 10)`

= 0.035

posterior

$$p(\text{sport} = \text{basketball} \mid \text{height} = 175) = \frac{\overbrace{p(175 \mid \text{basketball})}^{\text{likelihood}} \cdot \overbrace{p(\text{basketball})}^{\text{prior}}}{\underbrace{p(175)}_{\text{data}}}$$

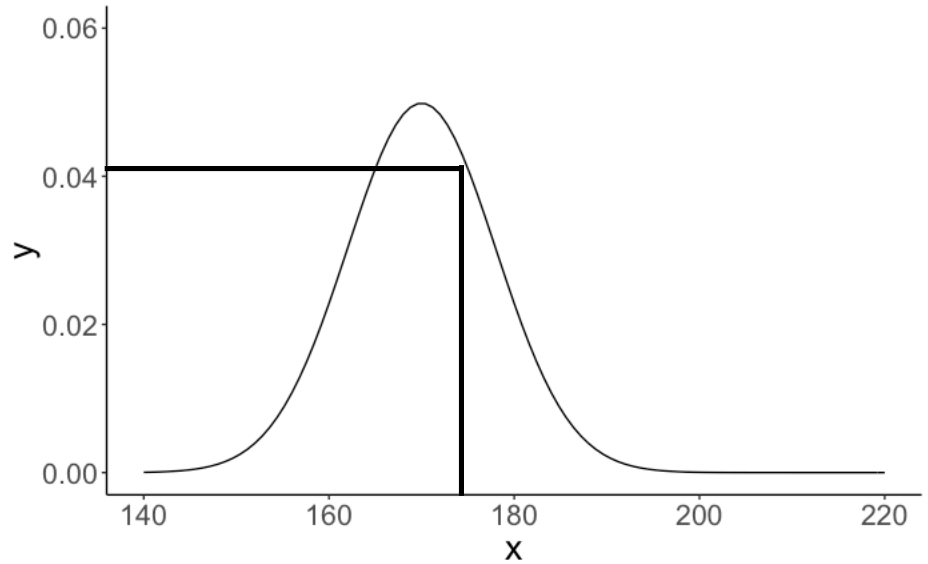
$$p(\text{basketball} \mid 175) = \frac{p(175 \mid \text{basketball}) \cdot p(\text{basketball})}{p(175 \mid \text{basketball}) \cdot p(\text{basketball}) + p(175 \mid \text{chess}) \cdot p(\text{chess})}$$

Summer camp

prior

$$p(\text{chess}) = \frac{1}{3} \qquad p(\text{basketball}) = \frac{2}{3}$$

likelihood



`dnorm(175, mean = 170, sd = 8)`

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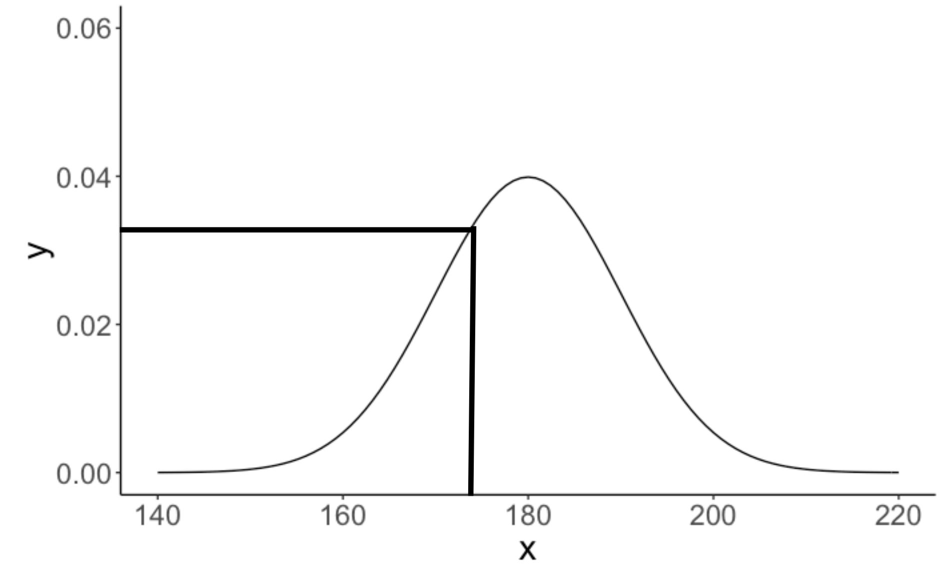


`dnorm(175, mean = 180, sd = 10)`

= 0.035

posterior

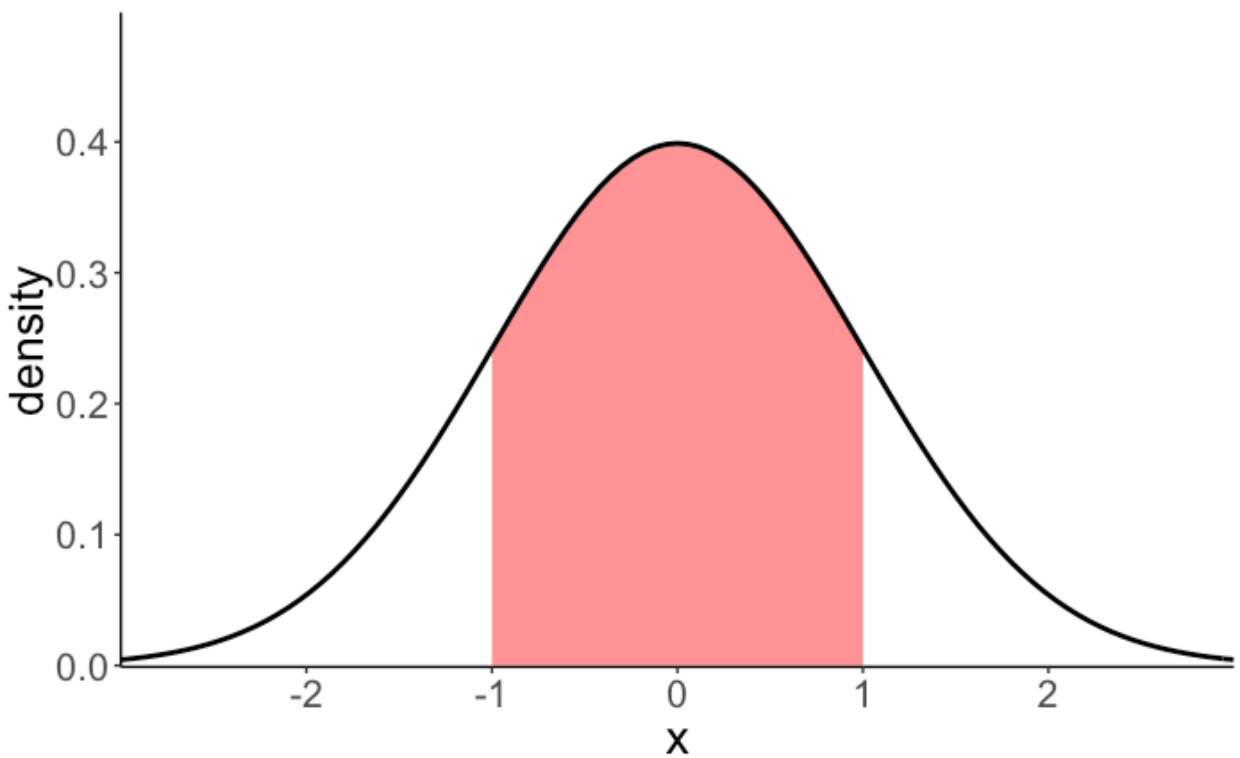
$$p(\text{basketball} \mid 175) = \frac{p(175 \mid \text{basketball}) \cdot p(\text{basketball})}{p(175 \mid \text{basketball}) \cdot p(\text{basketball}) + p(175 \mid \text{chess}) \cdot p(\text{chess})}$$

$$p(\text{basketball} \mid 175) = \frac{0.035 \cdot 2/3}{0.035 \cdot 2/3 + 0.041 \cdot 1/3} \approx 0.63$$

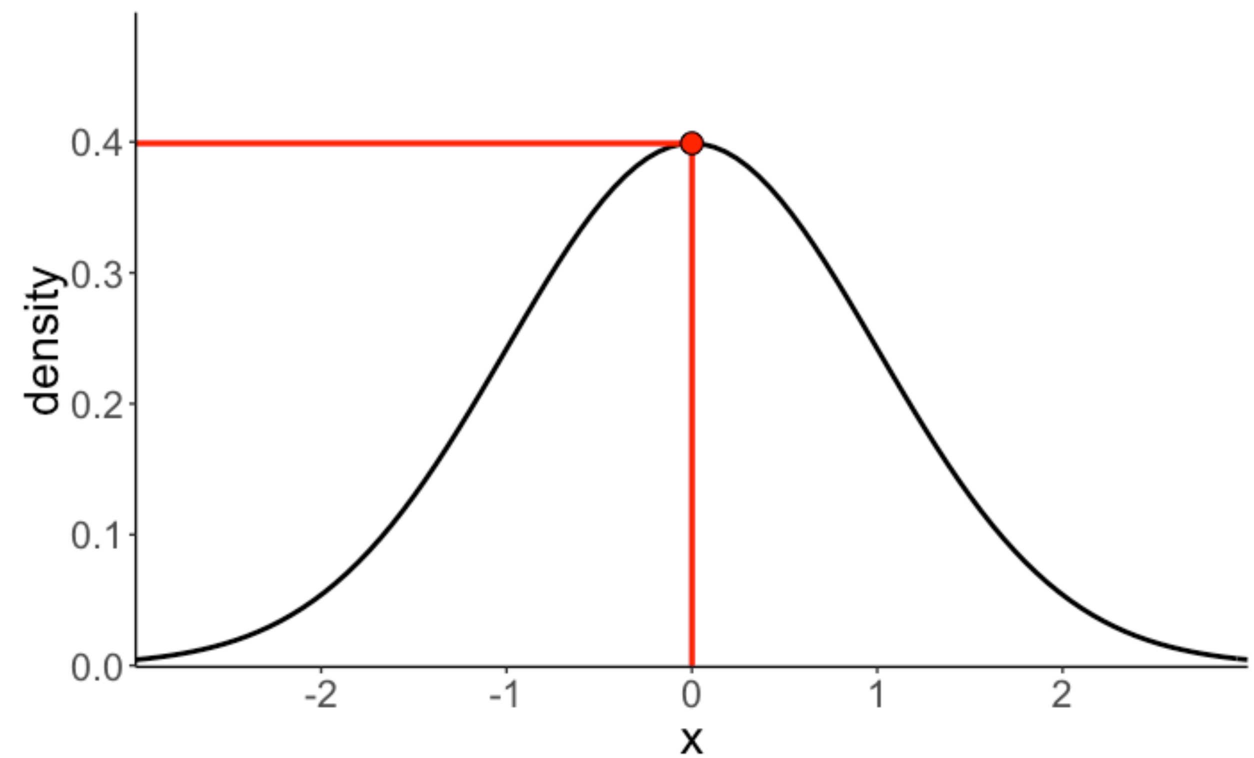
send the kid to the basketball gym!

