Statistical Inference via Data Science: A ModernDive into R & the Tidyverse

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Vancouver BC Canada
Tuesday May 19, 2020

Slides available at twitter.com/rudeboybert

Statistical inference **via** data science…

Guiding paper

“Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum from the Ground Up” by Cobb RIP (TAS 2015)

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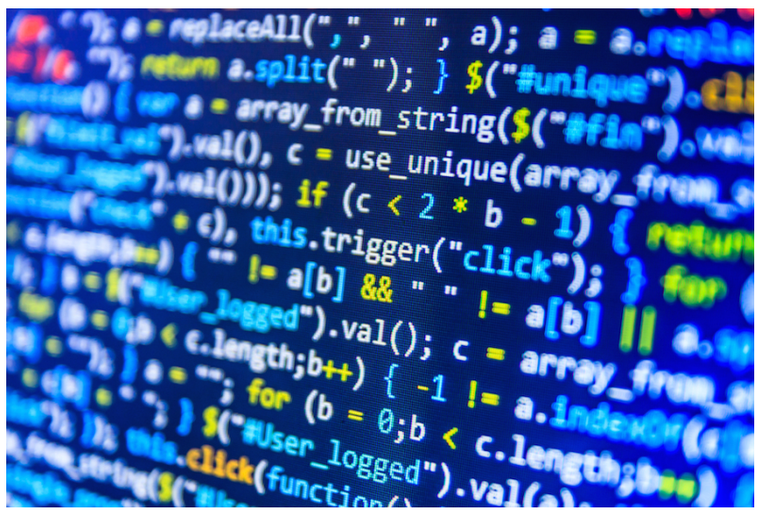

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i.e. Teach Data Science first, Statistics second

Ch3 Data Viz with `ggplot2`

"You don't need no PhD in Stats, just EDA"
Question: Is there a difference in response?

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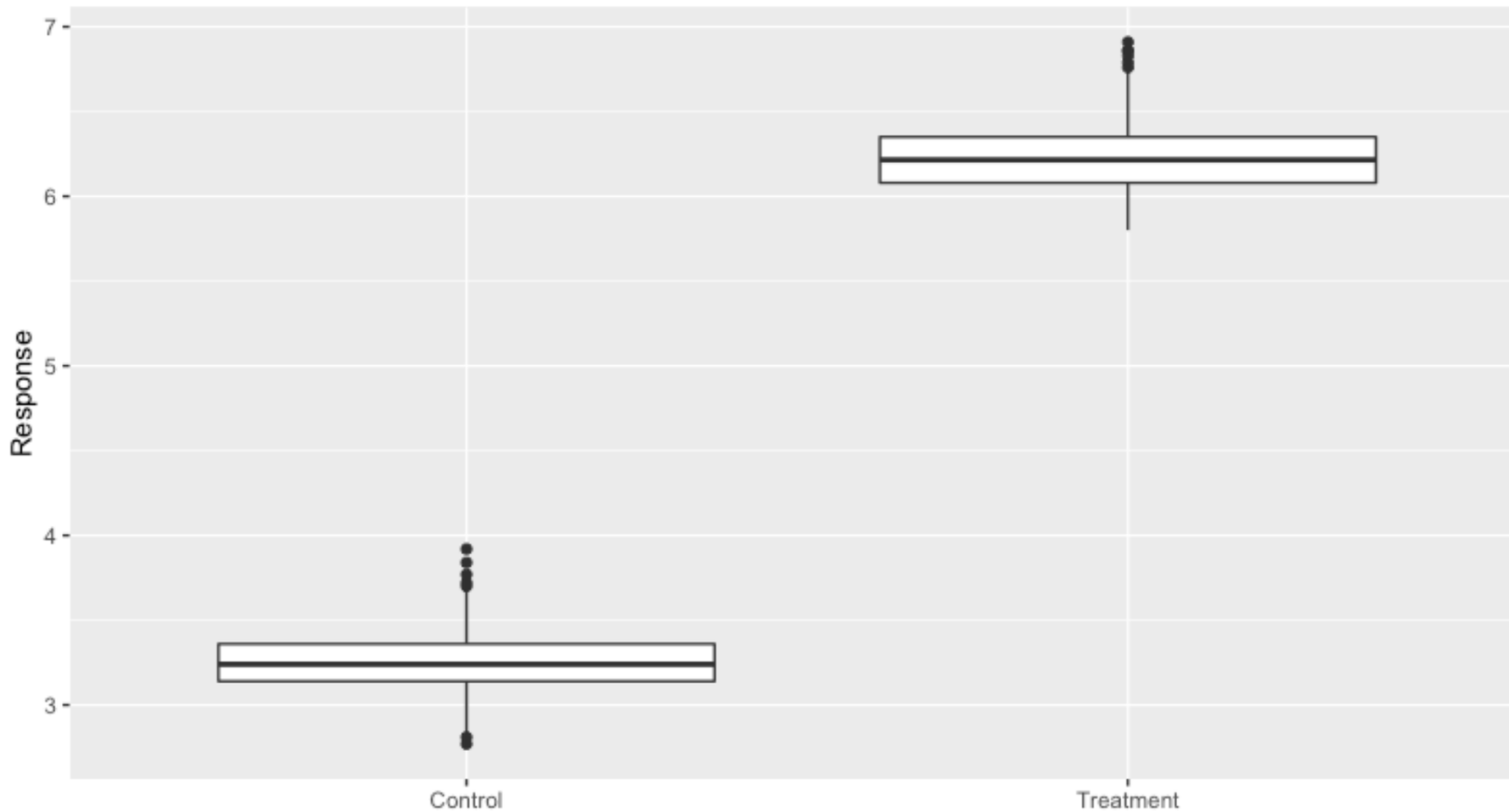

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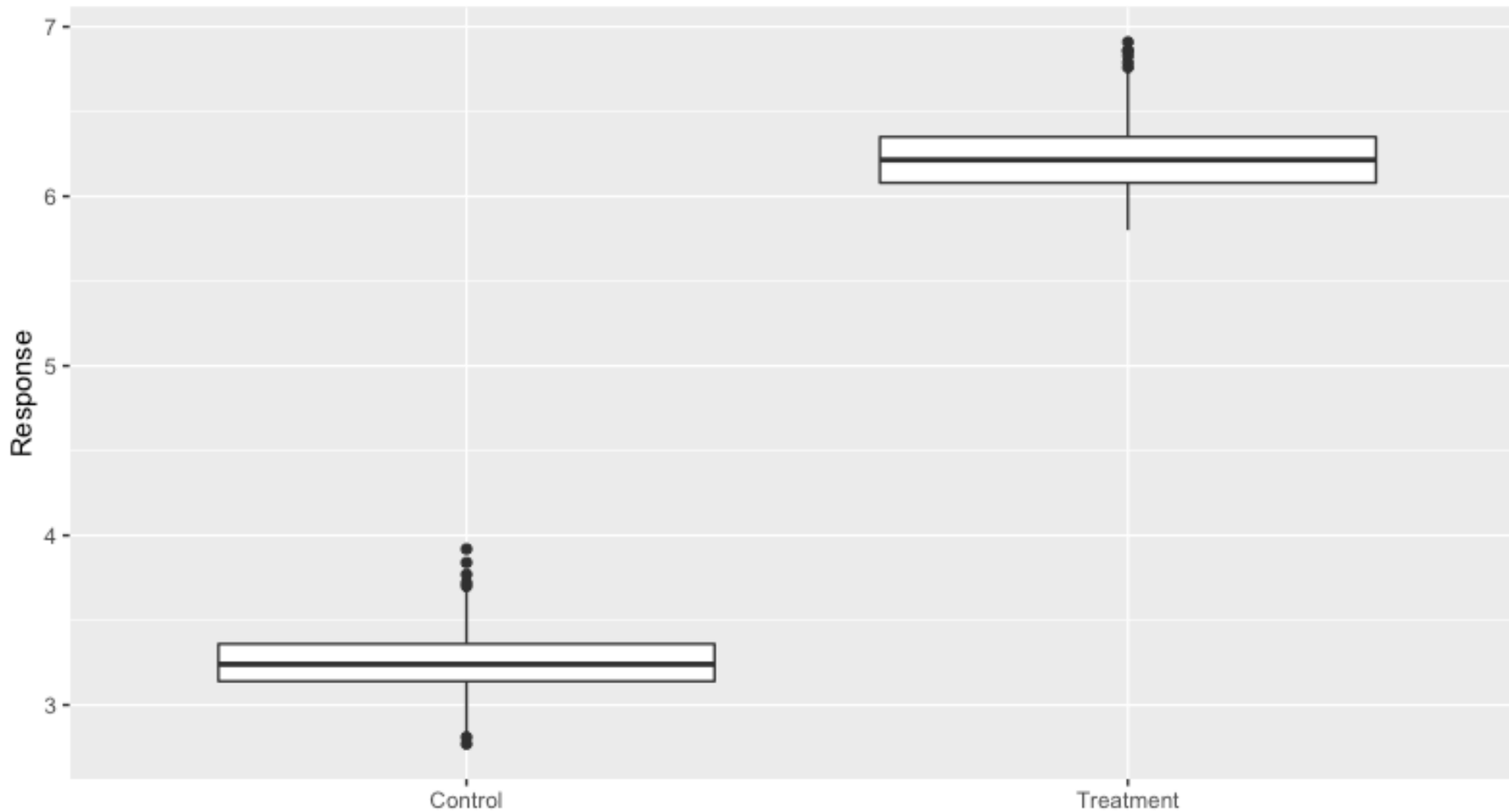

Versus just saying: "The p-value is 0!"