Probability vs. likelihood

Probability

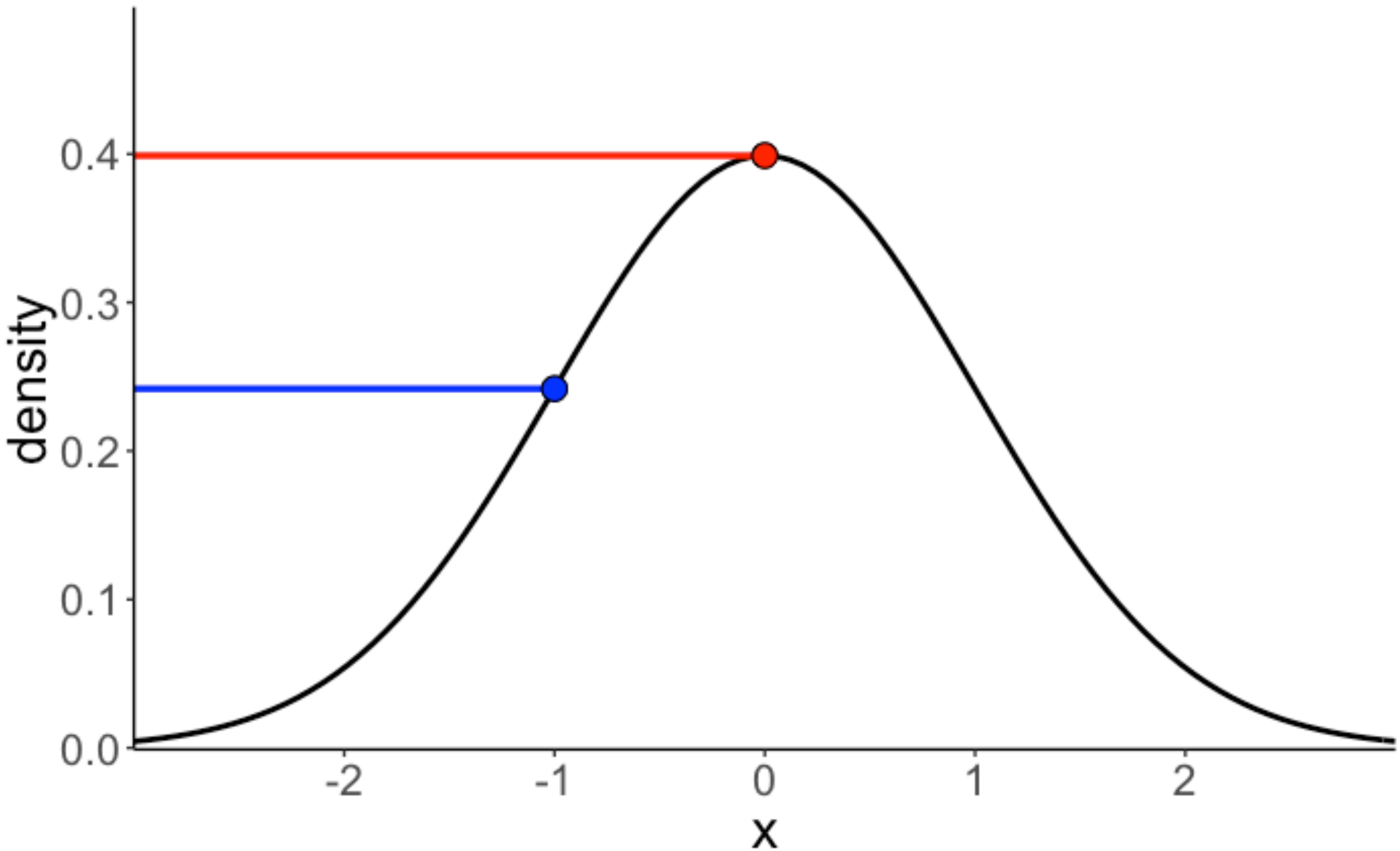


Likelihood



Probability vs. likelihood

`dnorm(0)/dnorm(-1) = 1.6487`

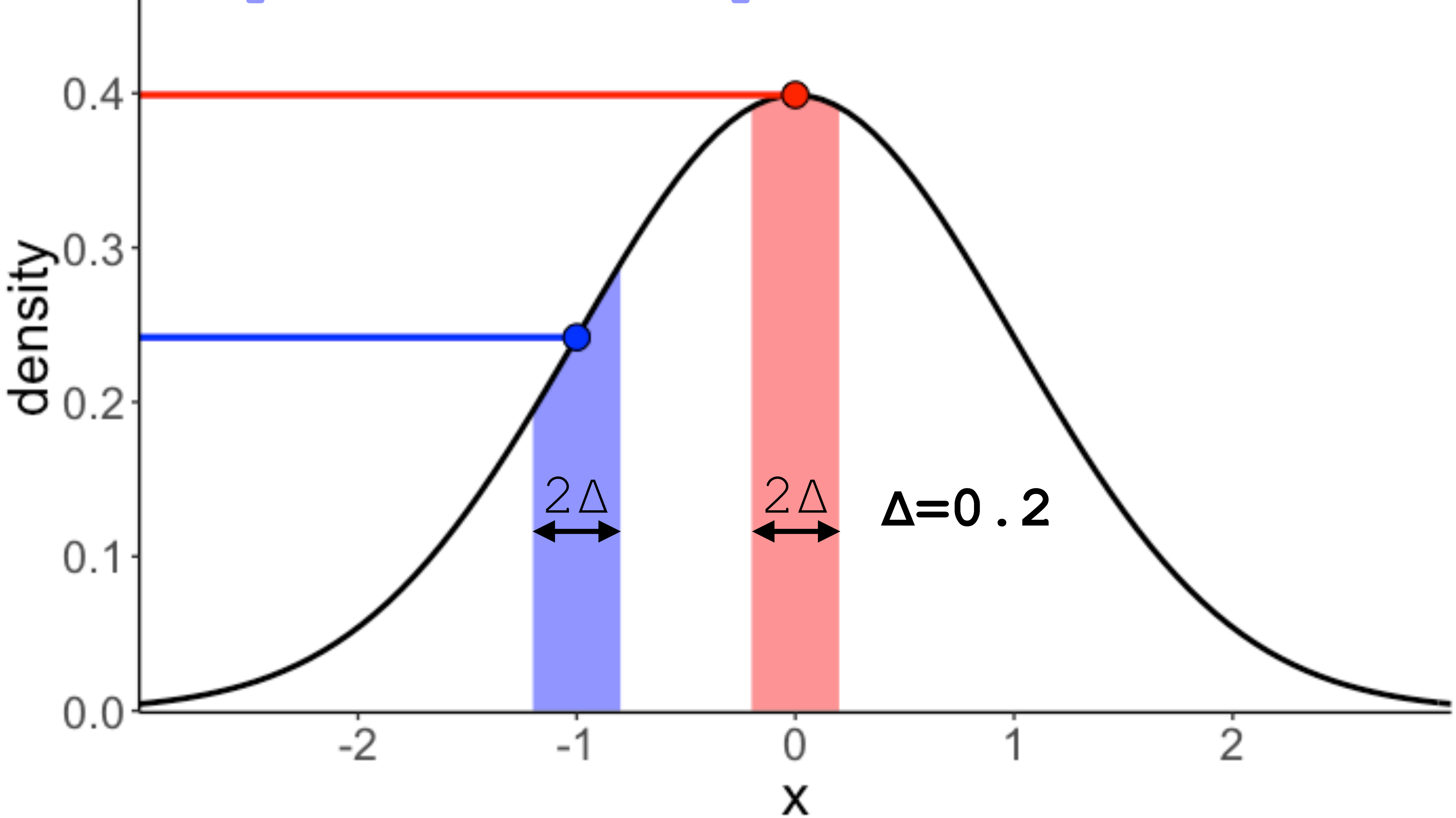


relative probability of one value vs. another

Probability vs. likelihood

`dnorm(0)/dnorm(-1) = 1.6487`

`(pnorm(0+Δ)- pnorm(0-Δ))/`
`(pnorm(-1+Δ) -(pnorm(-1-Δ) =` **`1.6378`**

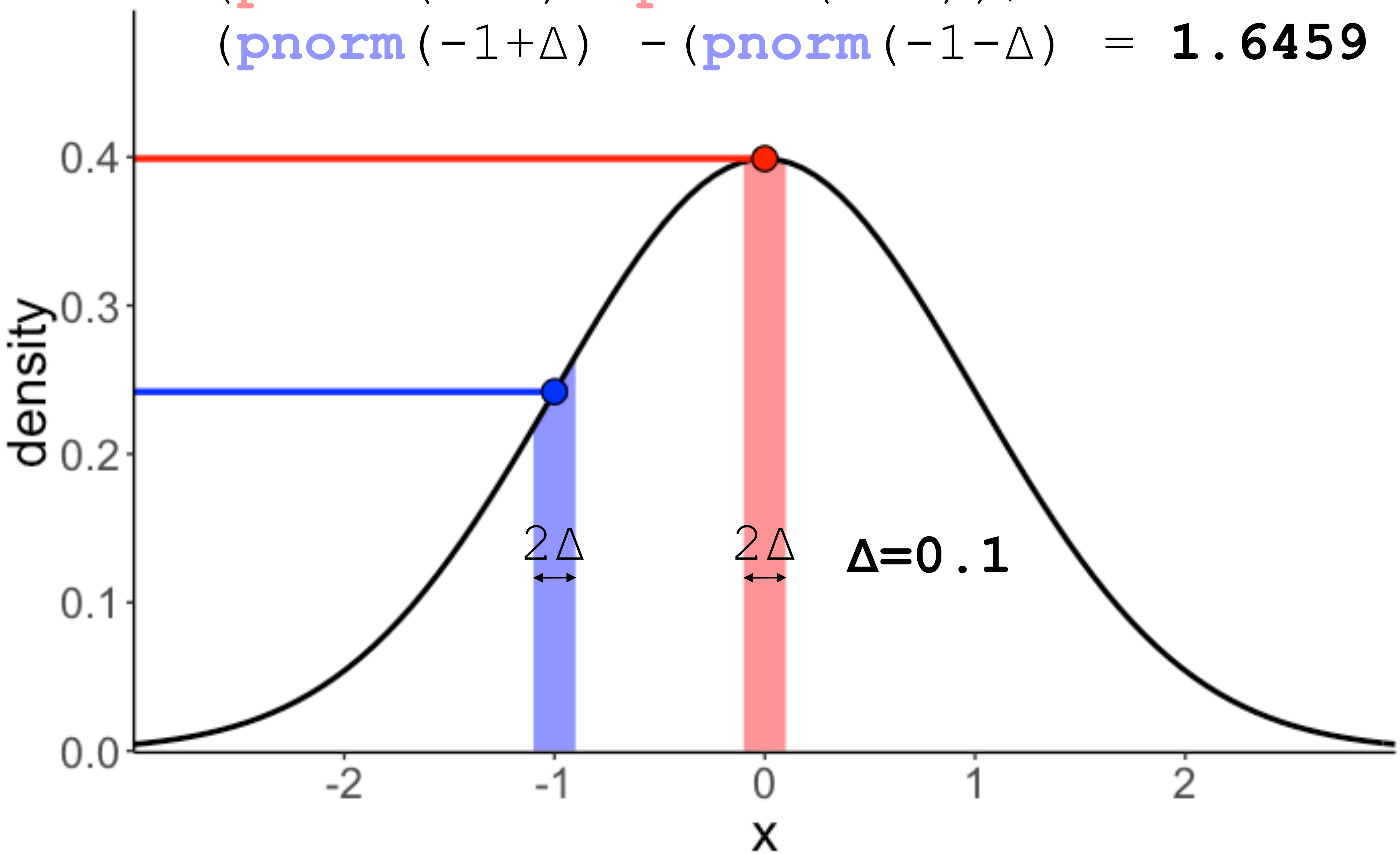


relative probability of one value vs. another

Probability vs. likelihood

```
dnorm(0)/dnorm(-1) = 1.6487
```

```
(pnorm(0+Δ)- pnorm(0-Δ))/
(pnorm(-1+Δ) -(pnorm(-1-Δ) = 1.6459
```

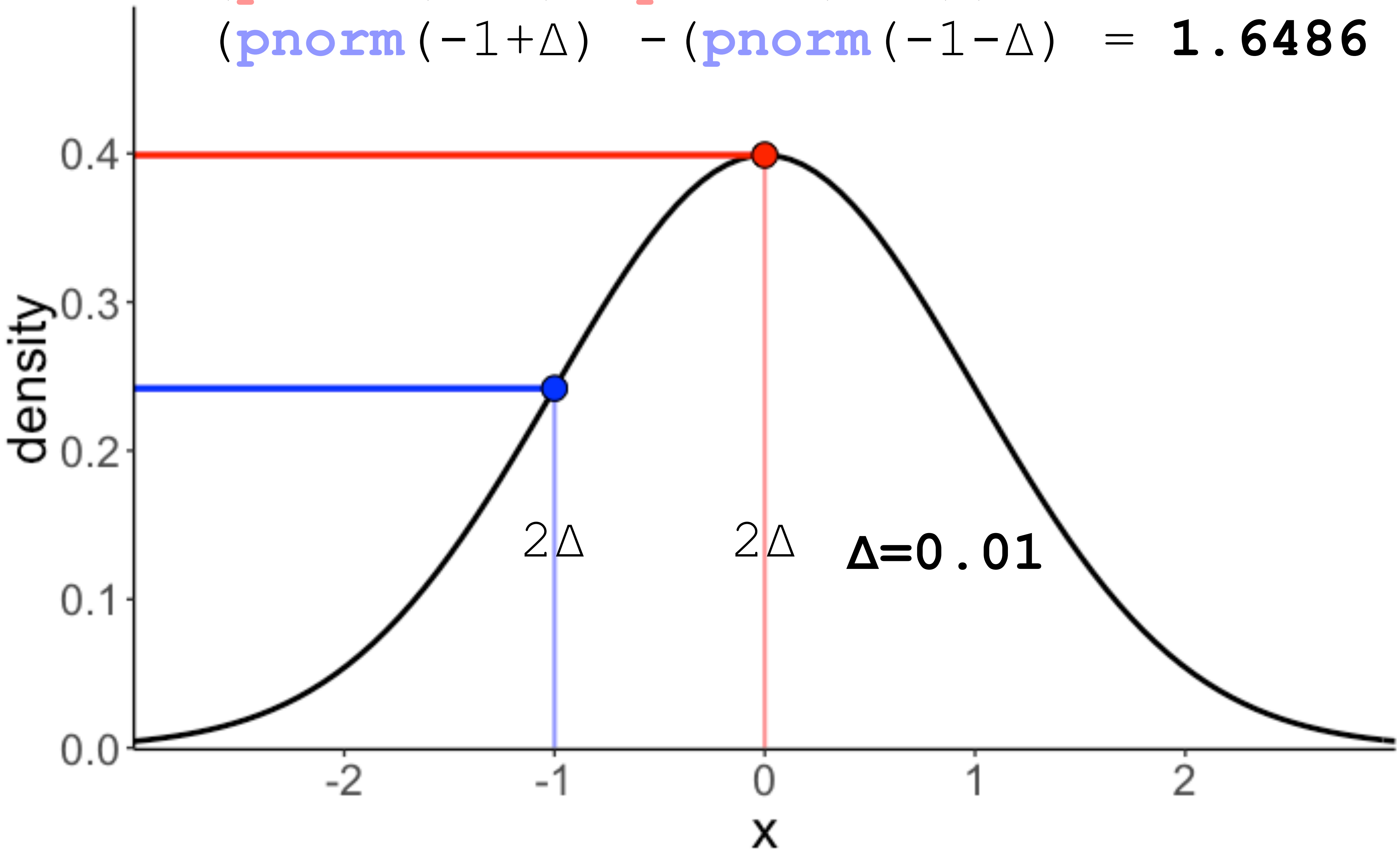


relative probability of one value vs. another

Probability vs. likelihood

`dnorm(0)/dnorm(-1) = 1.6487`

`(pnorm(0+Δ)- pnorm(0-Δ))/`
`(pnorm(-1+Δ) -(pnorm(-1-Δ) =` **`1.6486`**



relative probability of one value vs. another

Sampling solution

Summer camp: Via sampling

```r
df.camp = tibble(
  kid = 1:1000,
  sport = sample(c("chess", "basketball"),
                 size = 1000,
                 replace = T,
                 prob = c(1/3, 2/3))) %>%
  rowwise() %>%
  mutate(height = ifelse(test = sport == "chess",
                         yes = rnorm(., mean = 170, sd = 8),
                         no = rnorm(., mean = 180, sd = 10))) %>%
  ungroup()
```

kid	sport	height
1	basketball	164.84
2	basketball	163.22
3	basketball	191.18
4	chess	160.16
5	basketball	182.99
6	chess	163.54
7	chess	168.56
8	basketball	192.99
9	basketball	171.91
10	basketball	177.12

```r
df.camp %>%
  filter(height == 175) %>%
  count(sport)
```

doesn't work!

Summer camp: Via sampling

```
df.camp = tibble(
  kid = 1:100000,
  sport = sample(c("chess", "basketball"),
                 size = 100000,
                 replace = T,
                 prob = c(1/3, 2/3))) %>%
  rowwise() %>%
  mutate(height = ifelse(test = sport == "chess",
                         yes = rnorm(., mean = 170, sd = 8),
                         no = rnorm(., mean = 180, sd = 10))) %>%
  ungroup()
```

kid	sport	height
1	basketball	164.84
2	basketball	163.22
3	basketball	191.18
4	chess	160.16
5	basketball	182.99
6	chess	163.54
7	chess	168.56
8	basketball	192.99
9	basketball	171.91
10	basketball	177.12

```
df.camp %>%
  filter(between(height,
                 left = 174,
                 right = 176)) %>%
  count(sport)
```

this works!

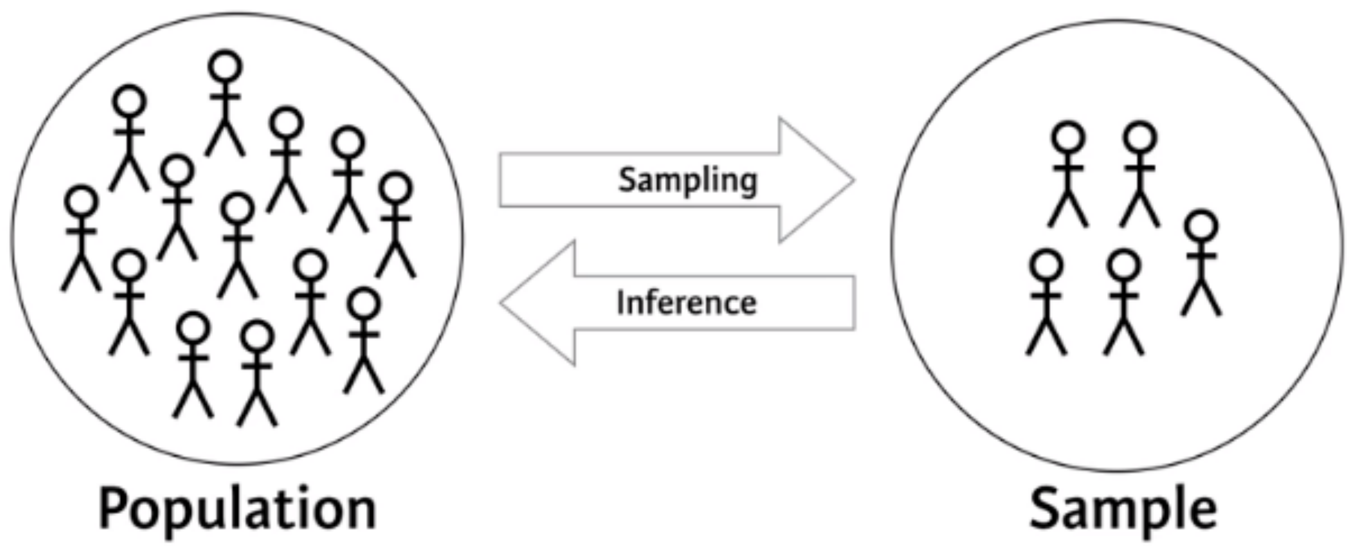
sport	n
basketball	469
chess	273

$$\frac{\text{basketball}}{\text{basketball} + \text{chess}} \approx 0.63$$

Inference in frequentist statistics

Statistical inference

The process of making claims about a population based on information from a sample.



Life would be easy if we were able to observe the whole population -- we could simply do descriptive analyses!

Key question:

What can we infer about the population from our sample?

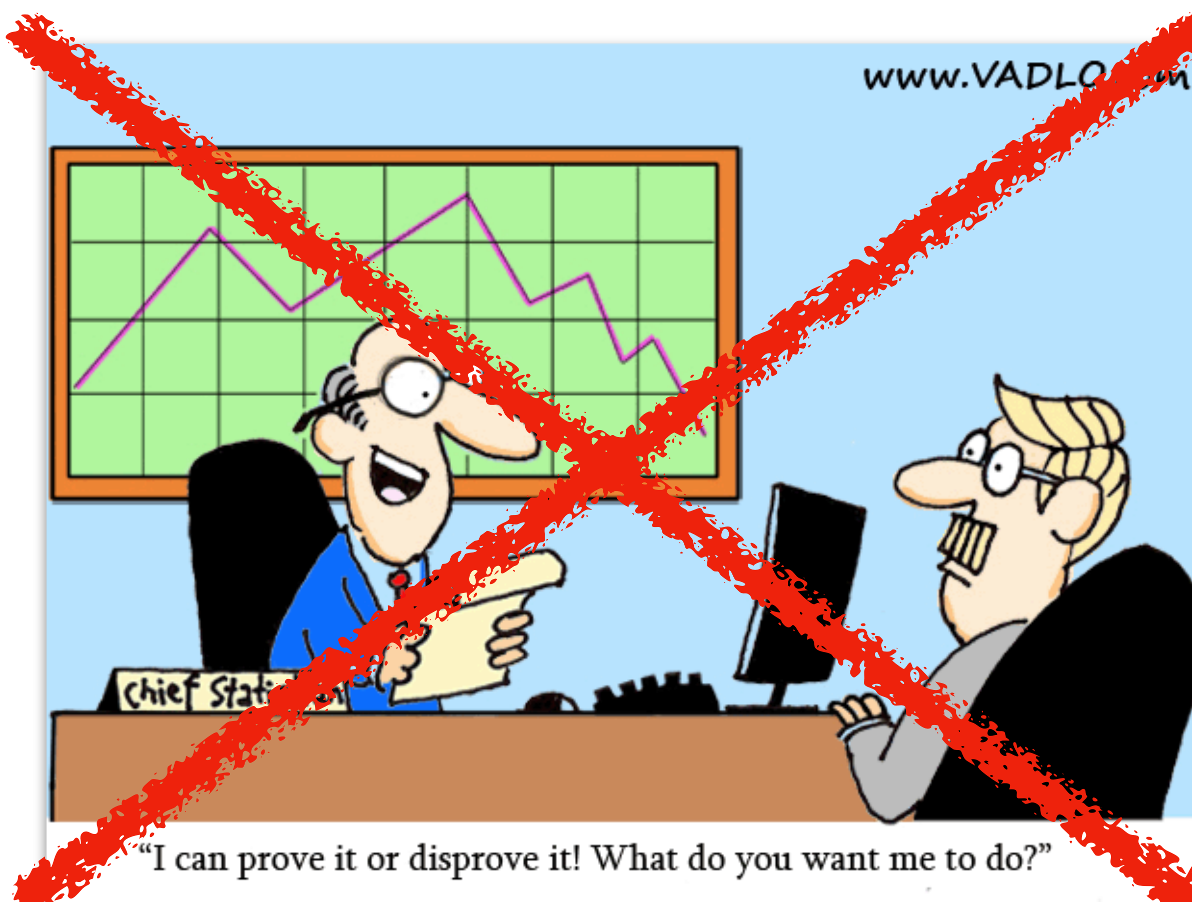
Statistical inference

Key question:

What can we infer about the population from our sample?

Answer:

- is not trivial
- mathematical, statistical, philosophical (Bayesian vs. frequentist) machinery involved
- **important**: we can never make deterministic statements!



Underlying principle of statistical testing

1. Define population, state hypotheses
2. Draw one (ideally large) random sample
3. Compute measure of interest (e.g. mean, correlation coefficient, difference between condition means), and then the test statistic
4. Apply statistical distribution theory to get the **sampling distribution of a test statistic**
5. Evaluate the observed test statistic on the sampling distribution; make a decision (either reject or don't reject H_0) based on pre-specified significance level α

The magical component

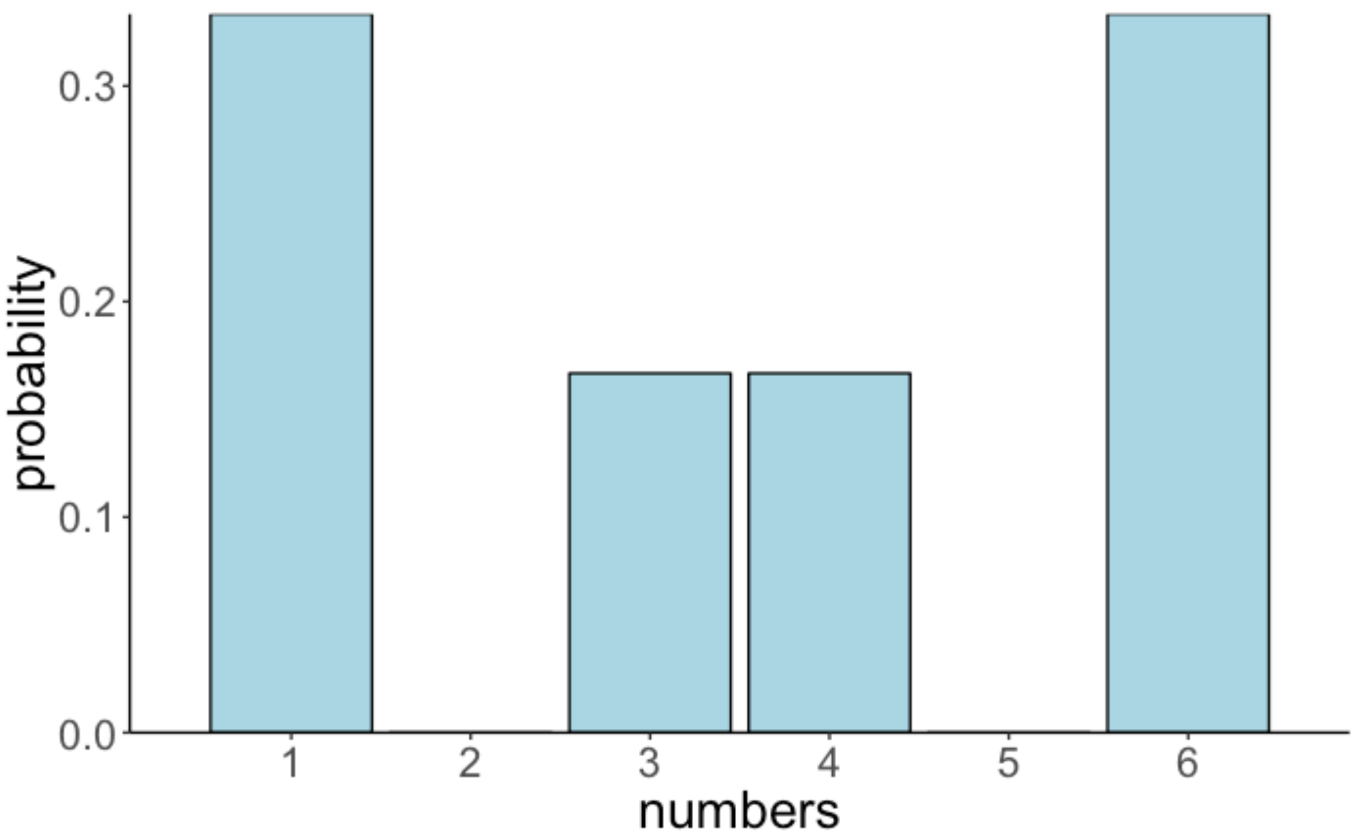
"4. Apply statistical distribution theory to get the **sampling distribution of a test statistic**"

This dates back to pre-computer era where statisticians derived mathematically the distribution of statistical measures for an infinite amount of samples! That's are tricky thing to do and these approximations are typically tied to assumptions such as normality, homoscedasticity, independent observations, and: the sample needs to be "large".

instead: simulation-based approach

Sampling distributions

heavy metal distribution

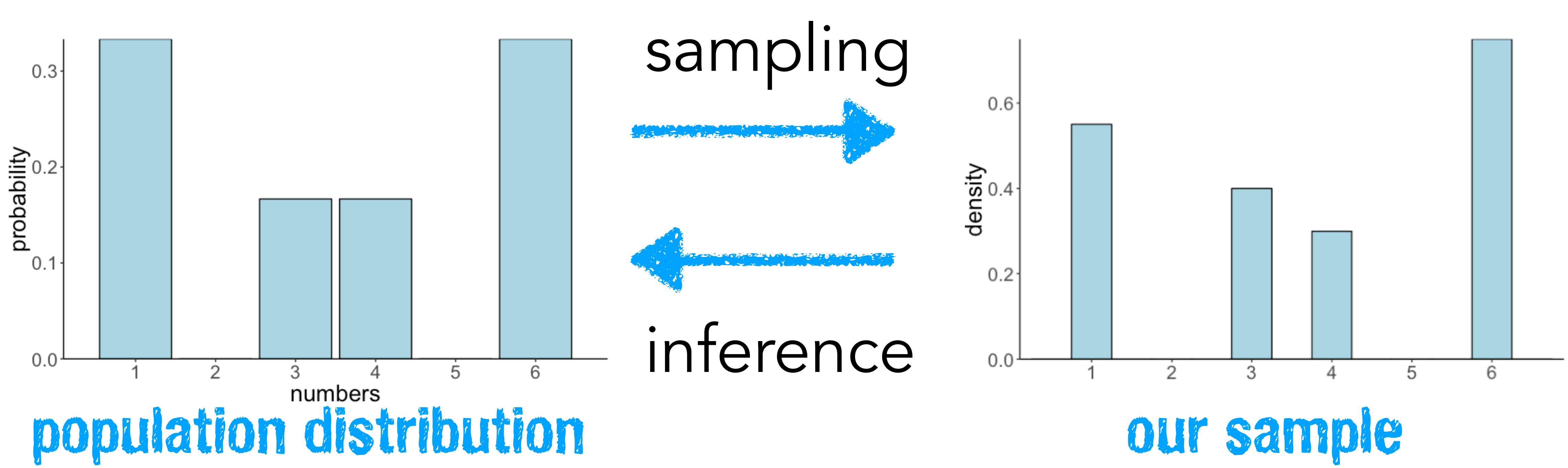


population distribution

Statistical inference

The process of making claims about a population based on information from a sample.

heavy metal distribution

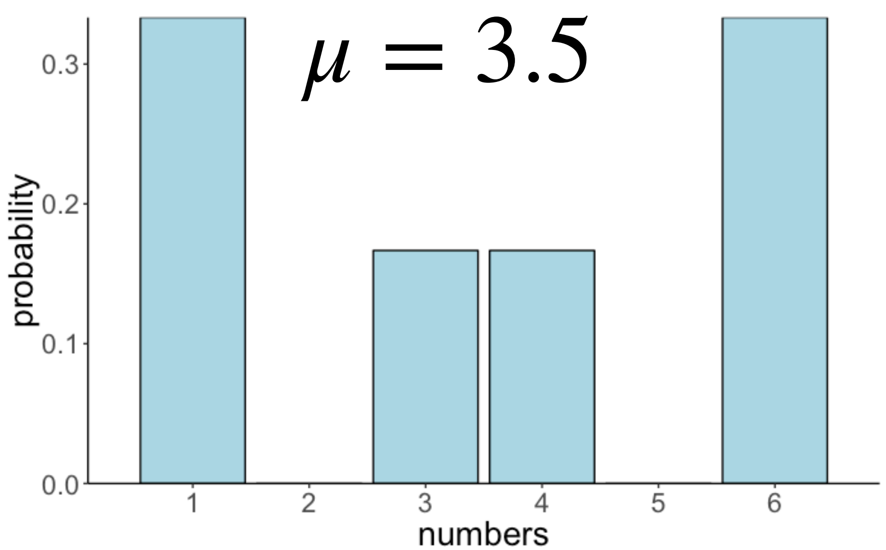


Statistical inference

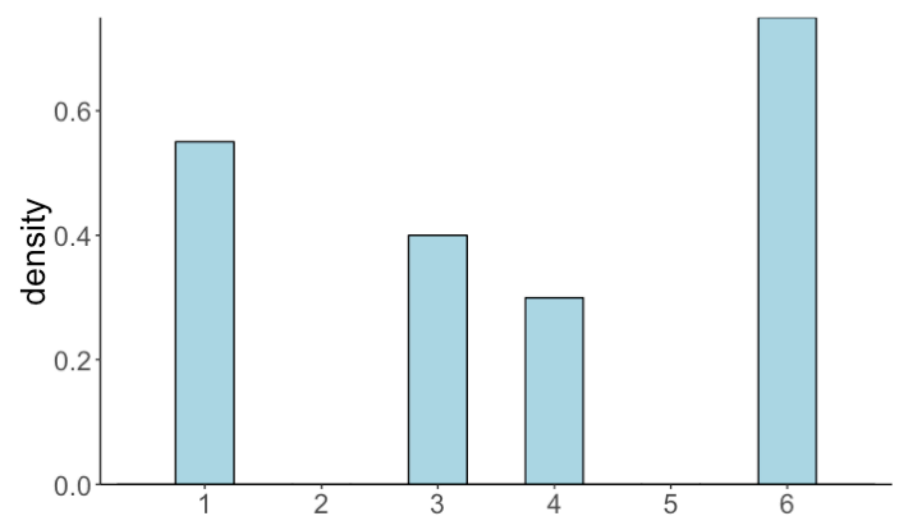
what's the
population mean?

```
sample mean = 3.725
standard deviation = 2.05
n = 40
```