Ch2,4,5 Data Wrangling, Importing, “Tidy”

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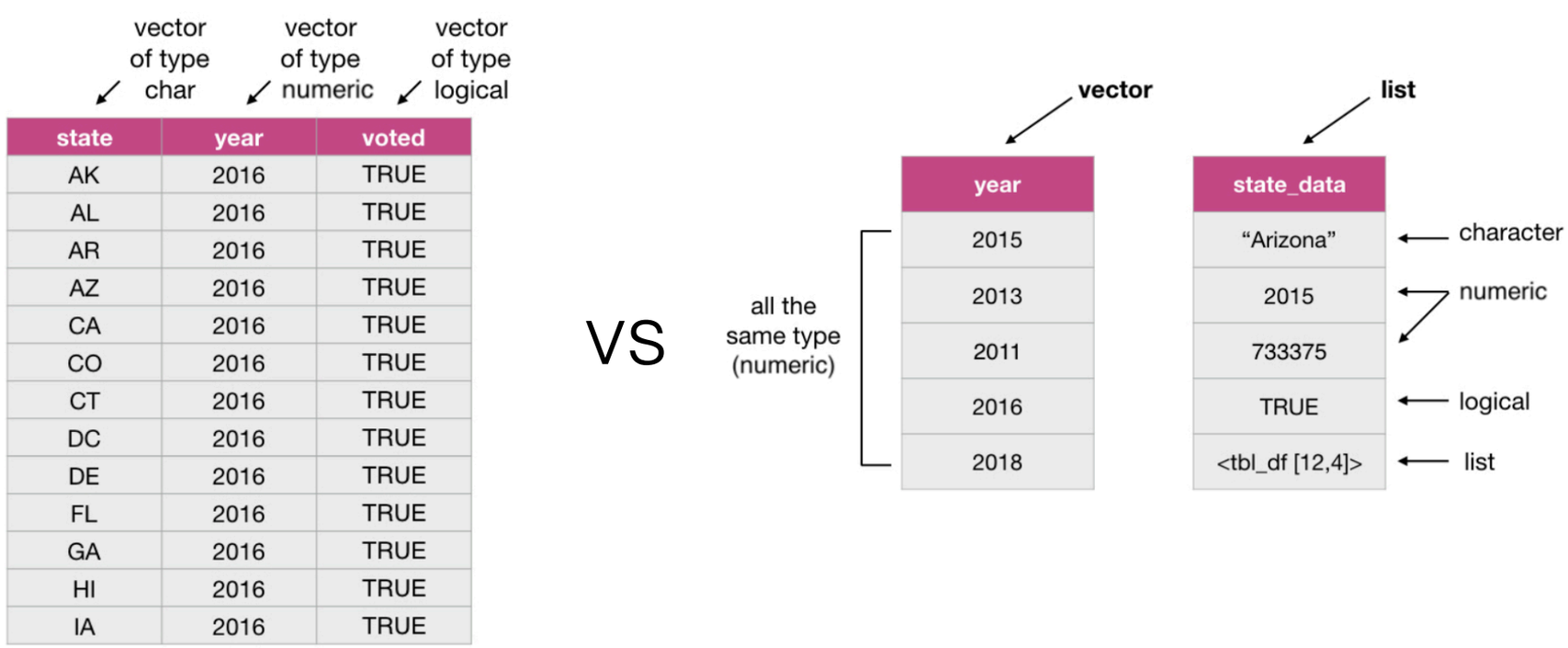


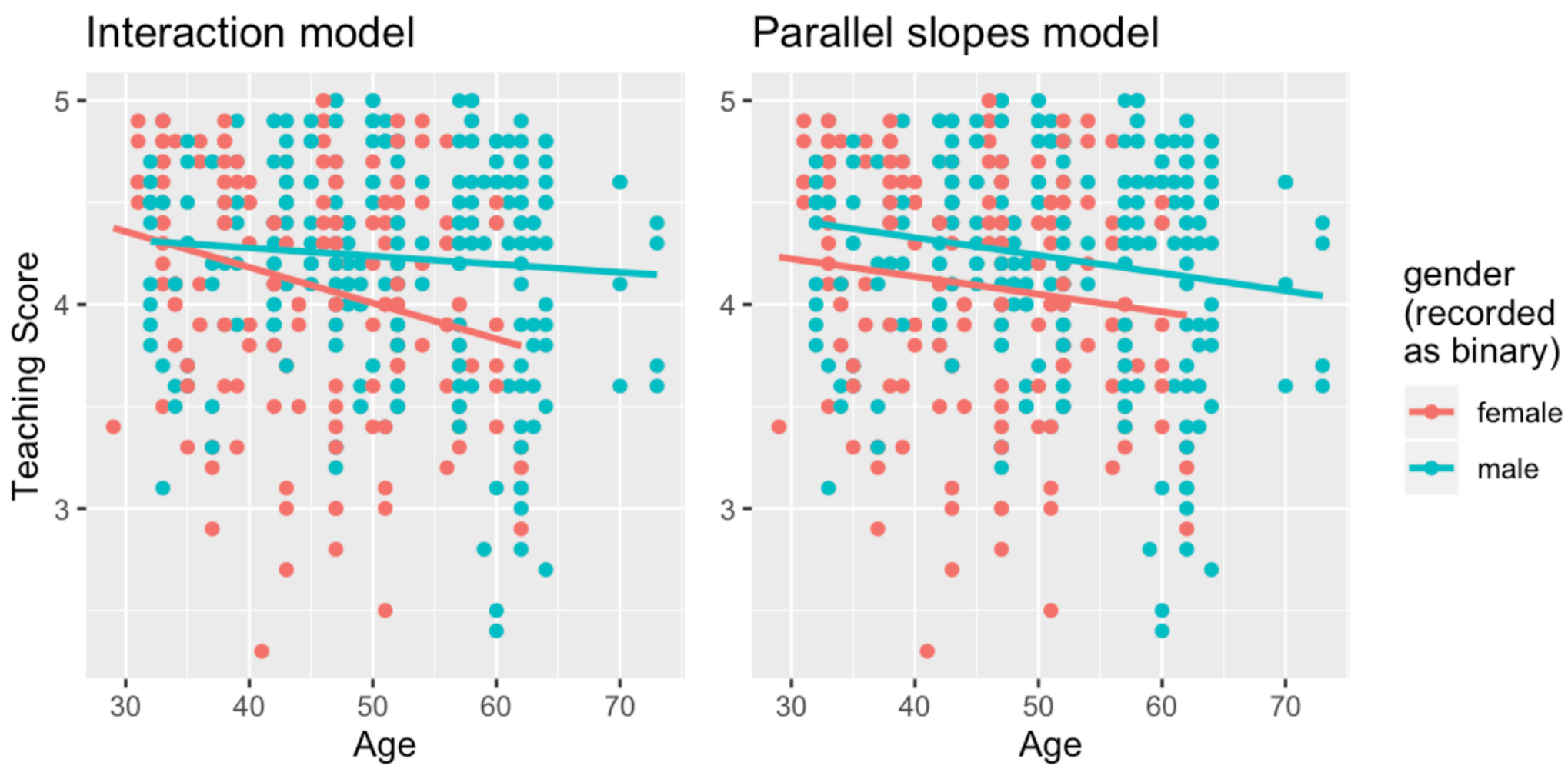
state	year	voted
AK	2016	TRUE
AL	2016	TRUE
AR	2016	TRUE
AZ	2016	TRUE
CA	2016	TRUE
CO	2016	TRUE
CT	2016	TRUE
DC	2016	TRUE
DE	2016	TRUE
FL	2016	TRUE
GA	2016	TRUE
HI	2016	TRUE
IA	2016	TRUE

year
2015
2013
2011
2016
2018

state_data
“Arizona”
2015
733375
TRUE
<tbl_df [12,4]>

An aside: Ch6,7 Linear Regression

"Visual" model selection using teaching evals data



From: [OpenIntro]

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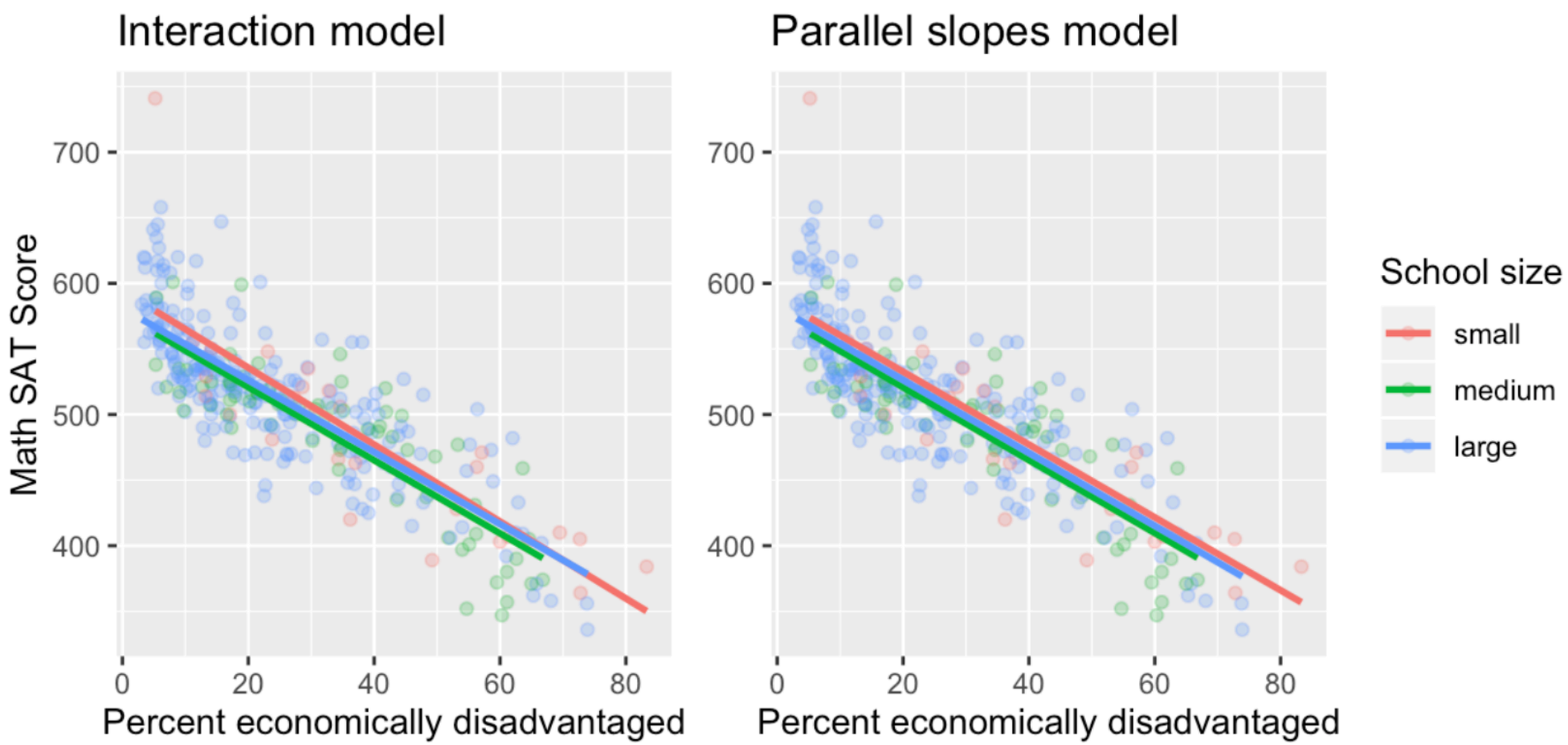
“Visual” model selection using 2017 MA Public HS Data