heavy metal distribution

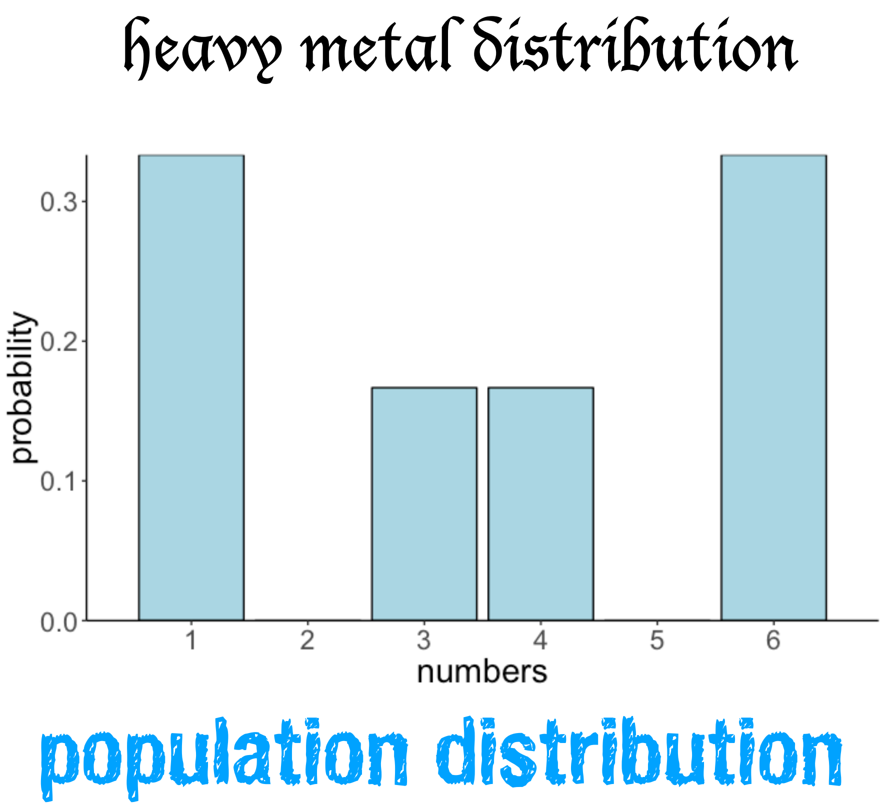


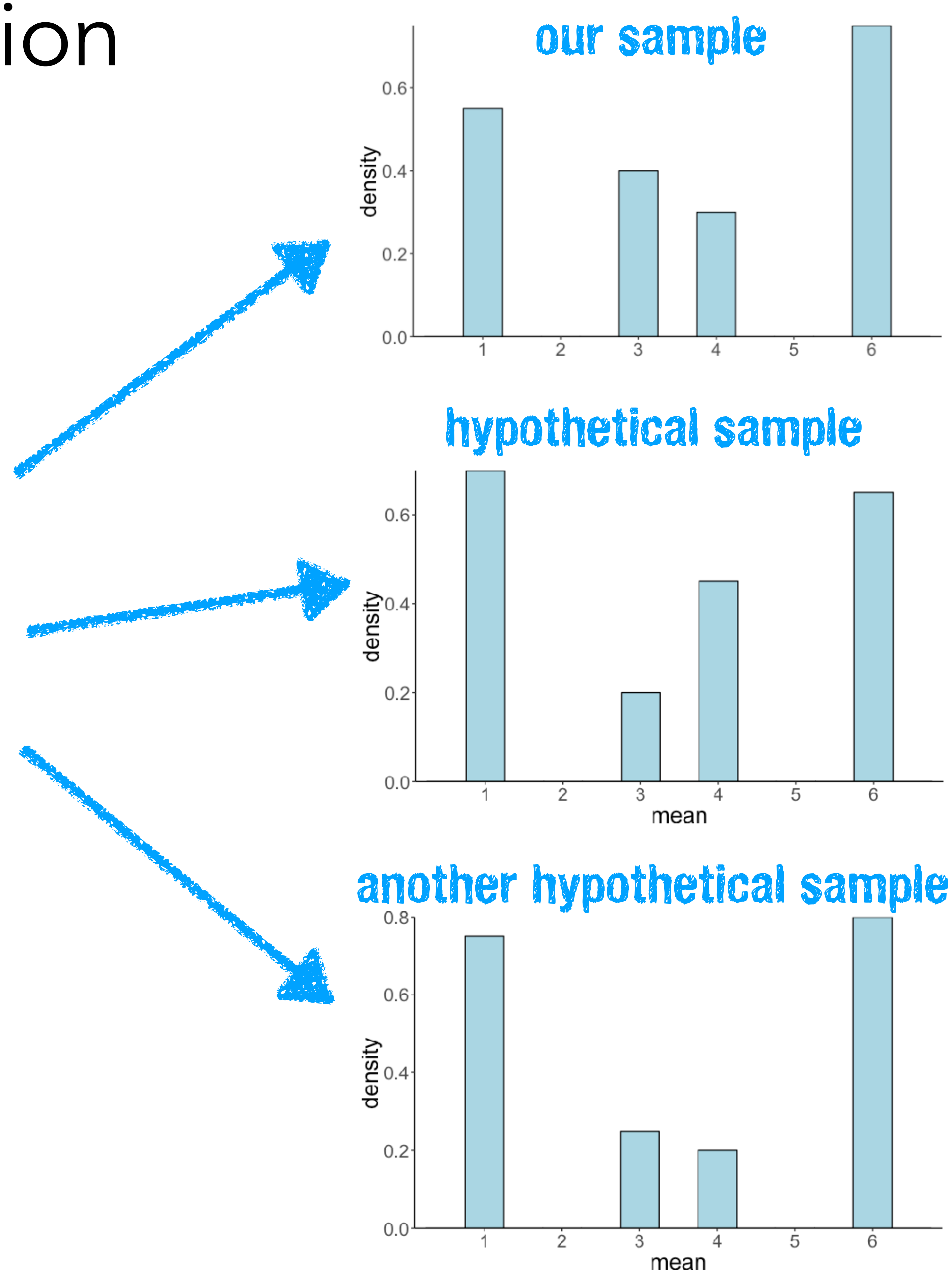
true unknown distribution



our sample

Sampling variation

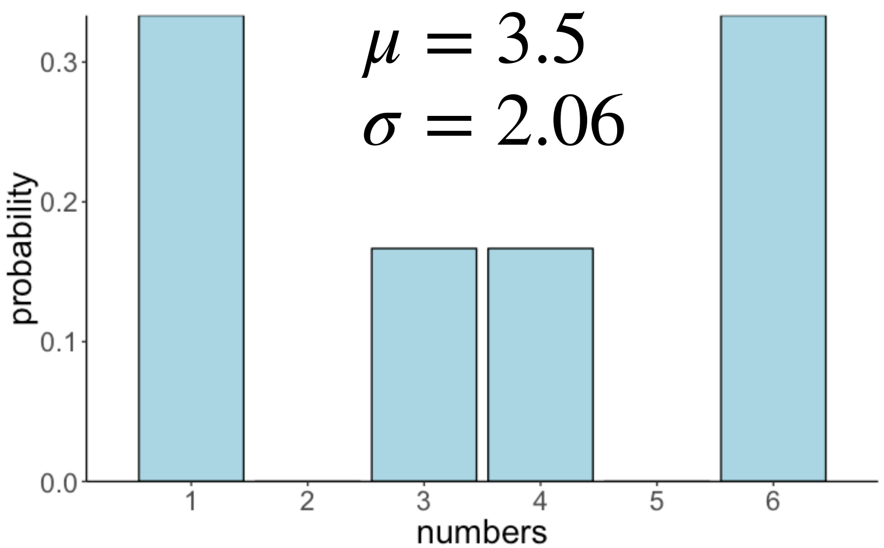




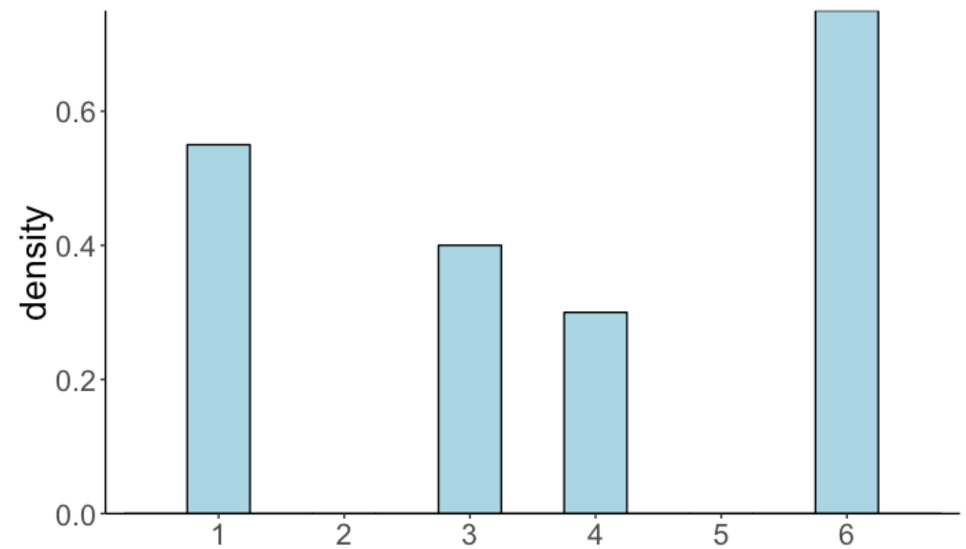
Sampling distribution

population distribution

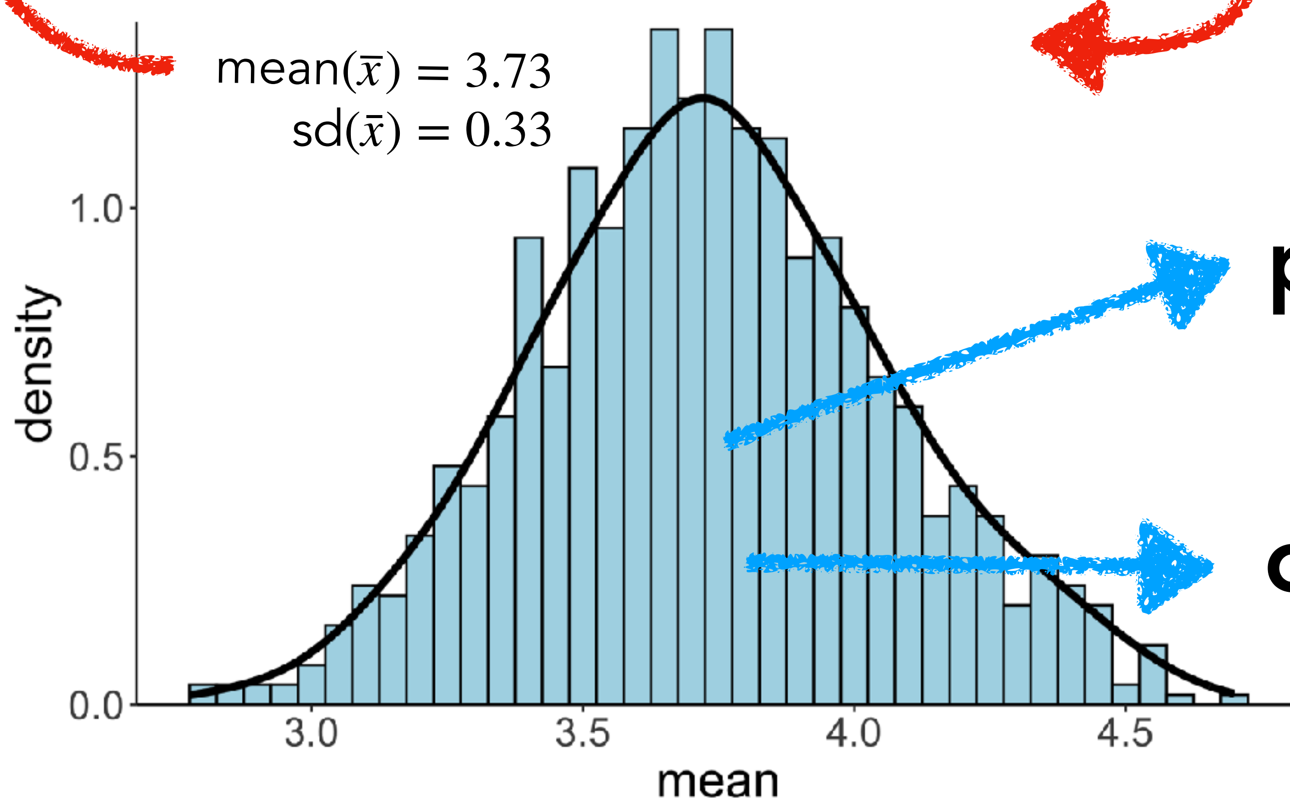
heavy metal distribution



our sample



mean$(x) = 3.72$
sd$(x) = 2.05$
n $= 40$

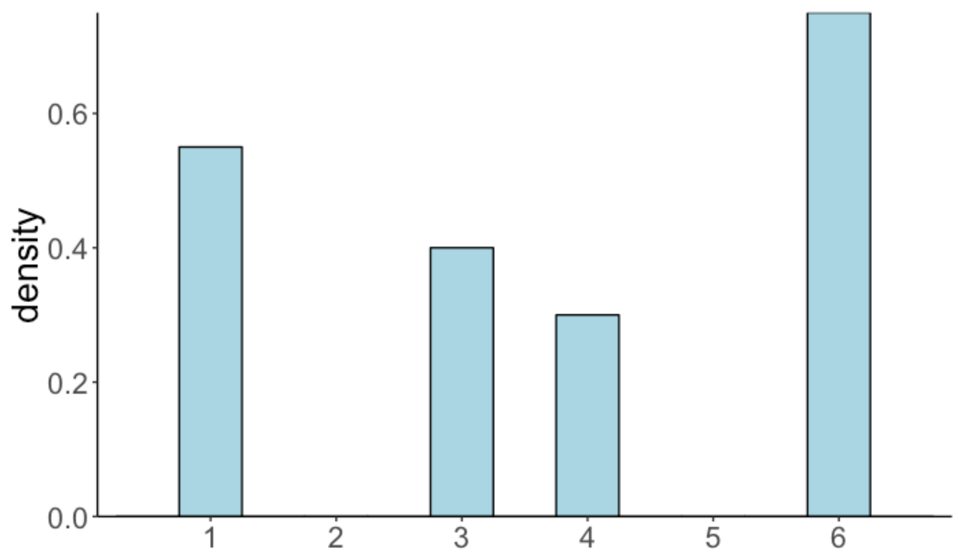


p-values

confidence intervals

sampling distribution of the mean

our sample

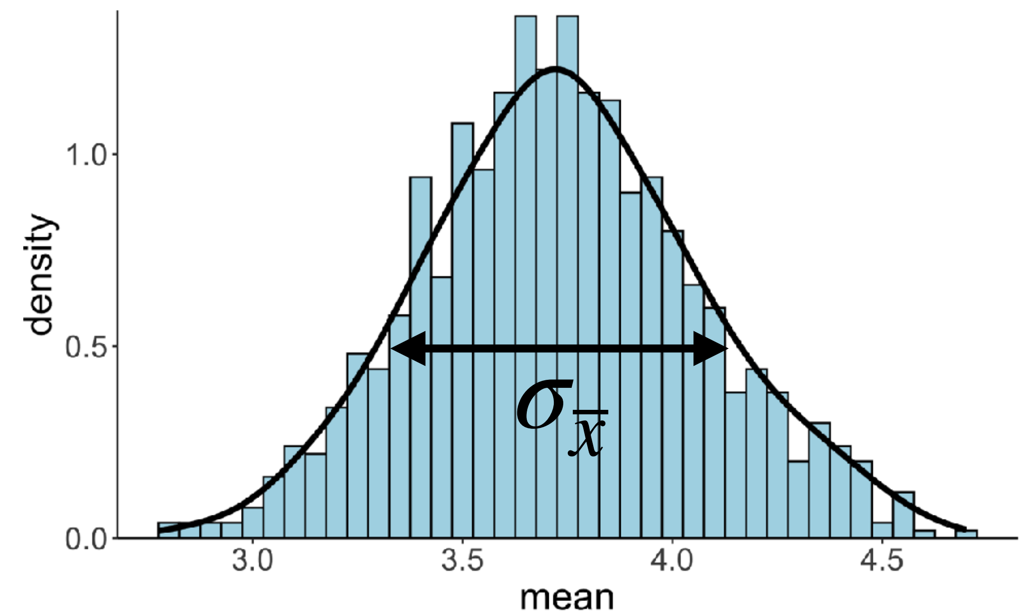


standard deviation

$$s = \sqrt{\frac{\sum (x_i - \overline{x})^2}{N - 1}}$$

gives a sense for how well the mean summarizes the data

sampling distribution



standard error

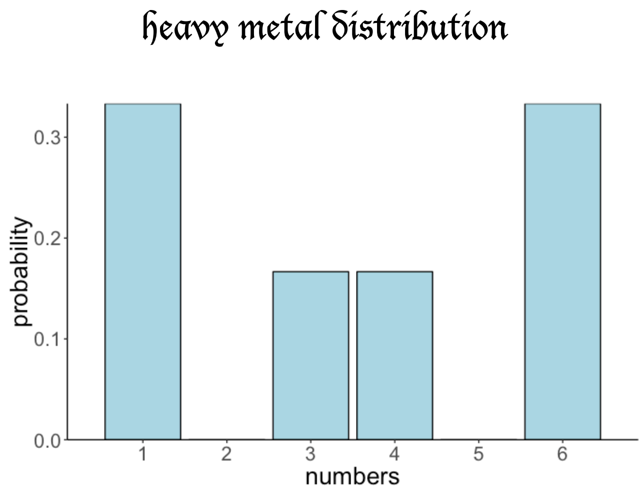
$$\sigma_{\overline{x}} = \frac{\sigma}{\sqrt{N}}$$

the standard deviation of the sampling distribution

how much variation would we expect between the means of different samples

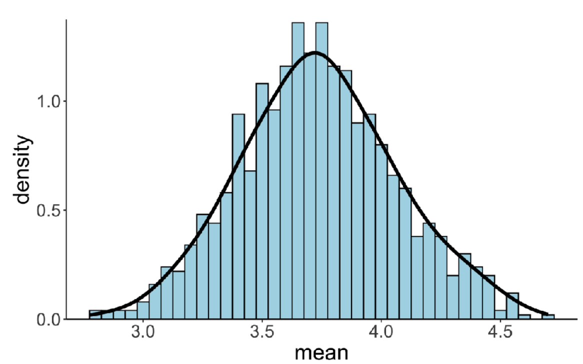
how likely is it that our sample mean is representative of the population mean?