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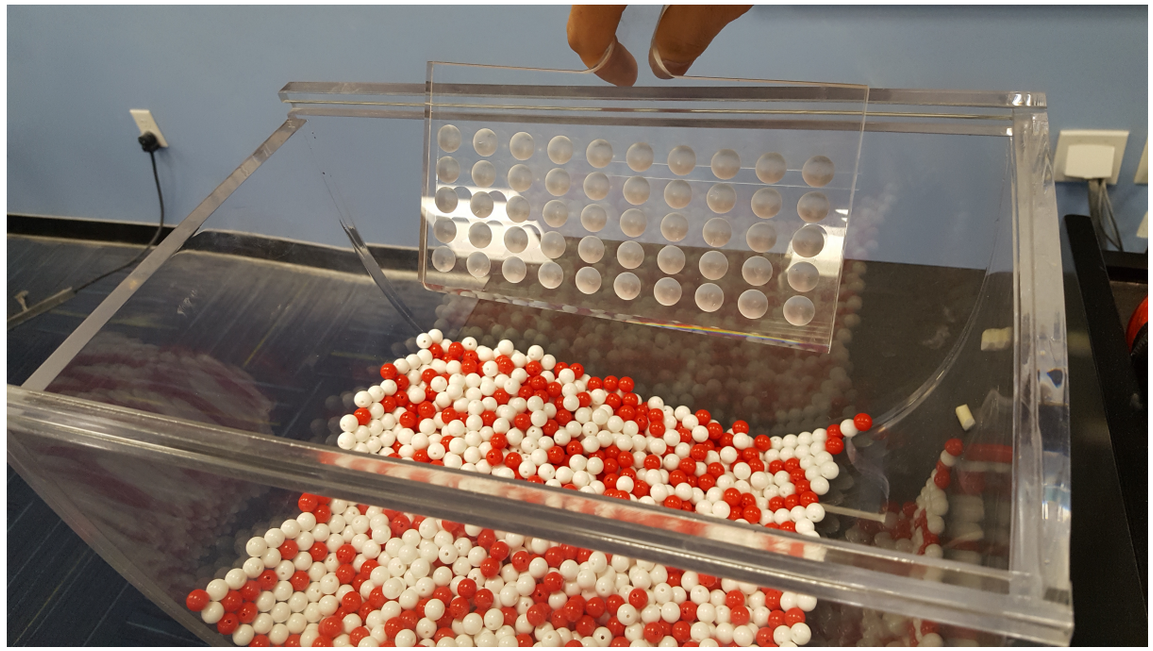
Ch7 What proportion of bowl's balls are red?



Read: Do things by hand first! Hancock & Rummerfield (2020)

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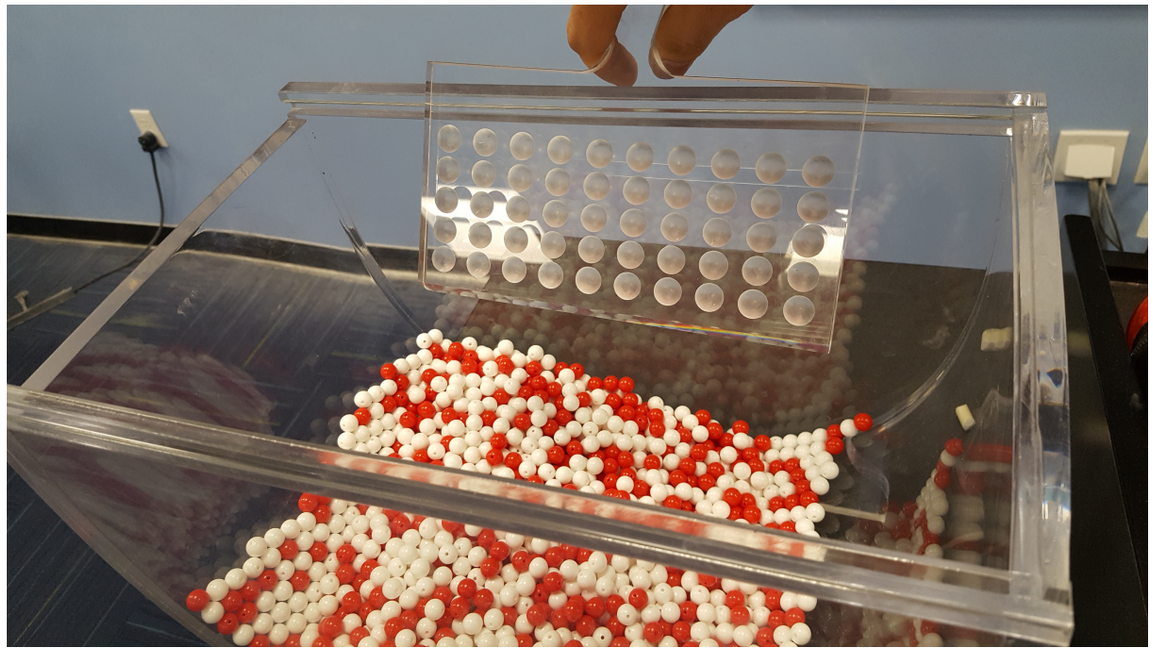