3 distributions in statistical inference



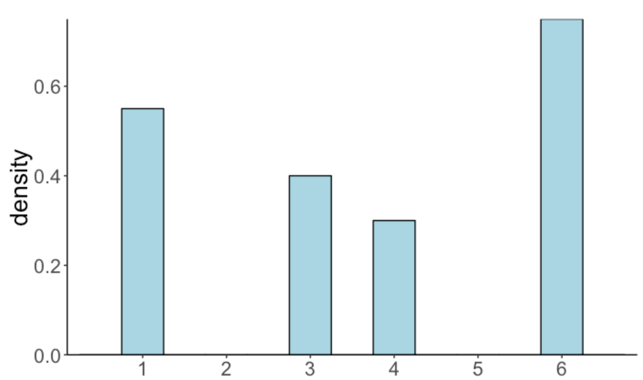
population distribution

- unknown
- our target for inference
- e.g. we might be interested in the mean of the population distribution



sampling distribution

- bridge between sample and population
- derived mathematically / computationally
- asymptotic distribution theory or resampling approaches
- shows how test statistic varies between samples



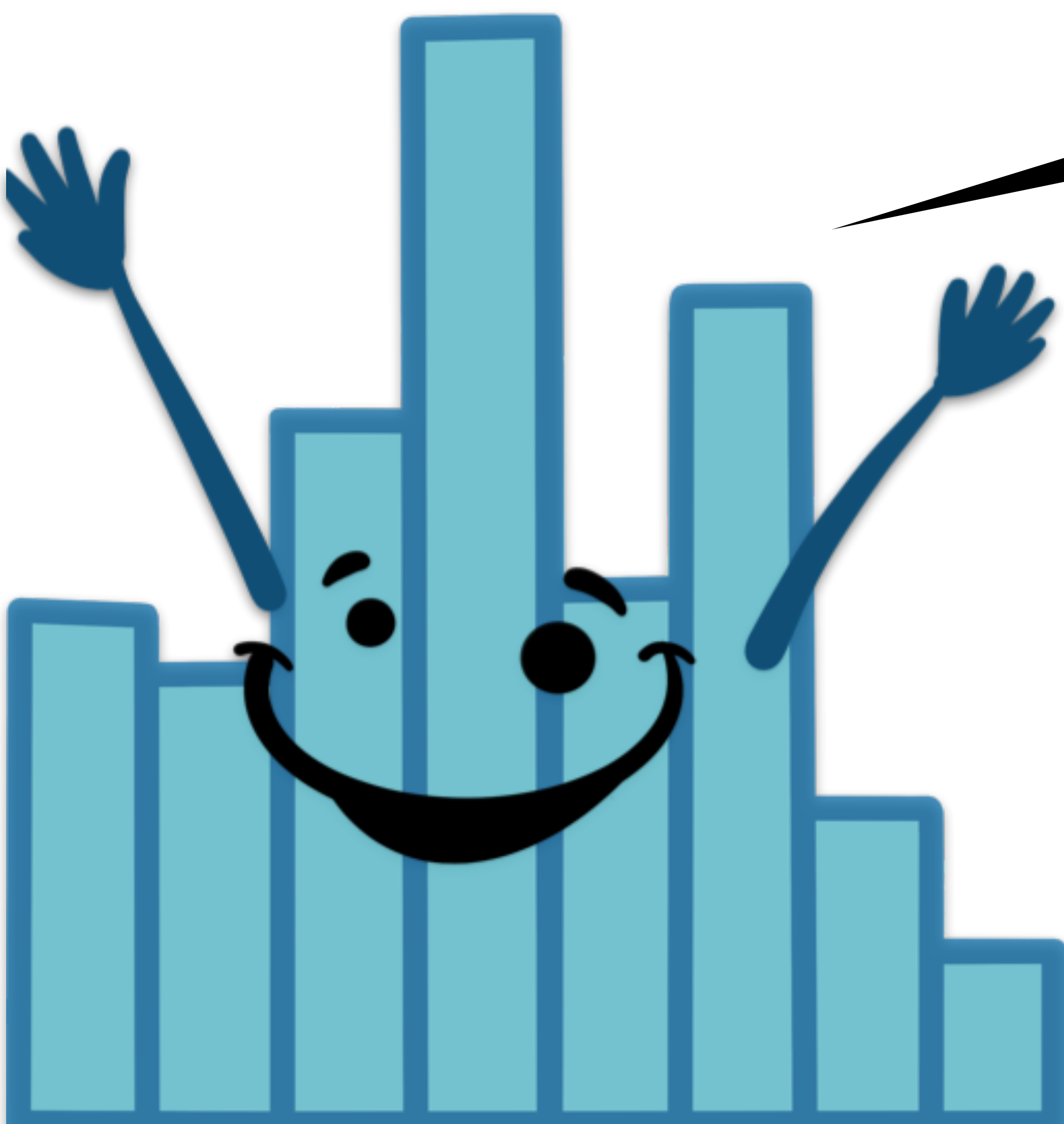
sample distribution

- our observed sample
- we compute statistics of interest (mean, variance, correlation, ...)
- make an inference about the population via the sampling distribution

We're listening to "On my own" by "Whitney"

02:00

stretch break!



What is a p-value?

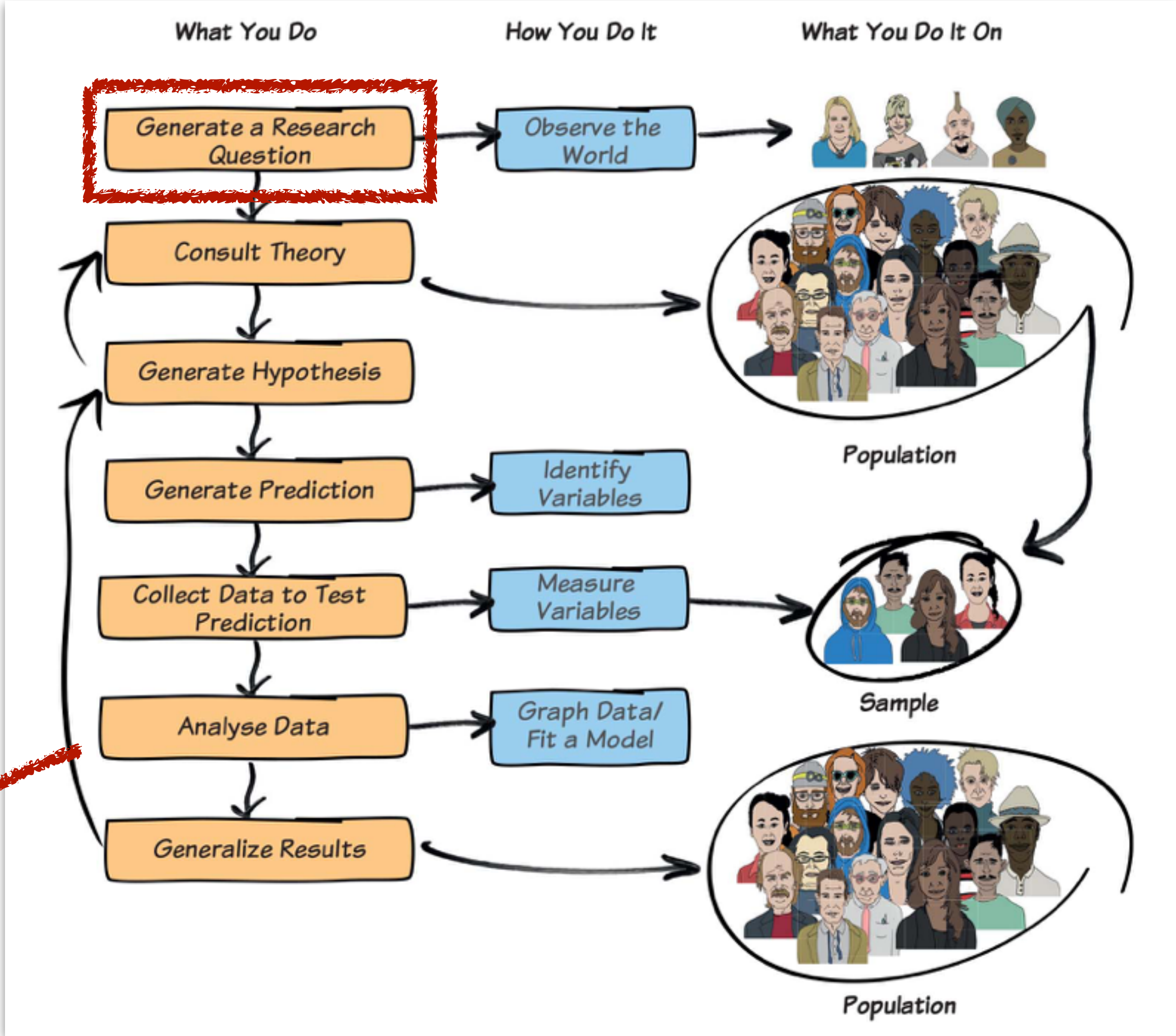
Statistical inference

null hypothesis

$$H_0 : \mu_1 = \mu_2$$

alternative hypothesis

$$H_1 : \mu_1 < \mu_2$$



a p-value, yay!

Which of the following statements about the p-value do you believe to be true?

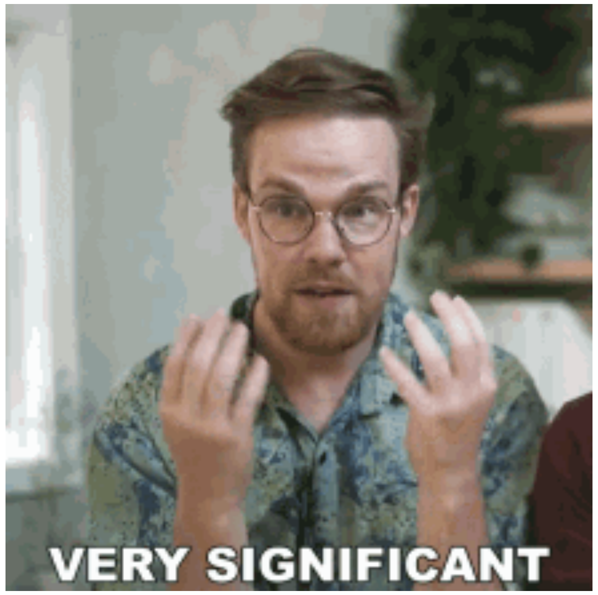
The p-value is the probability that the null hypothesis is true.

The p-value is the probability that the alternative hypothesis is true.

The p-value is the probability of obtaining the observed or more extreme results if the alternative hypothesis is true.

The p-value is the probability of obtaining the observed results or results which are more extreme if the null hypothesis is true.

What is a p-value? Your answers



- probability of rejecting null hypothesis
- the type-1 (false positive) error rate (the probability that your data actually were generated as a result of your manipulation and not by sampling error or due to some random noise)
- (I know this is not right…) the probability of finding the same result in a random sample.
- the probability of difference between observed and true value
- Probability of the results being due to chance
- If the p-value < alpha, we reject the null hypothesis and results are significant.
- given the null hypothesis, the probability of obtaining a result as extreme as the one observed. If a p-value is very small, it means that there is a low probability this would have happened if the null hypothesis is true.

What is a p-value?

The **p-value** is the probability of finding the observed (or more extreme) results when the null hypothesis (H_0) is true.

$$p(\text{test statistic} \geq \text{observed value} \mid H_0 = \text{true})$$

what we're actually interested in!

$$\cancel{p(H_1 = \text{true} \mid \text{test statistic} \geq \text{observed value})}$$

... we'll have to wait for Reverend Bayes

$$p(H \mid D) = \frac{p(D \mid H) \cdot p(H)}{p(D)}$$

$H = \text{Hypothesis}$

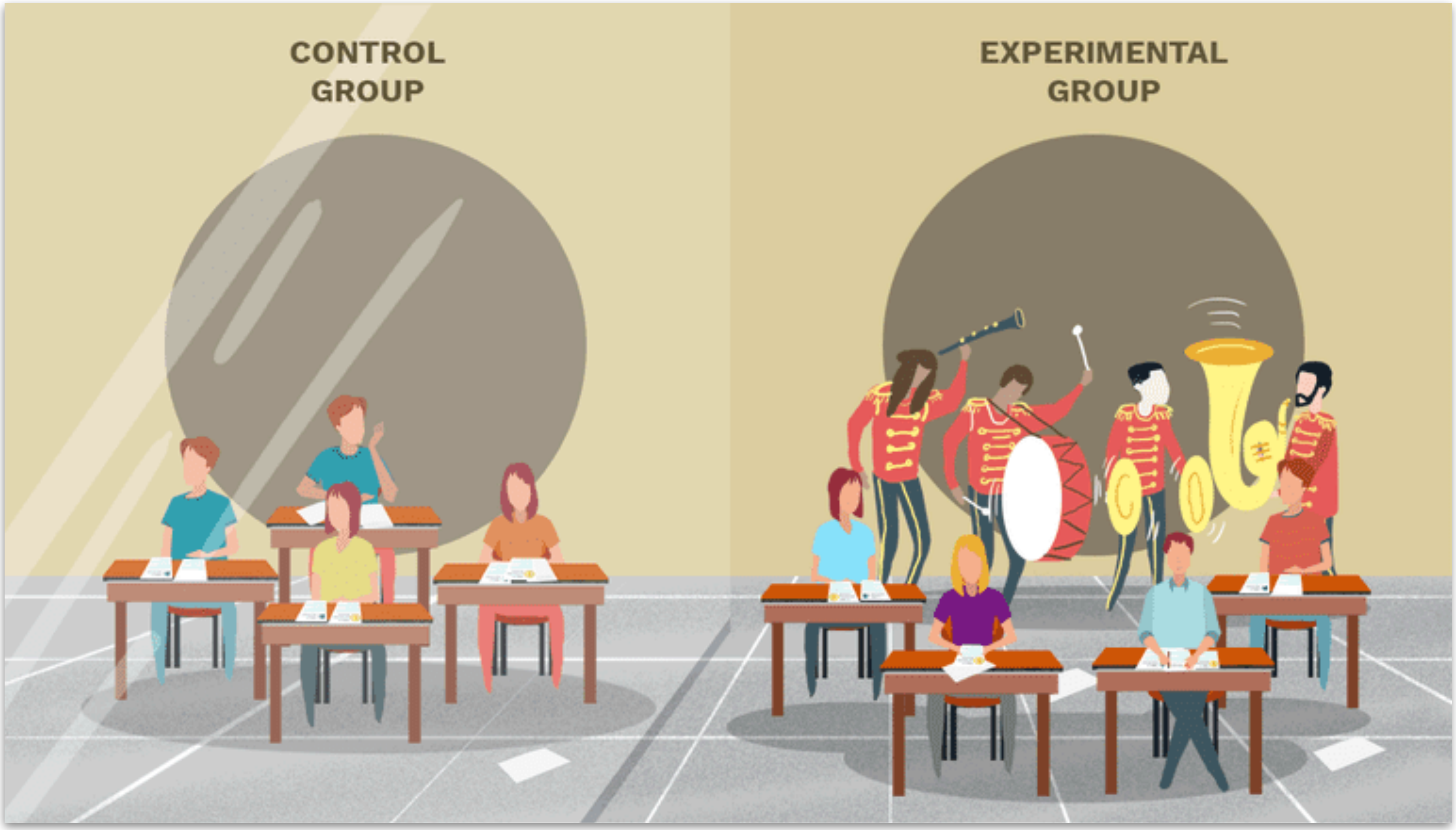
$D = \text{Data}$

Logic of inference

- calculate a **test statistic** based on the sample
  - for example, the difference between the means of two conditions
- build a **sampling distribution** of this statistic assuming that the null hypothesis is true
  - use math or resampling methods
- **calculate the probability** of the observed statistic on the sampling distribution
- reject the null hypothesis if the probability of the observed statistic is less than the pre-specified α level

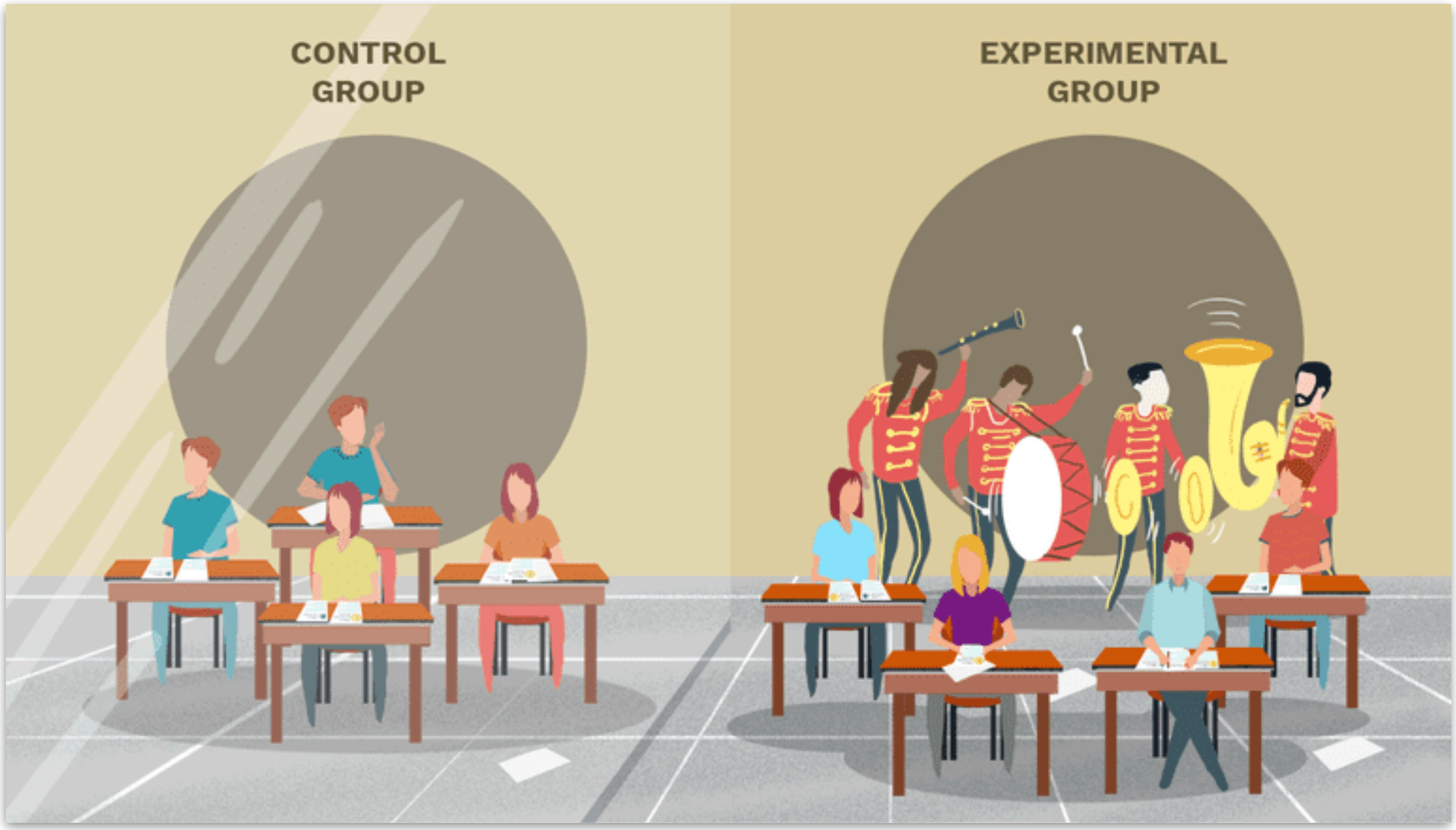
Permutation test

Permutation test



Research question:
Will student test scores be affected by distracting sounds (e.g. the Stanford marching band)?

Permutation test



$H_0 : \mu_{\text{control}} = \mu_{\text{experimental}}$

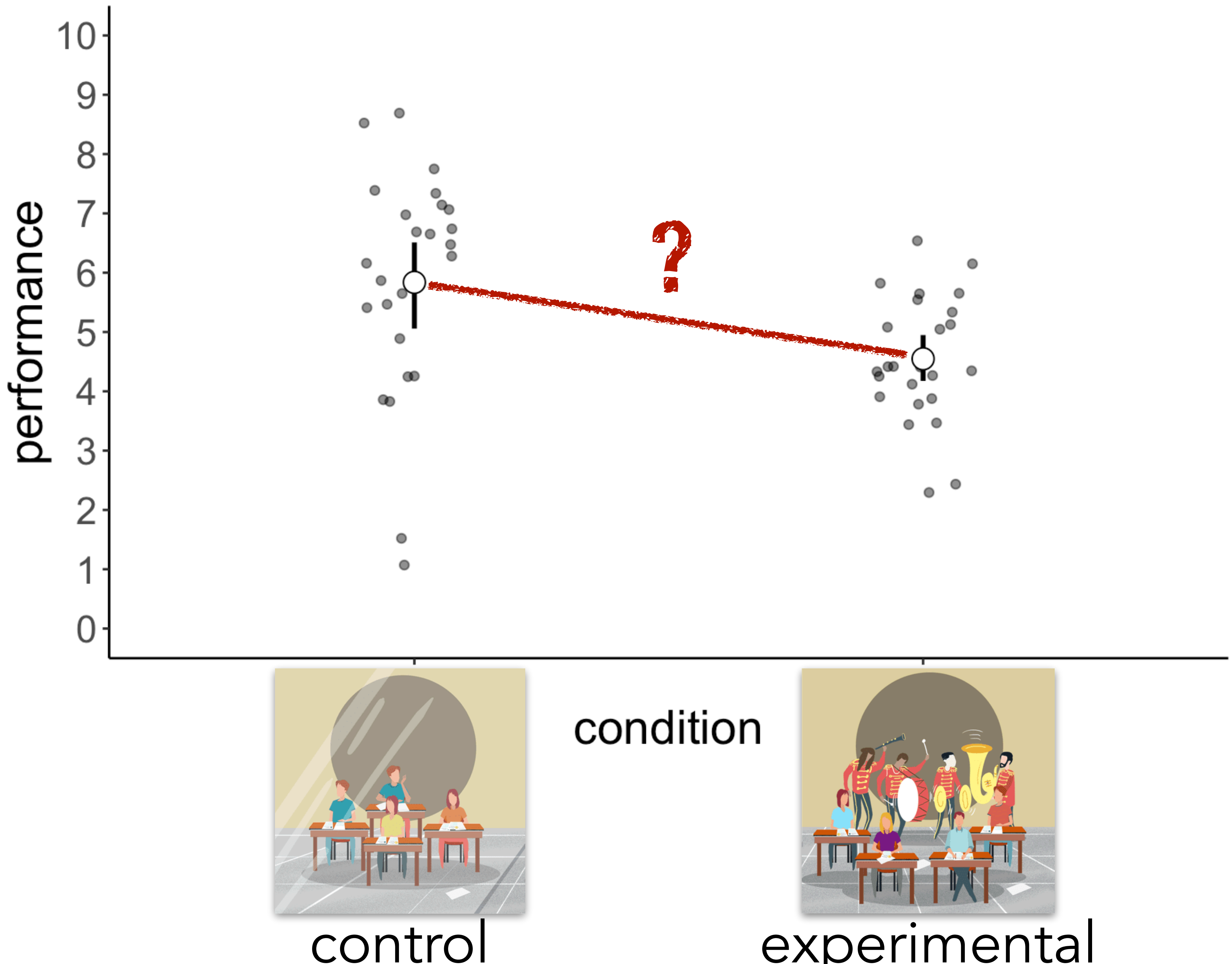
There is no difference between the control group and the experimental group

$H_1 : \mu_{\text{control}} > \mu_{\text{experimental}}$

Performance in the control group is better than in the experimental group

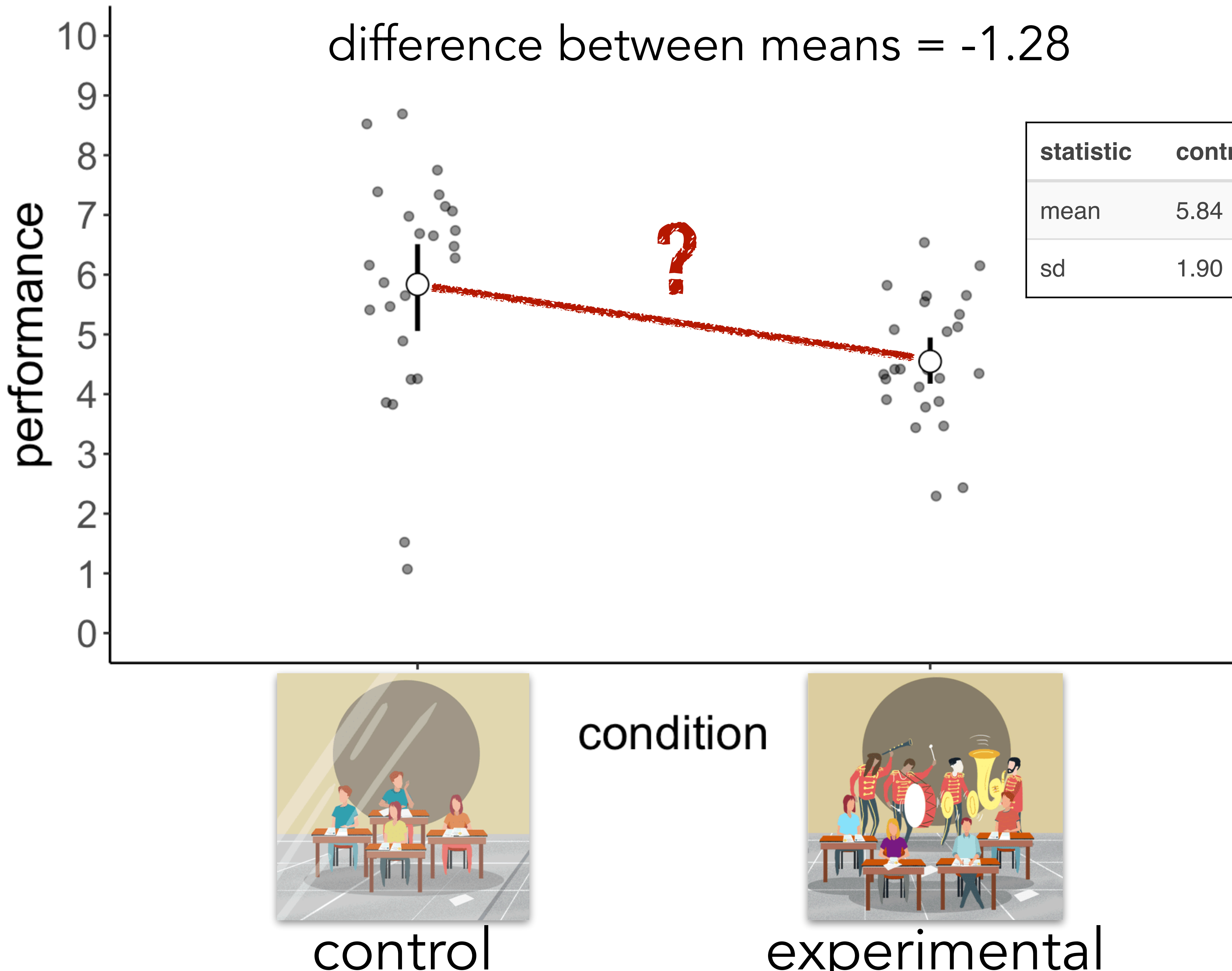
Permutation test

Is the difference in performance statistically significant?