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> library(moderndive)
> bowl
# A tibble: 2,400 x 2
   ball_ID color
     <int> <chr>
 1       1 white
 2       2 white
 3       3 white
 4       4 red
 5       5 white
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 7       7 red
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10      10 white
# … with 2,390 more rows
```

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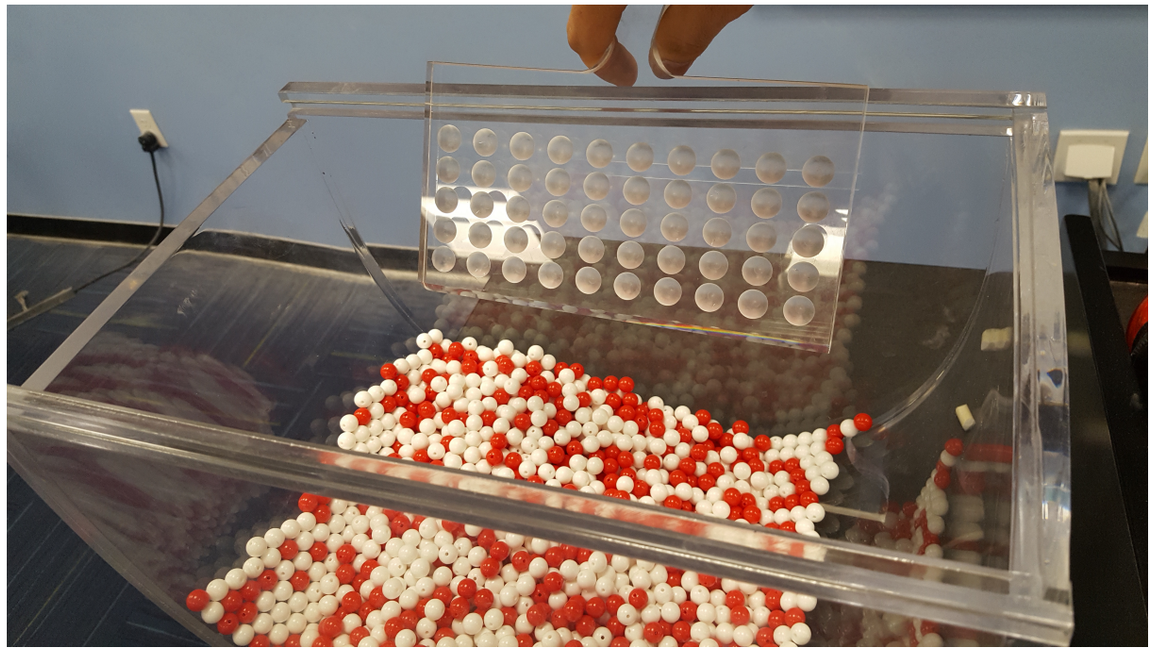

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> # Use shovel with n = 2 five times
> bowl %>% rep_sample_n(size = 2, reps = 5)
# A tibble: 10 x 3
# Groups:   replicate [5]
   replicate ball_ID color
       <int>   <int> <chr>
 1         1    1376 red
 2         1    1810 red
 3         2     606 red
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 5         3    1783 red
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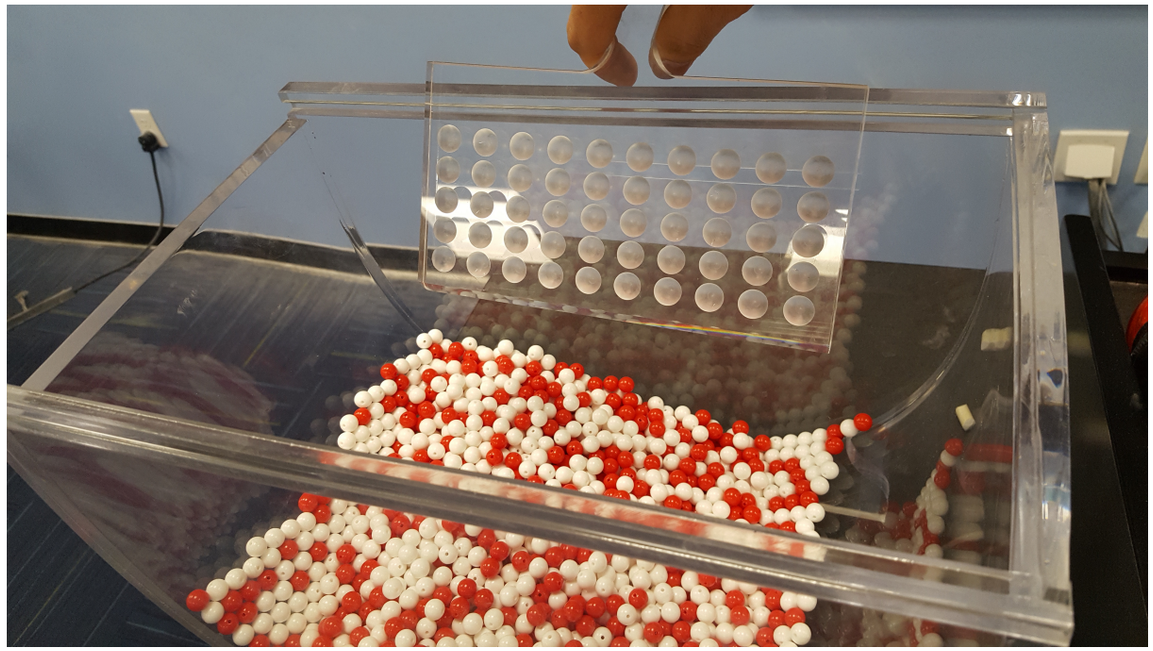

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Simulating repeated sampling:

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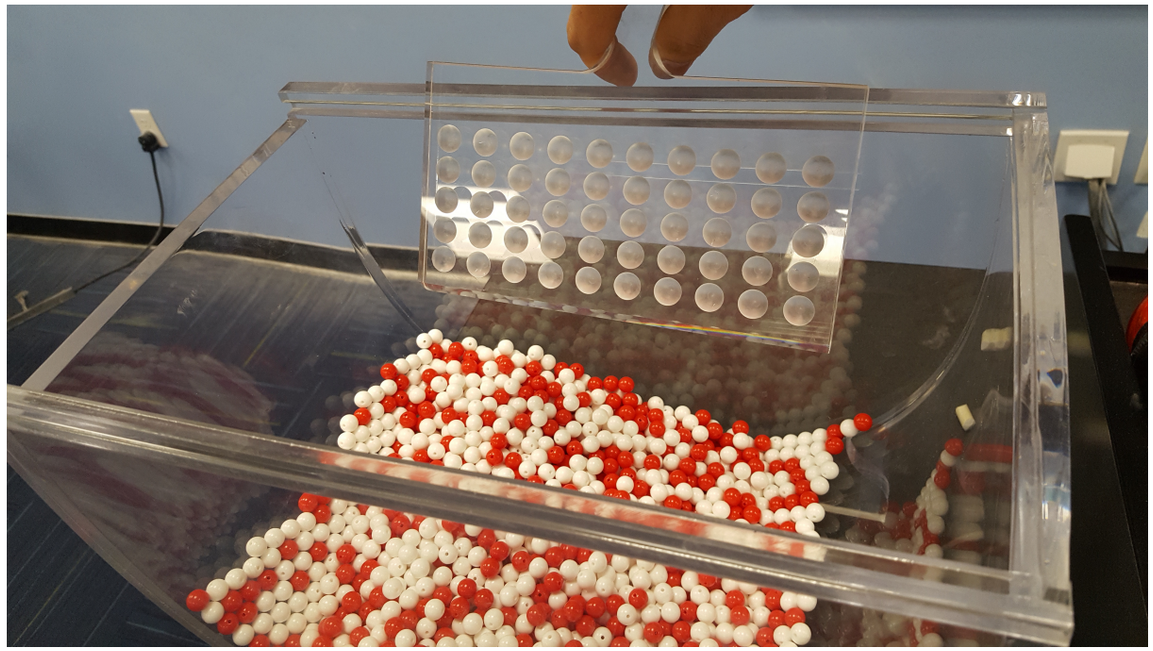

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Simulating repeated sampling:

```r
library(tidyverse)
library(moderndive)

bowl %>%
  rep_sample_n(size = 50, reps = 1000)
  group_by(replicate) %>%
  summarize(red = sum(color == "red")/ 50)
```

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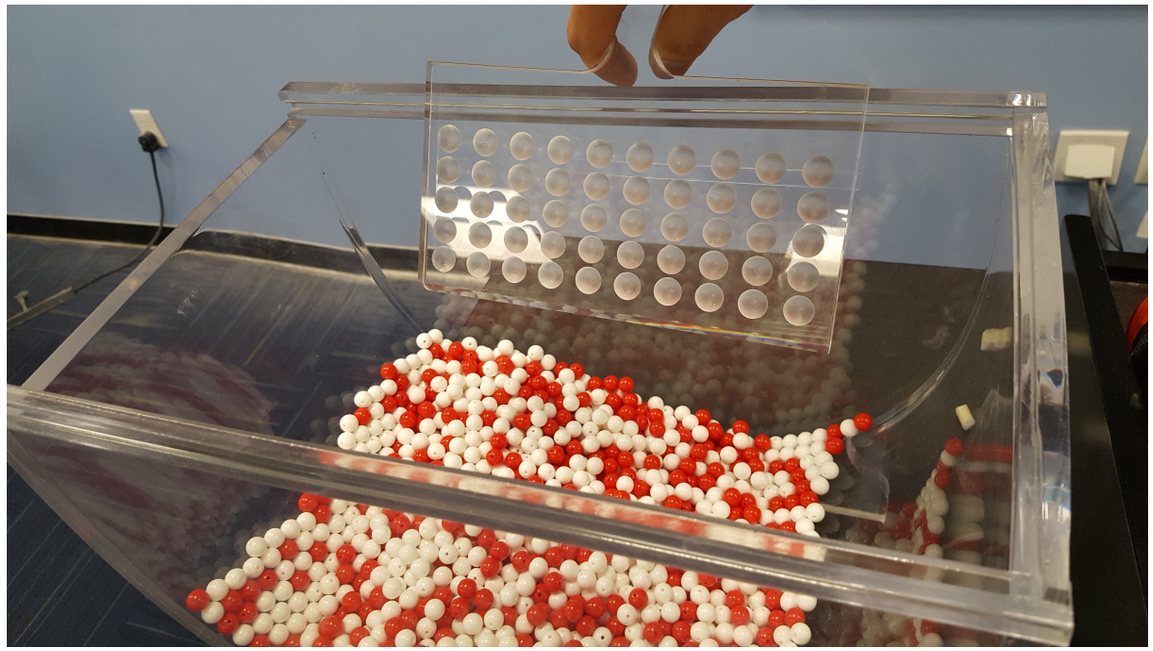

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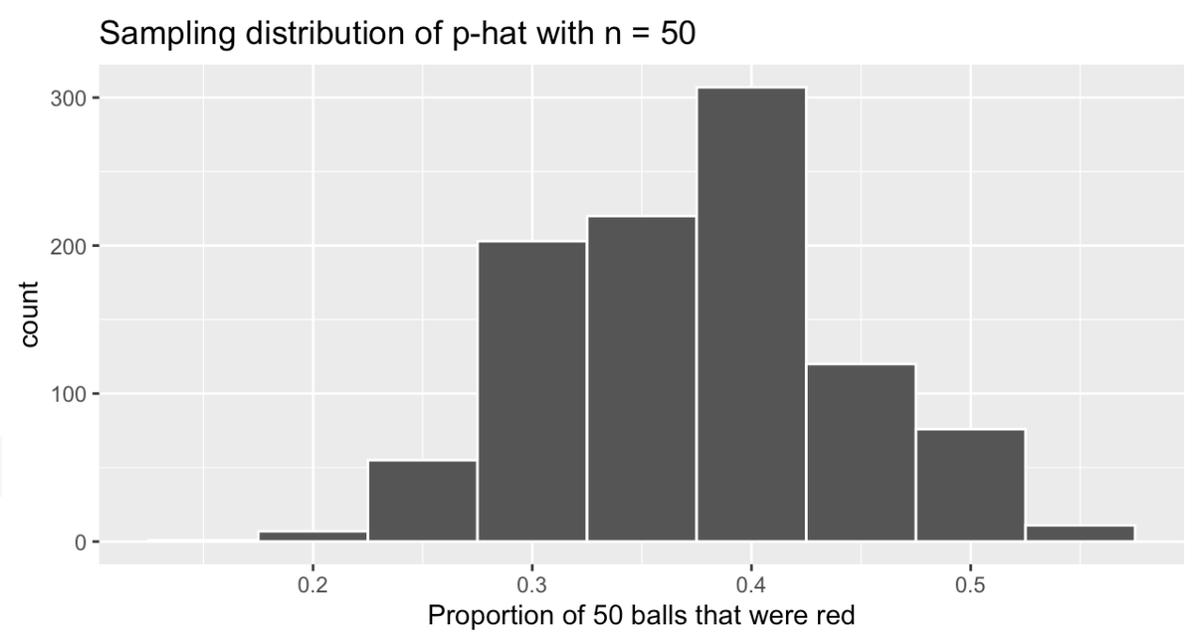

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Ch7 Sampling

Two goals of this sampling simulation:

1. Understanding the effect of sampling variation
2. Understanding the effect of sample size on sampling variation

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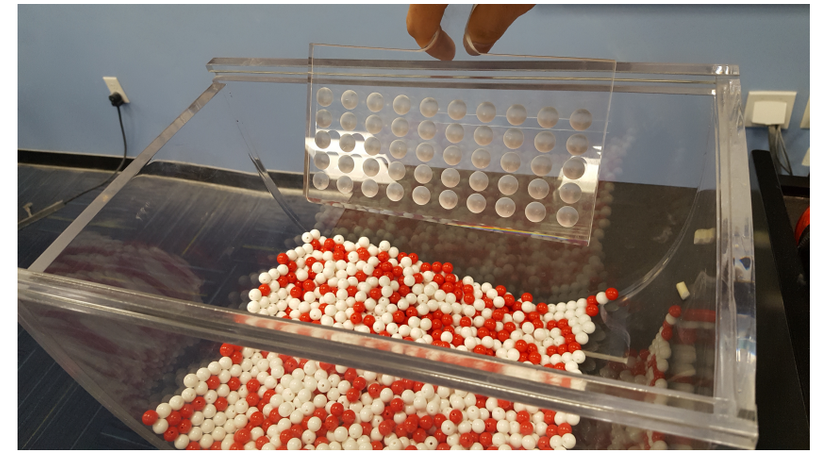

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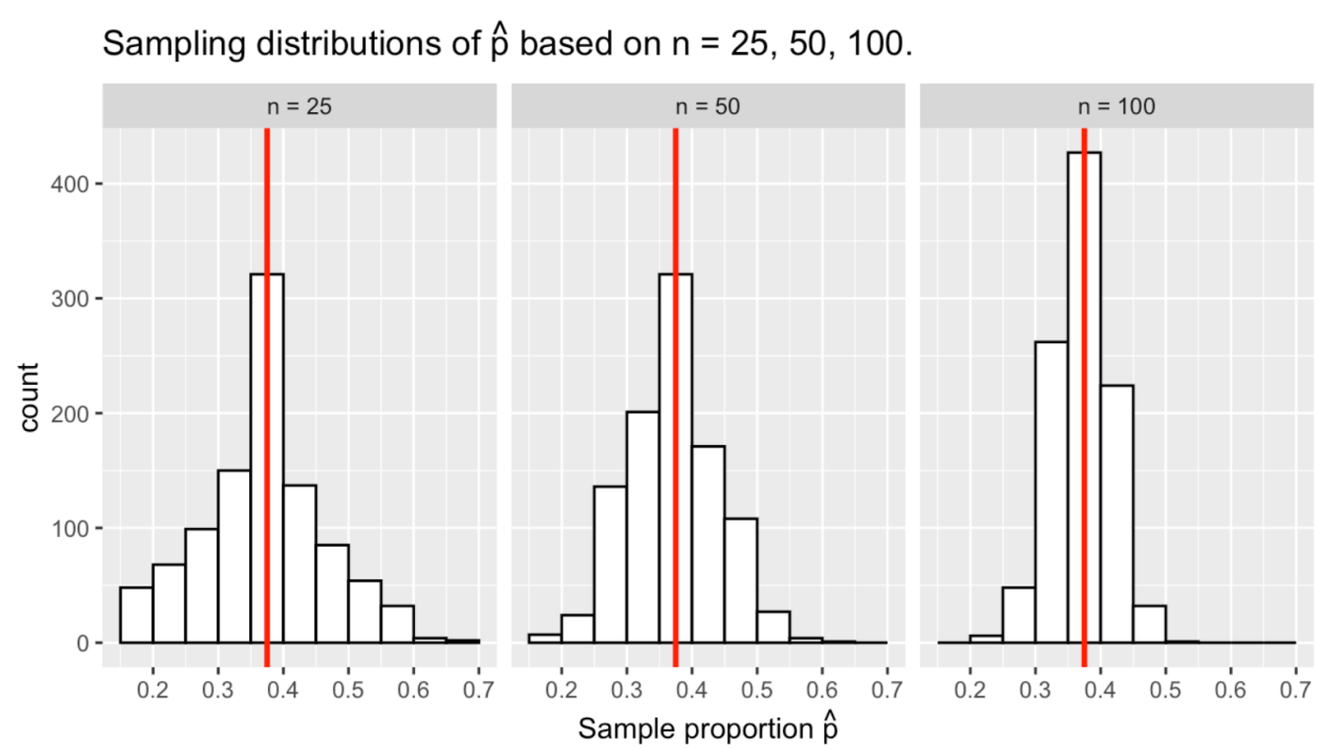
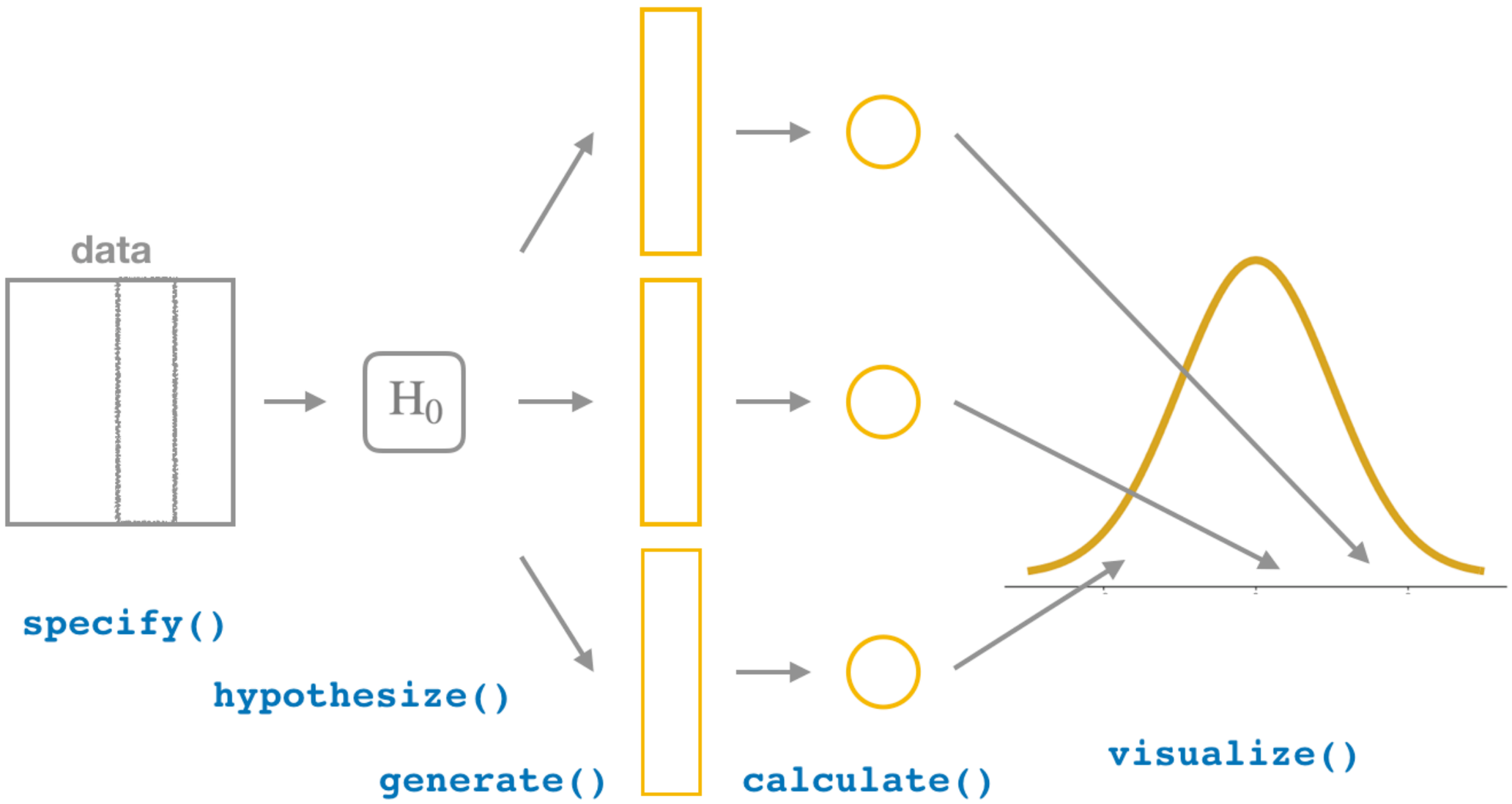


Sampling scenarios covered in ModernDive

TABLE 7.5: Scenarios of sampling for inference

Scenario	Population parameter	Notation	Point estimate	Symbol(s)
1	Population proportion	p	Sample proportion	$\hat{p}$
2	Population mean	μ	Sample mean	$\overline{x}$ or $\widehat{\mu}$