Permutation test

Is the difference in performance statistically significant?



statistic	control	experimental
mean	5.84	4.55
sd	1.90	1.06

Permutation test

- **logic**:
  - assuming our experimental manipulation made no difference, what would be the probability of observing the data that we did?
  - if, assuming that the null hypothesis is true, the probability of observing the data (or data that is more extreme) is less than 5%, we reject the null hypothesis

we need a sampling distribution of our test statistic (difference between means)

Permutation test

observed data

participant	condition	performance
1	control	4.25
2	control	5.87
3	control	3.83
4	control	8.69
5	control	6.16
26	experimental	4.42
27	experimental	4.27
28	experimental	2.29
29	experimental	3.78
30	experimental	5.13

random permutation

participant	condition	performance
1	control	4.25
2	experimental	5.87
3	control	3.83
4	experimental	8.69
5	control	6.16
26	control	4.42
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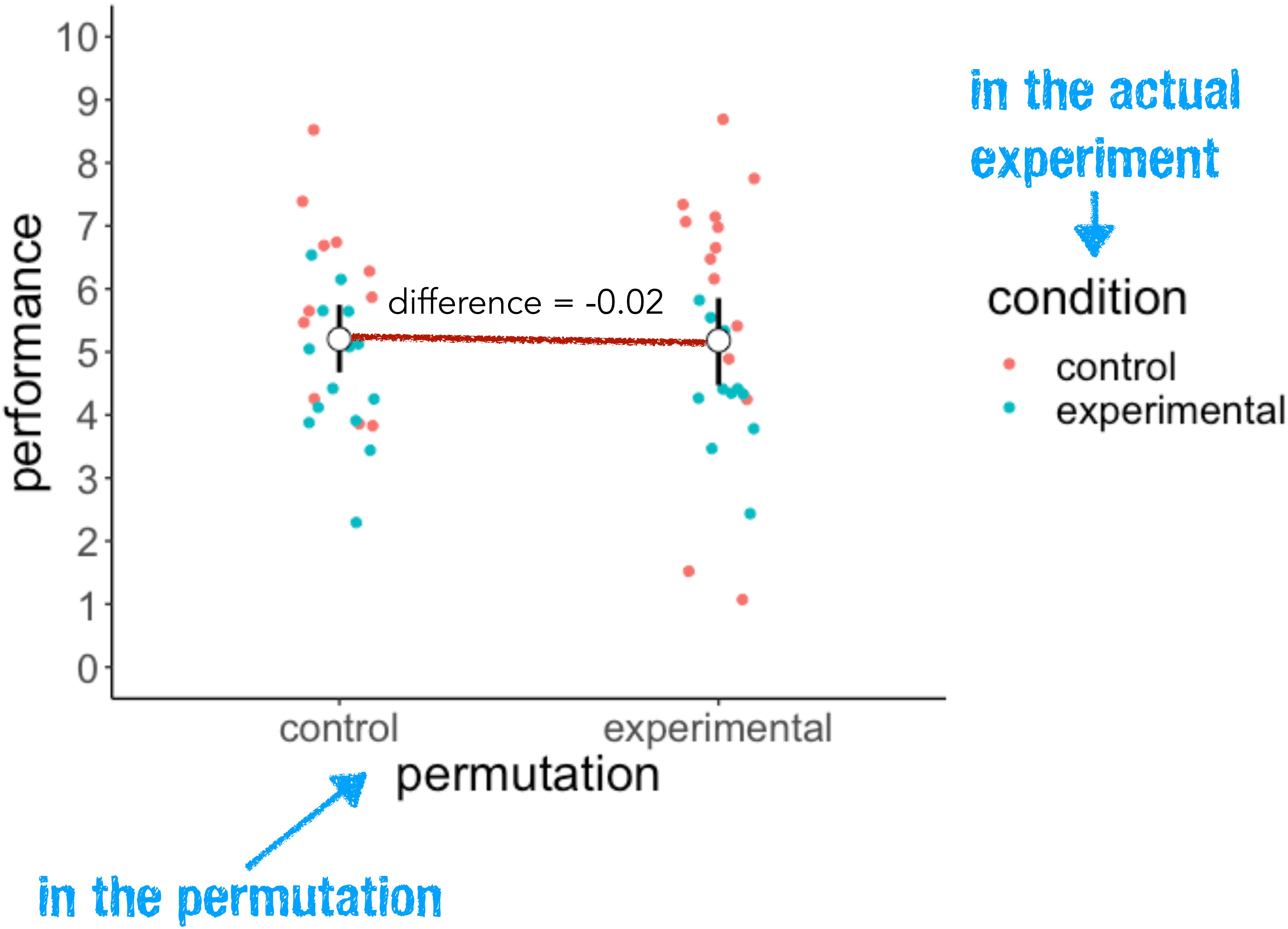
Permutation test



Permutation test

observed data

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1	control	4.25
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1

participant	condition	performance
1	experimental	4.25
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5	experimental	6.16
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28	control	2.29
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30	experimental	5.13

2

participant	condition	performance
1	experimental	4.25
2	control	5.87
3	experimental	3.83
4	experimental	8.69
5	experimental	6.16
26	control	4.42
27	control	4.27
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30	experimental	5.13

3

participant	condition	performance
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3	control	3.83
4	experimental	8.69
5	control	6.16
26	control	4.42
27	experimental	4.27
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29	experimental	3.78
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⋮

permutation	mean_difference
1	-0.88
2	-0.26
3	-0.94
4	0.47
5	-0.28
6	1.15
7	0.98
8	0.38
9	-0.08
10	0.31

Permutation test

df.permutations

permutation	mean_difference
1	-0.88
2	-0.26
3	-0.94
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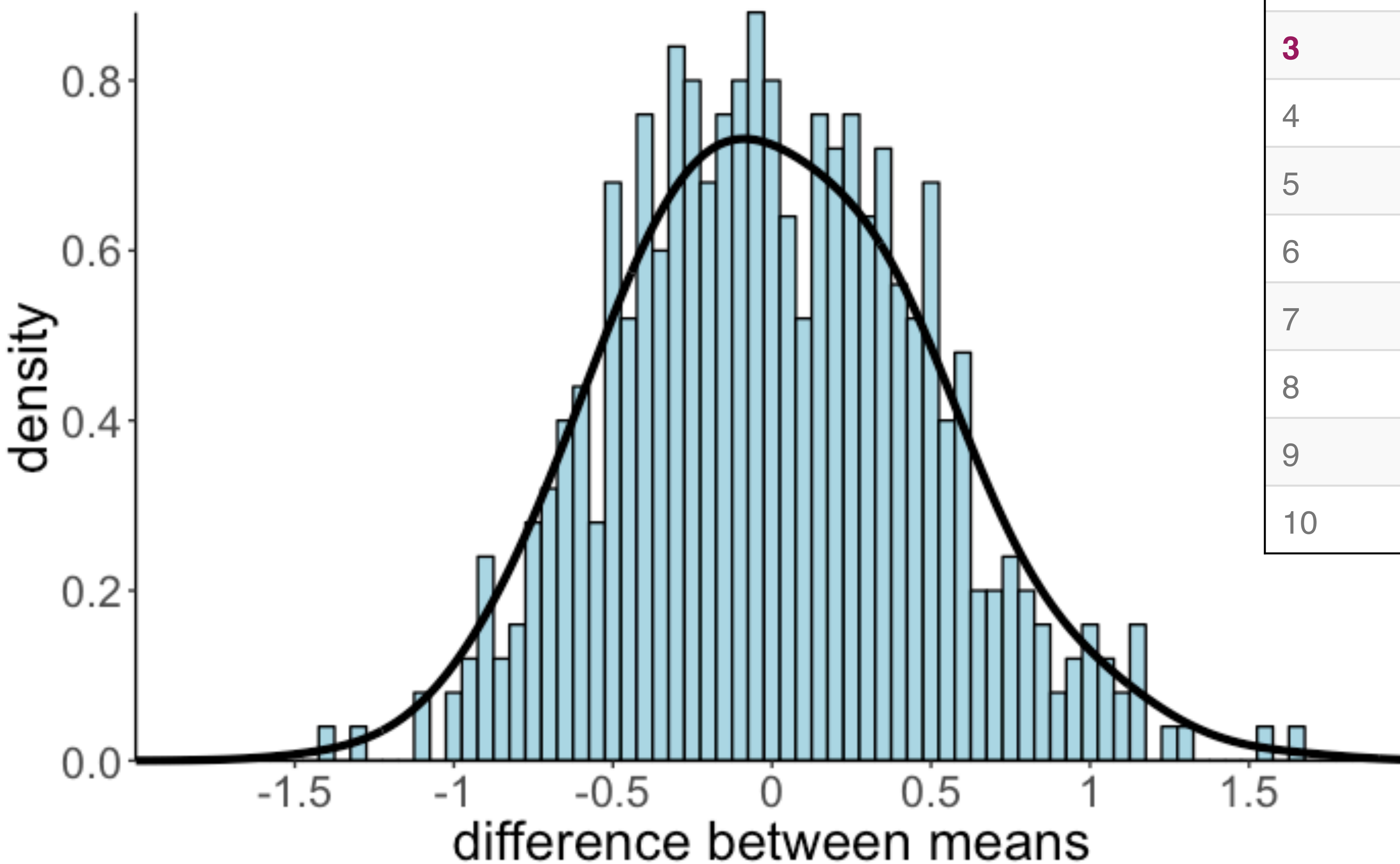
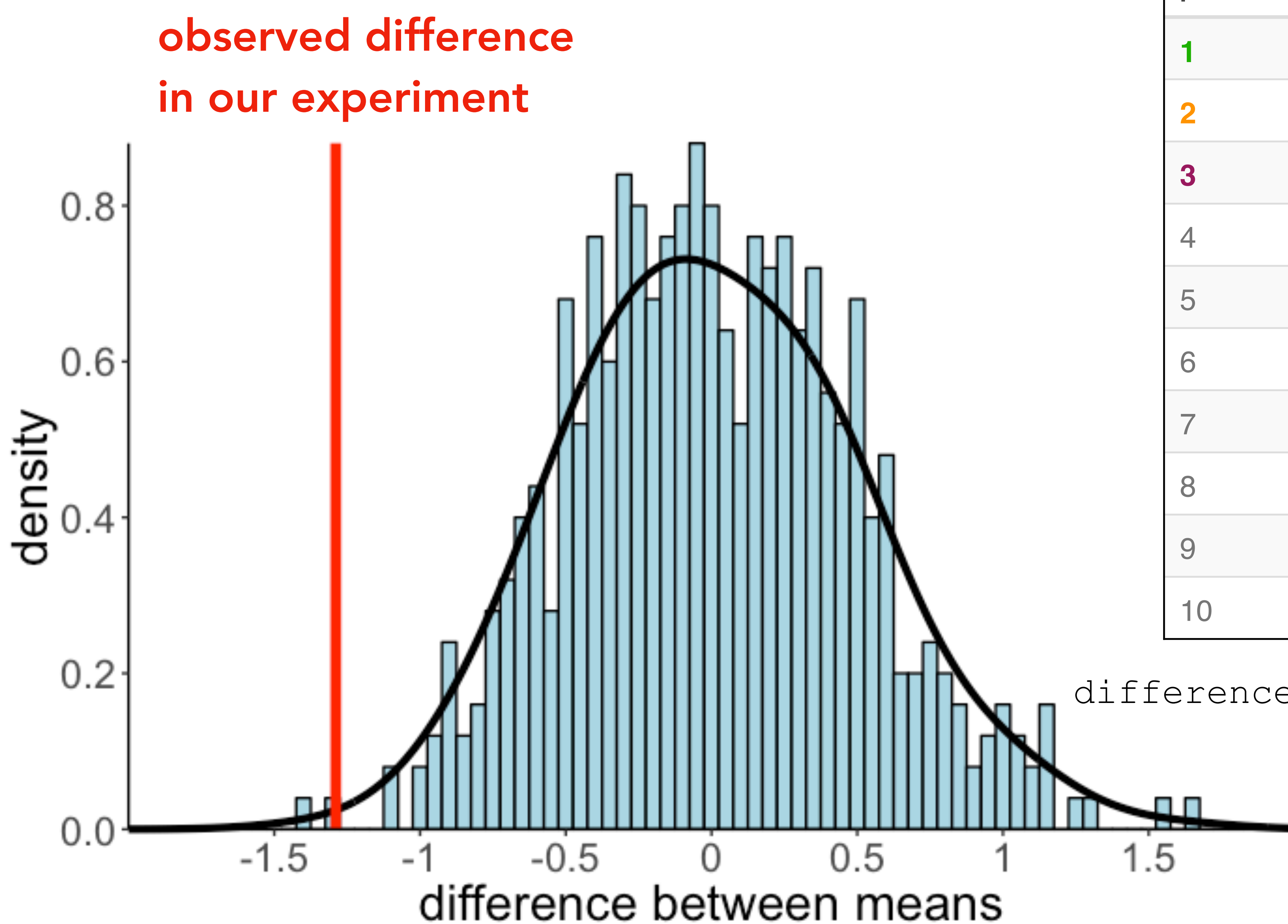


Sampling distribution of differences
(expected differences if the null hypothesis was true)

Permutation test



`df.permutations`

permutation	mean_difference
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2	-0.26
3	-0.94
4	0.47
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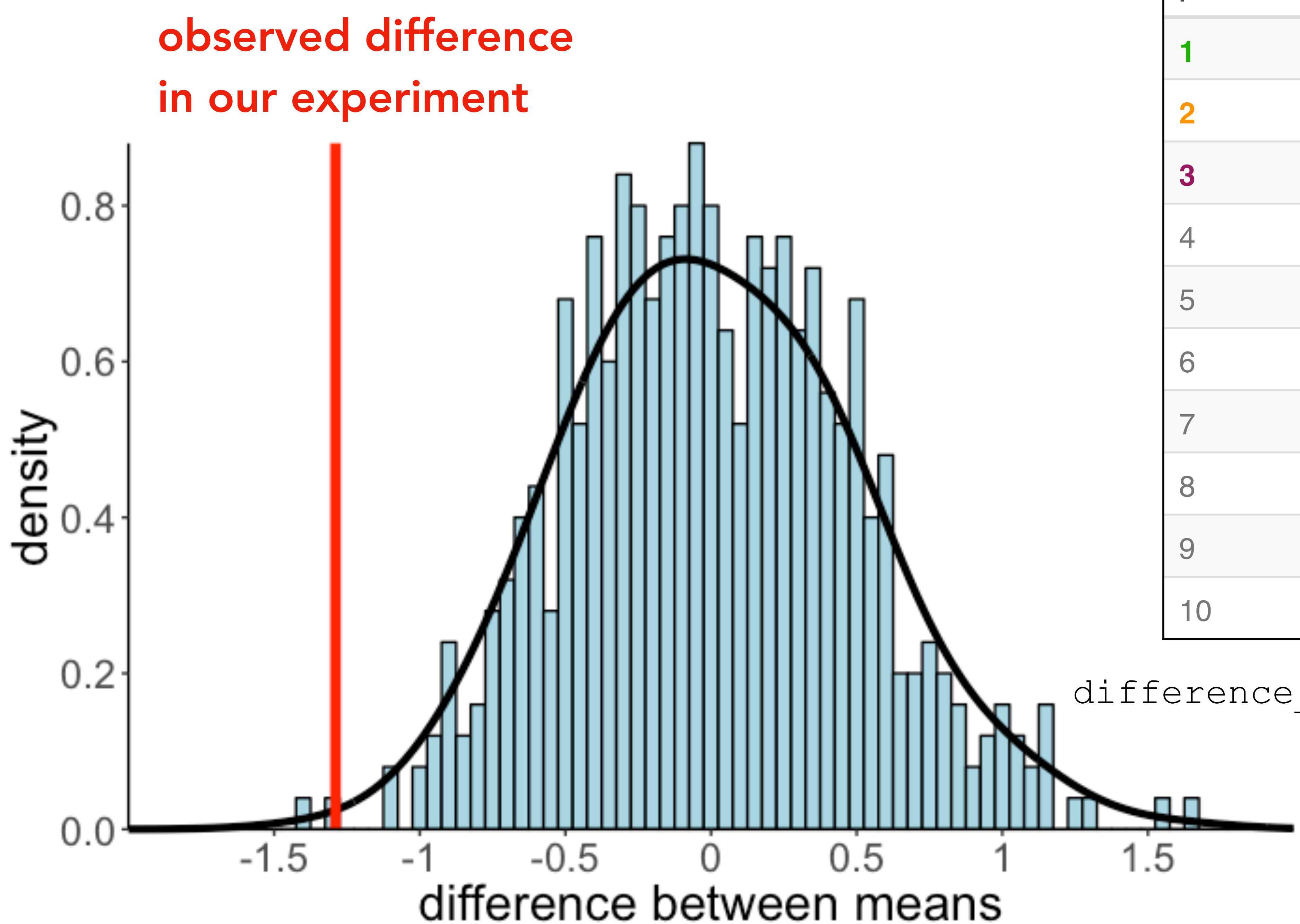
9	-0.08
10	0.31