3	Difference in population proportions	$p_1 - p_2$	Difference in sample proportions	$\hat{p}_1 - \hat{p}_2$
4	Difference in population means	$\mu_1 - \mu_2$	Difference in sample means	$\overline{x}_1 - \overline{x}_2$
5	Population regression slope	β_1	Fitted regression slope	b_1 or $\widehat{\beta}_1$

infer package for “tidy” statistical inference



From: [Bray, Ismay, Chasnovski, Baumer, and Cetinkaya-Rundel]

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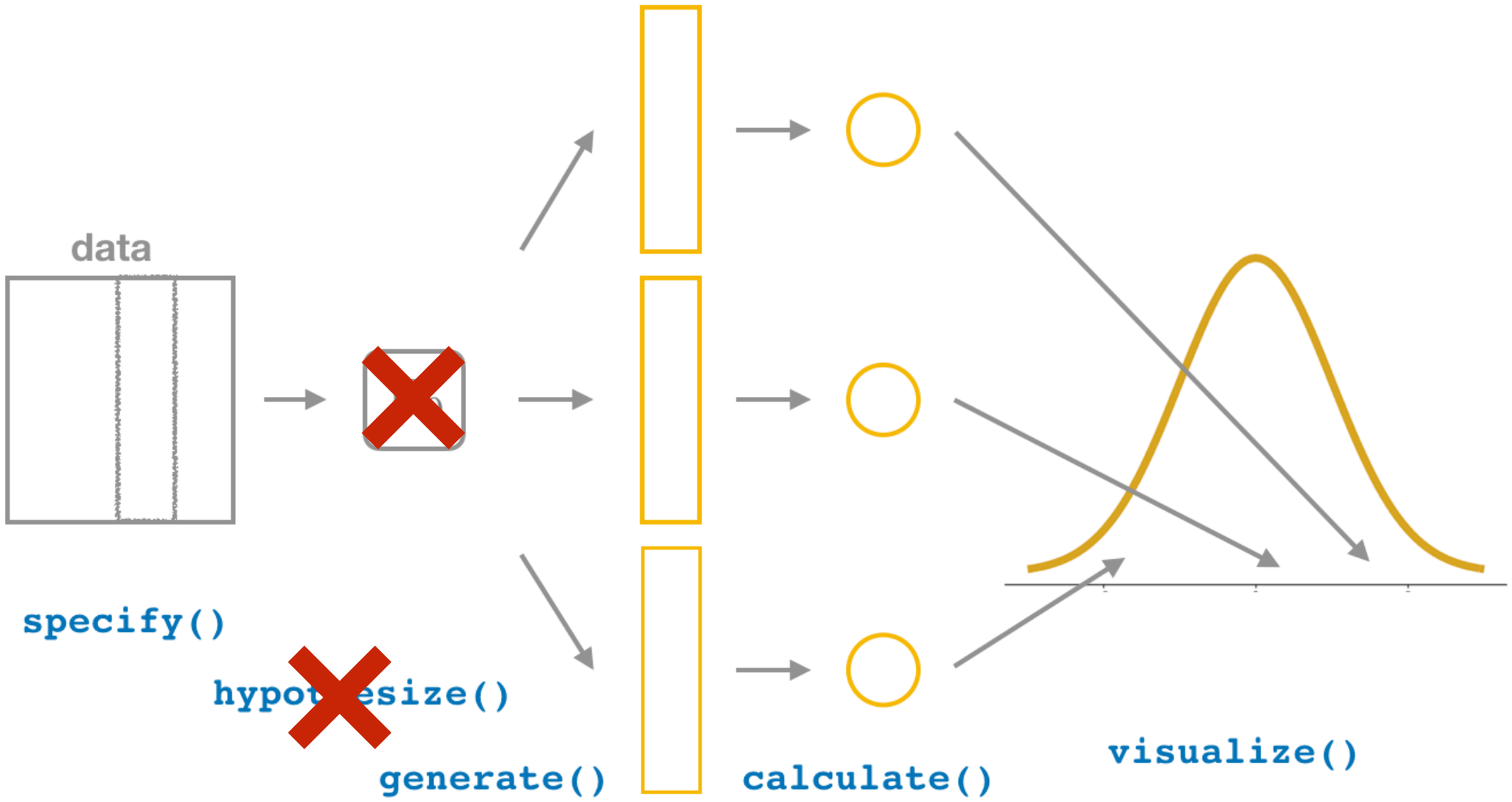

Skip this step for confidence intervals

From: [Bray, Ismay, Chasnovski, Baumer, and Cetinkaya-Rundel]

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```
> library(moderndive)
> pennies_sample
# A tibble: 50 x 2
      ID  year
   <int> <dbl>
 1     1  2002
 2     2  1986
 3     3  2017
 4     4  1988
 5     5  2008
 6     6  1983
 7     7  2008
 8     8  1996
 9     9  2004
10    10  2000
# … with 40 more rows
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Using bootstrap resampling with replacement:

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Using bootstrap resampling with replacement:

```r
library(tidyverse)
library(infer)

pennies_sample %>%
  specify(response = year) %>%
  generate(reps = 1000) %>%
  calculate(stat = "mean")
```

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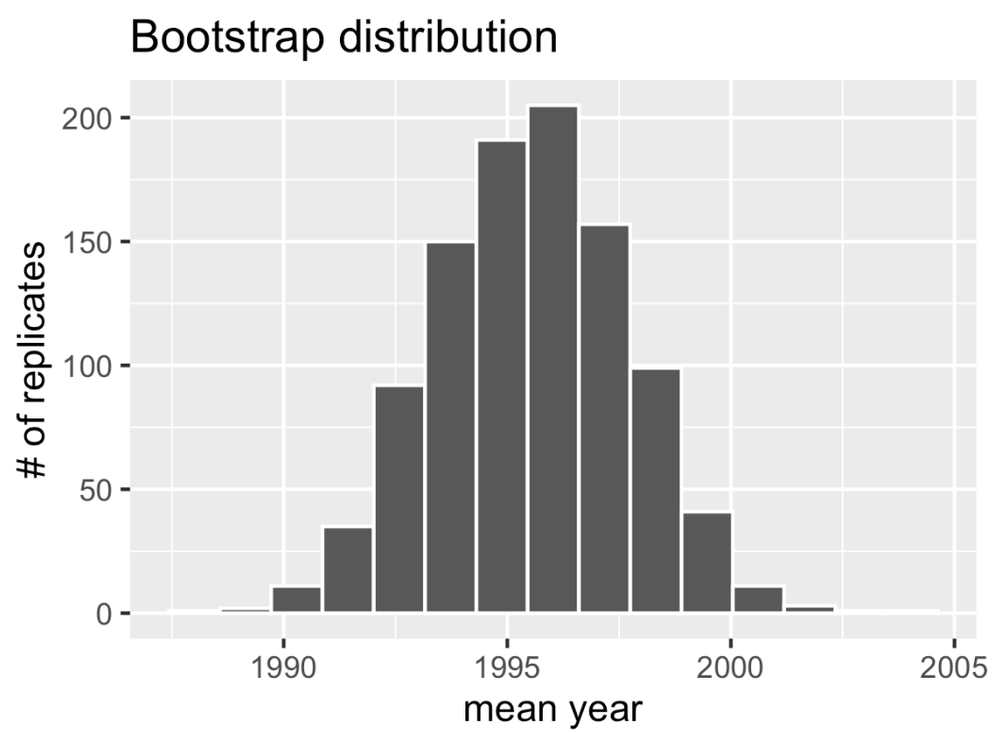

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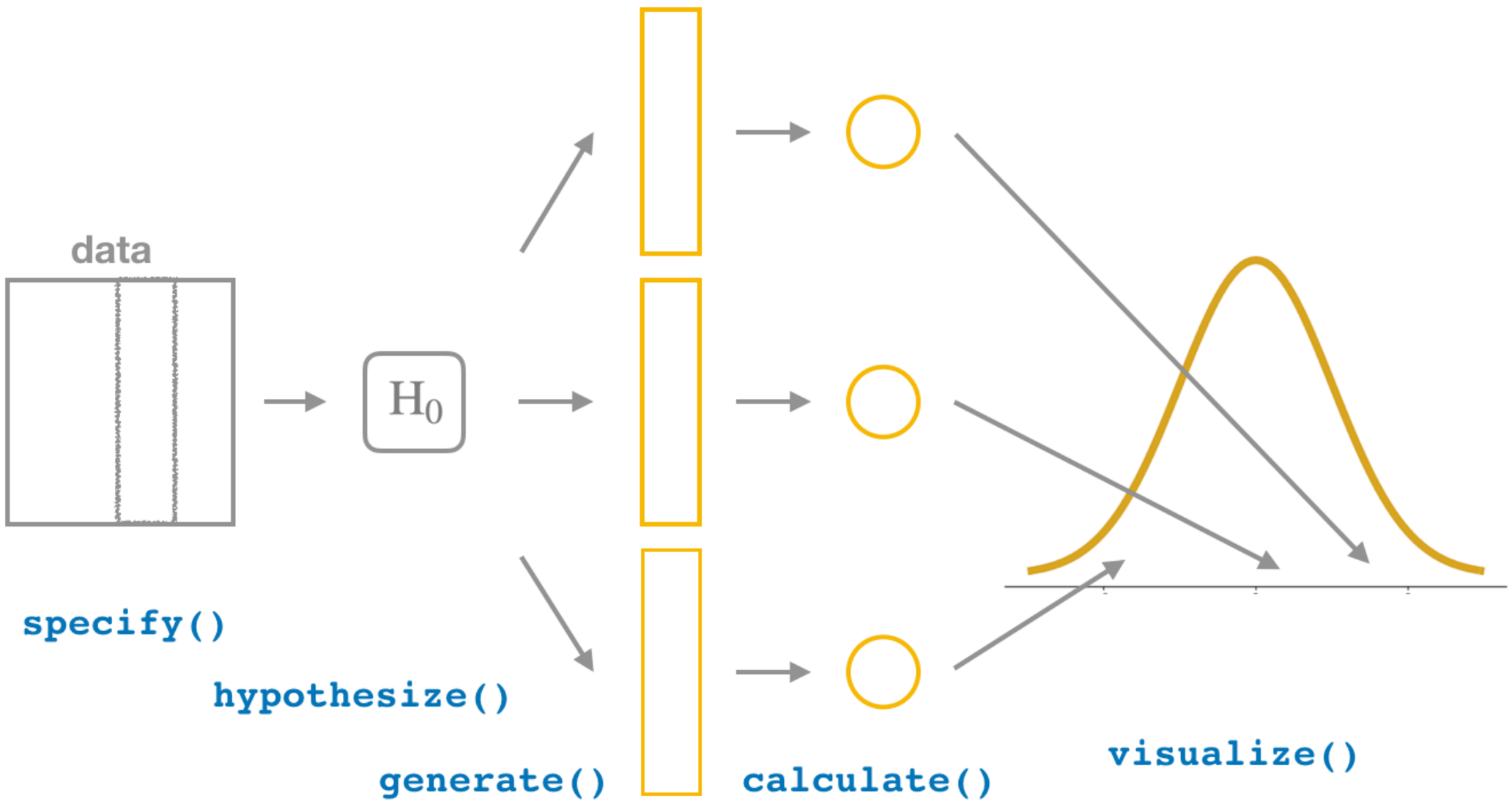

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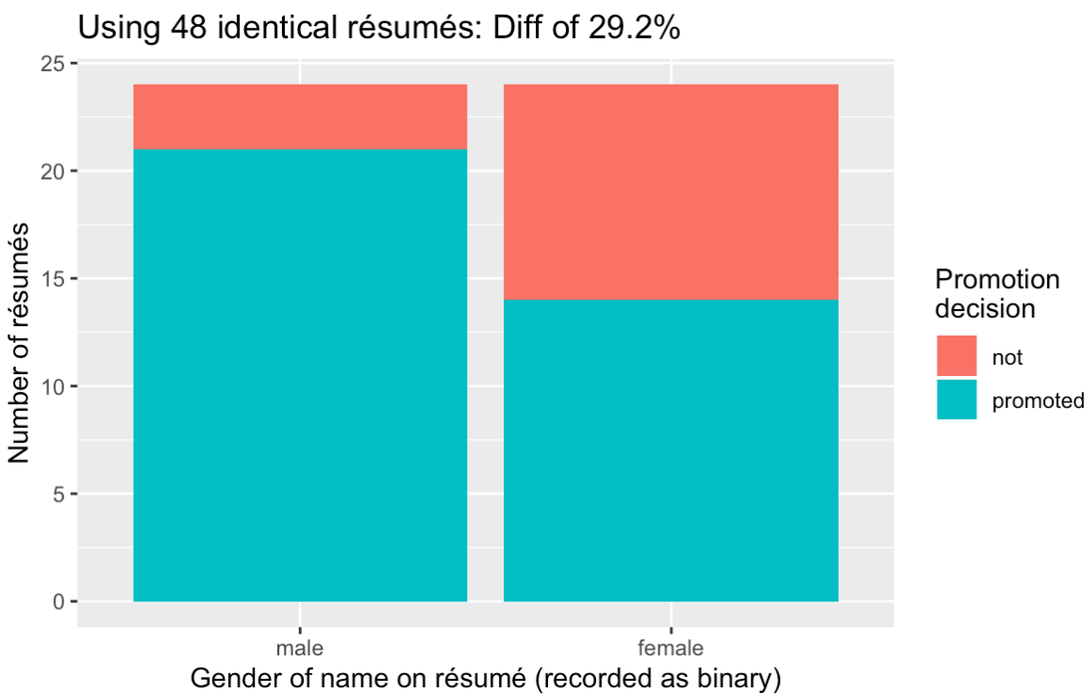

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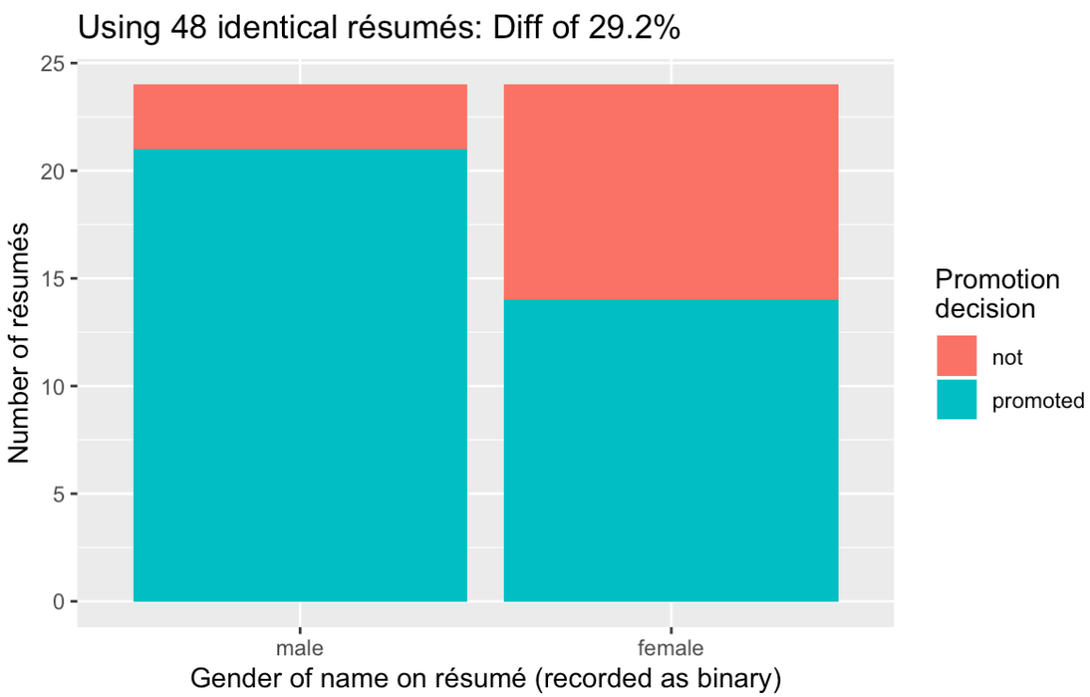


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> library(moderndive)
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# A tibble: 48 x 3
      id decision gender
   <int> <fct>    <fct>
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 2     3 promoted male
 3     7 promoted male
 4    44 not      female
 5    30 promoted female
 6    38 not      male
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 8    24 promoted female
 9     1 promoted male
10    20 promoted male
# … with 38 more rows
```

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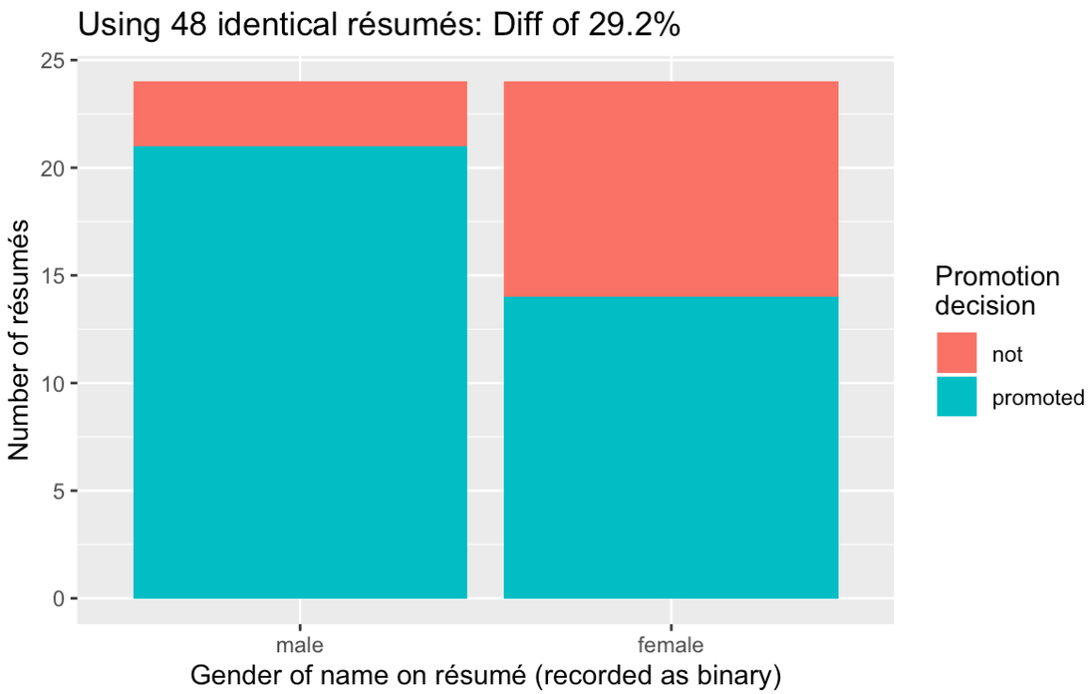