`difference_actual = -1.28`

Sampling distribution of differences
(expected differences if the null hypothesis is true)

Permutation test



df.permutations

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9	-0.08
10	0.31

difference_actual = -1.28

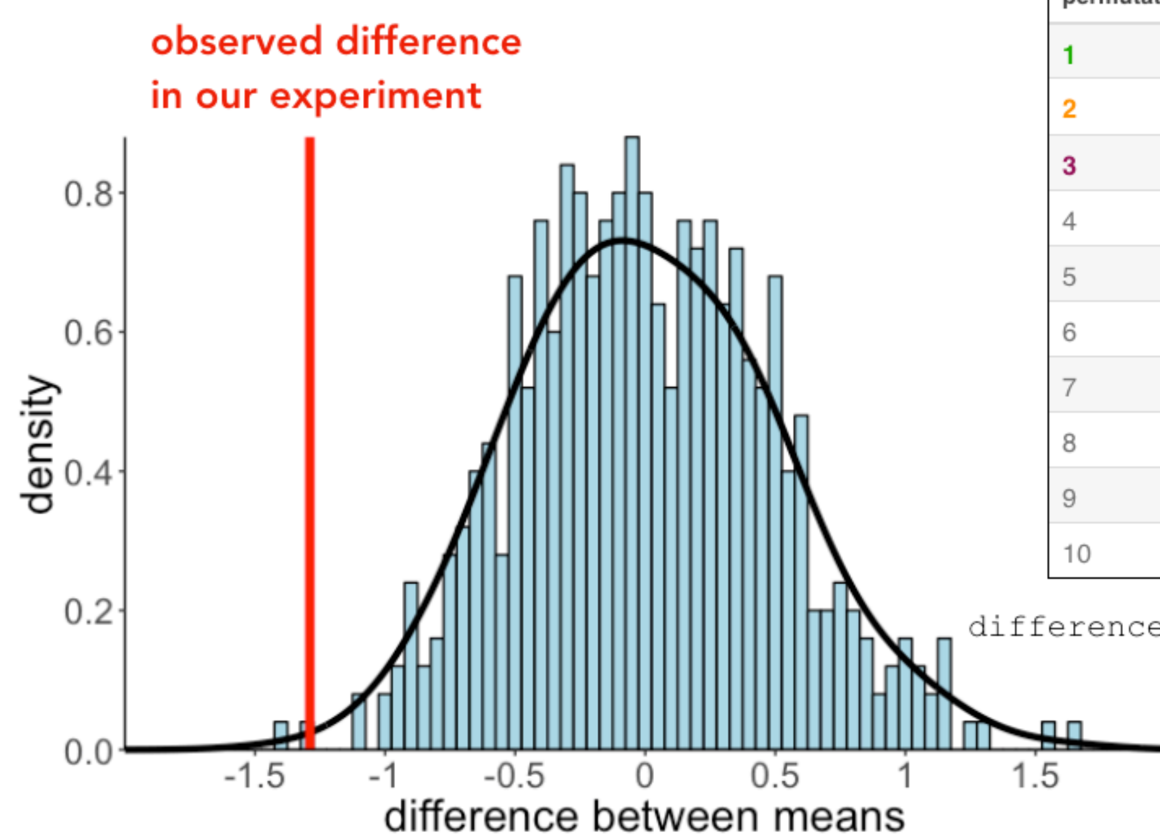
```
#calculate p-value of our observed result
df.permutations %>%
  summarize(p_value = sum(mean_difference <= difference_actual)/n())
```

p-value = .002

What is a p-value?

The **p-value** is the probability of finding the observed, or more extreme, results when the null hypothesis (H_0) is true.

Permutation test



df.permutations

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difference_actual = -1.28

```
#calculate p-value of our observed result
df.permutations %>%
  summarize(p_value = sum(mean_difference <= difference_actual)/n())
```

p-value = .002

57

Permutation test

```r
n_permutations = 500

# permutation function
func_permutations = function(df){
  df %>%
    mutate(condition = sample(condition)) %>%
    group_by(condition) %>%
    summarize(mean = mean(performance)) %>%
    pull(mean) %>%
    diff()
}
```

set the number of permutations

shuffle the condition labels

calculate difference between group means

observed data

participant	condition	performance
1	control	4.25
2	control	5.87
3	control	3.83
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26	experimental	4.42
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random permutation

participant	condition	performance
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Permutation test

```r
n_permutations = 500

# permutation function
func_permutations = function(df){
  df %>%
    mutate(condition = sample(condition)) %>%
    group_by(condition) %>%
    summarize(mean = mean(performance)) %>%
    pull(mean) %>%
    diff()
}

# data frame with permutation results
df.permutations = tibble(
  permutation = 1:n_permutations,
  mean_difference = replicate(n = n_permutations, func_permutations(df.data))
)
```

df.permutations

permutation	mean_difference
1	-0.88
2	-0.26
3	-0.94
4	0.47
5	-0.28
6	1.15
7	0.98
8	0.38
9	-0.08
10	0.31

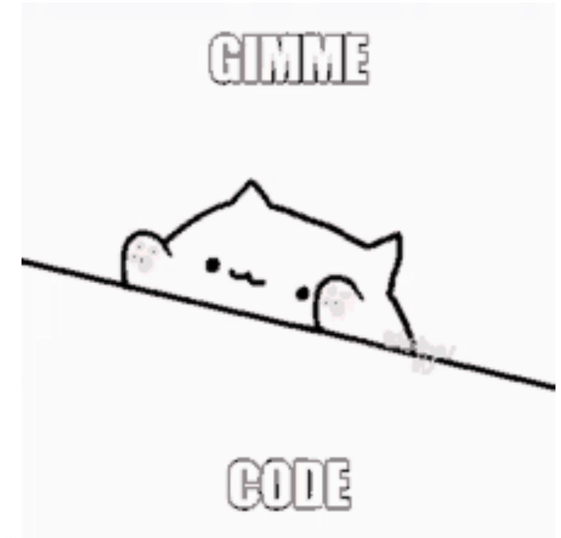
run the `func_permutations()` function many times

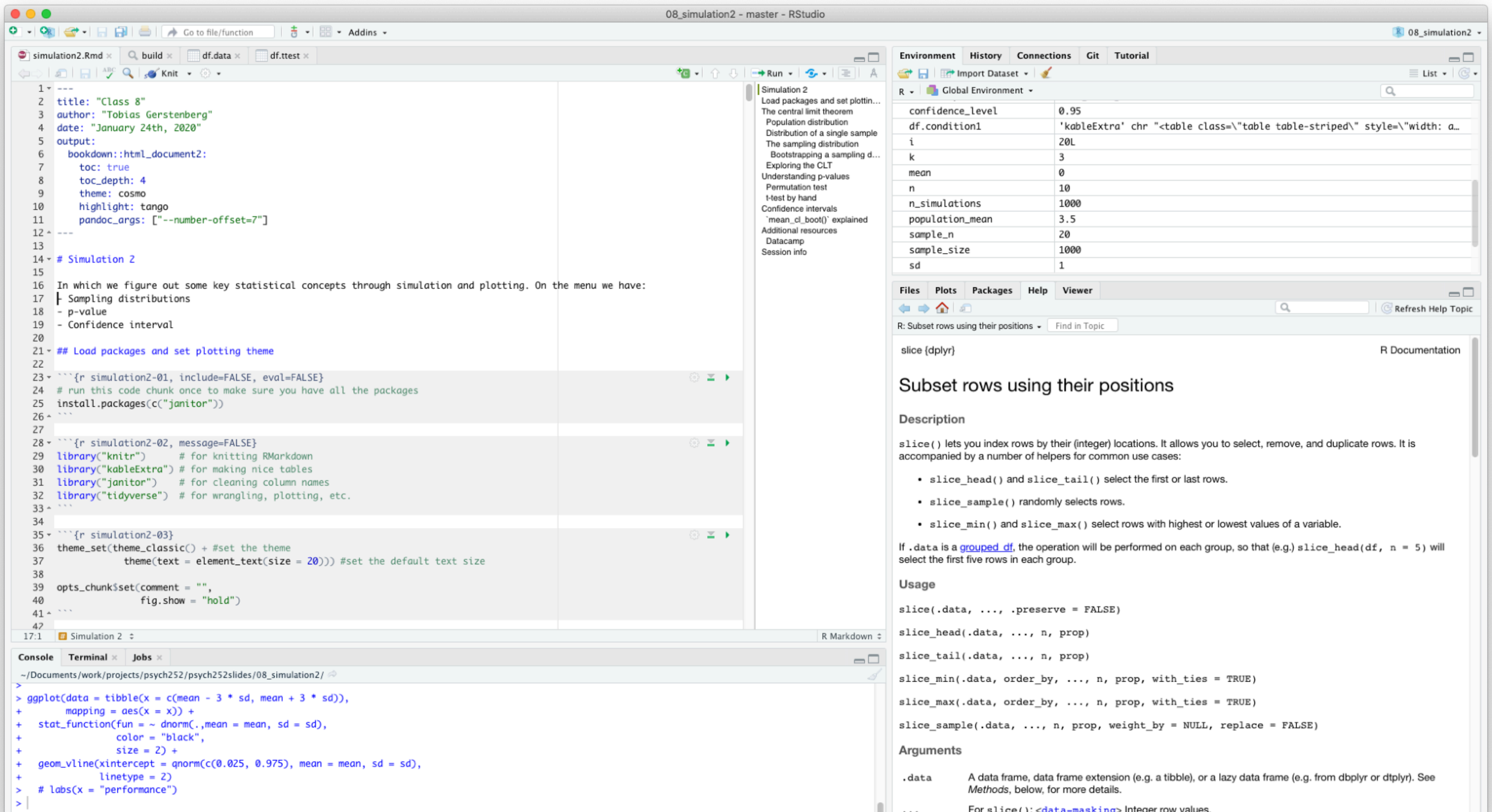
(instead of using a for loop)

Summary Revisit and understand key statistical concepts

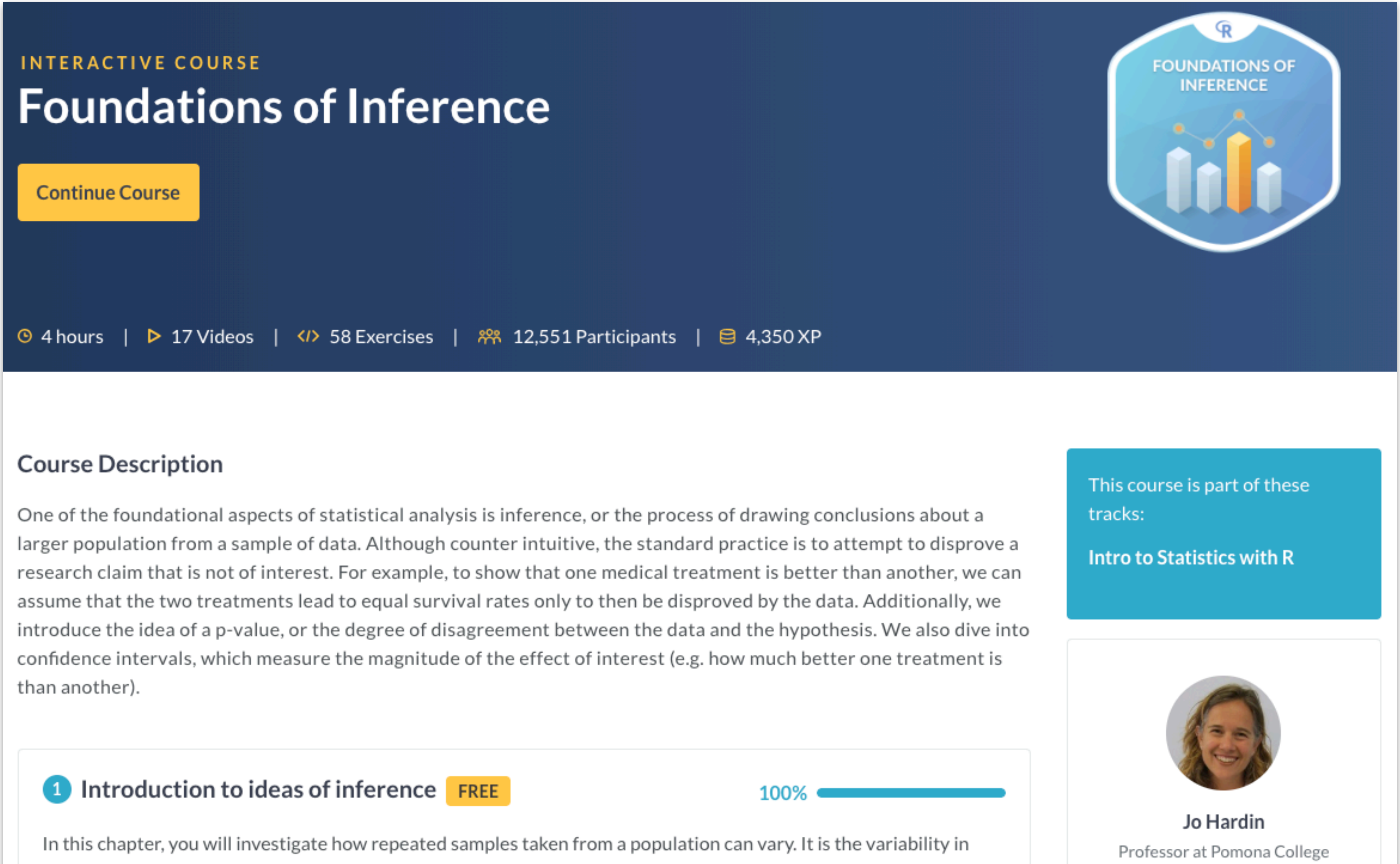
- **Inference in frequentist statistics**
  - goal is to make inference from sample to population
  - we do so via a complicated procedure that involves sampling distributions
- **Sampling distributions**
  - the link between sample and population in frequentist statistics
  - theoretical (or simulated) distribution of a test statistic
- **What is a p-value?**
  - the probability of the observed test result (or a more extreme result) assuming that the H_0 is true
- **Confidence interval (of the mean)**
  - "If we were to repeat the experiment over and over, then 95% of the time the confidence intervals contain the true mean."
- **Bootstrapping**
  - a way to generate sampling distributions (by sampling with replacement) without making any assumptions about the underlying population distribution

How to better understand!





Datacamp


INTERACTIVE COURSE

Foundations of Inference

Continue Course

FOUNDATIONS OF INFERENCE

4 hours | 17 Videos | 58 Exercises | 12,551 Participants | 4,350 XP

Course Description

One of the foundational aspects of statistical analysis is inference, or the process of drawing conclusions about a larger population from a sample of data. Although counter intuitive, the standard practice is to attempt to disprove a research claim that is not of interest. For example, to show that one medical treatment is better than another, we can assume that the two treatments lead to equal survival rates only to then be disproved by the data. Additionally, we introduce the idea of a p-value, or the degree of disagreement between the data and the hypothesis. We also dive into confidence intervals, which measure the magnitude of the effect of interest (e.g. how much better one treatment is than another).

1 Introduction to ideas of inference FREE 100%

In this chapter, you will investigate how repeated samples taken from a population can vary. It is the variability in

This course is part of these tracks:

Intro to Statistics with R

Jo Hardin

Professor at Pomona College

https://www.datacamp.com/courses/foundations-of-inference

Feedback

How was the pace of today's class?

much too slow

a little too slow

just right

a little too fast

much too fast

How happy were you with today's class overall?

What did you like about today's class? What could be improved next time?

Thank you!