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> # Under H0: p_m - p_f = 0
> promotions
# A tibble: 48 x 4
      id decision gender gender_shuffle
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 1    11 promoted male   male
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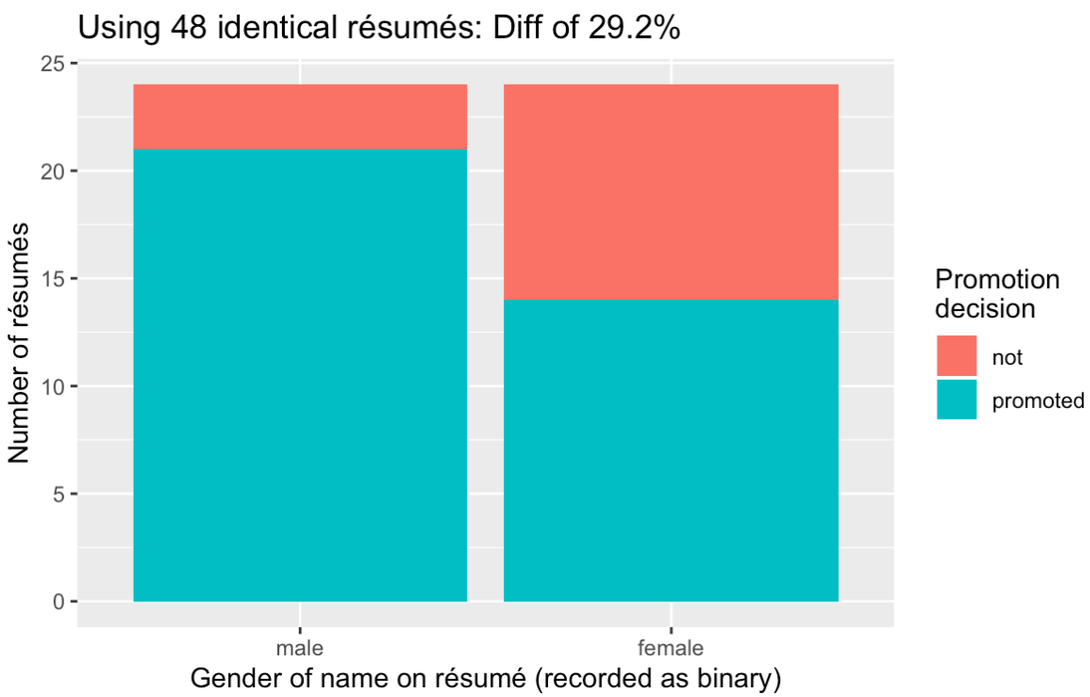


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 3     7 promoted male   male
 4    44 not      female female
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10    20 promoted male   male
# … with 38 more rows
```
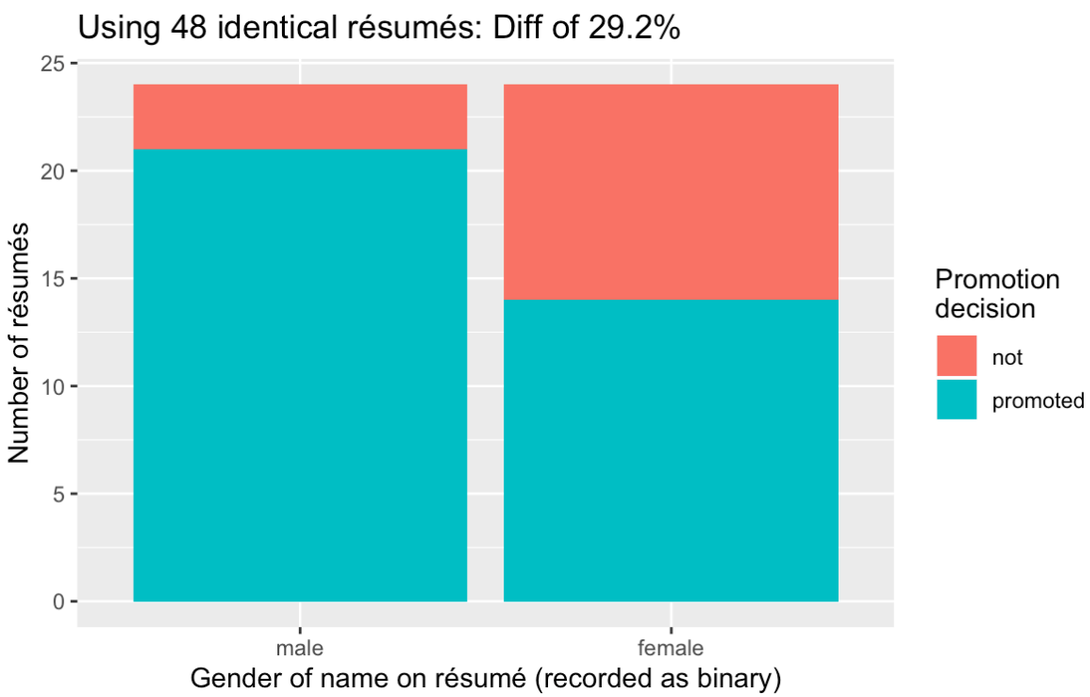

Using permutation “shuffling” assuming H_0 is true:

From: [OpenIntro]

Ch9 Does gender affect promotions at banks?




```
> library(moderndive)
> promotions
# A tibble: 48 x 3
      id decision gender
   <int> <fct>    <fct>
 1    11 promoted male
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# … with 38 more rows
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```
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# … with 38 more rows
```

Using permutation “shuffling” assuming H_0 is true:

```
promotions %>%
  specify(formula = decision ~ gender,
                                ) %>%
  hypothesize(null = "independence") %>%
  generate(reps = 1000, type = "permute") %>%
  calculate(stat = "diff in props”,
                                  )
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From: OpenIntro

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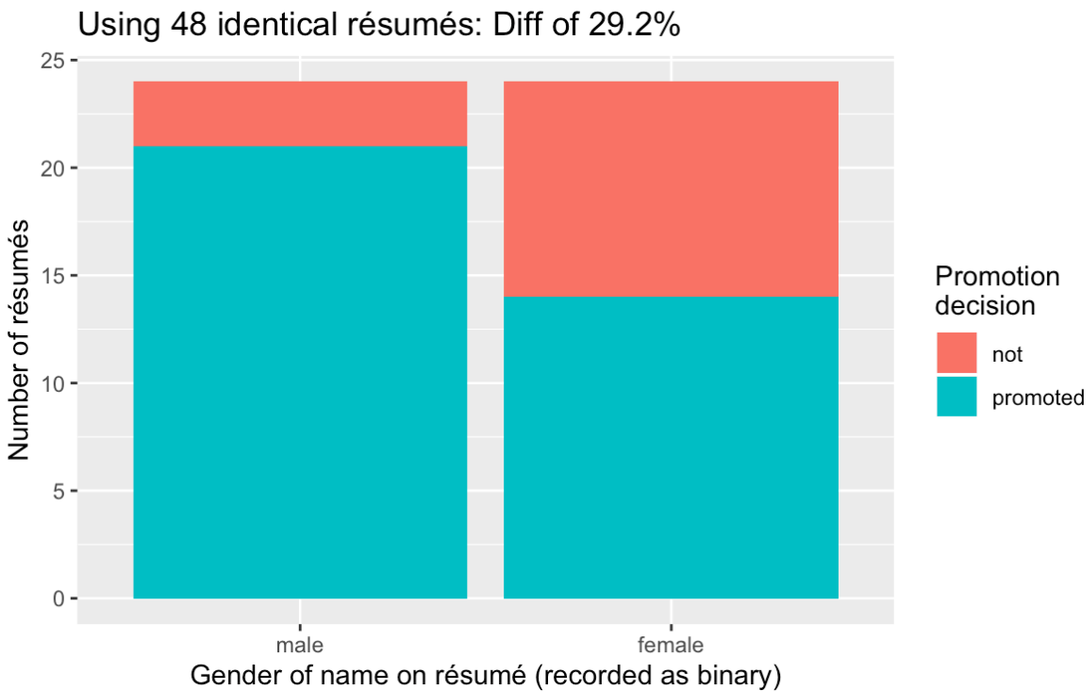


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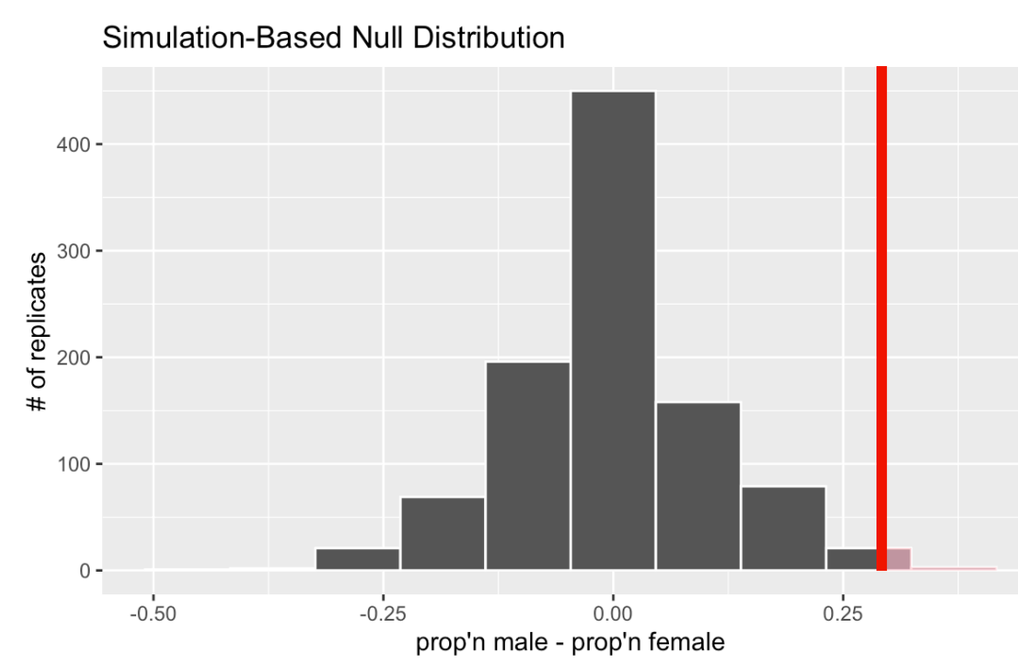
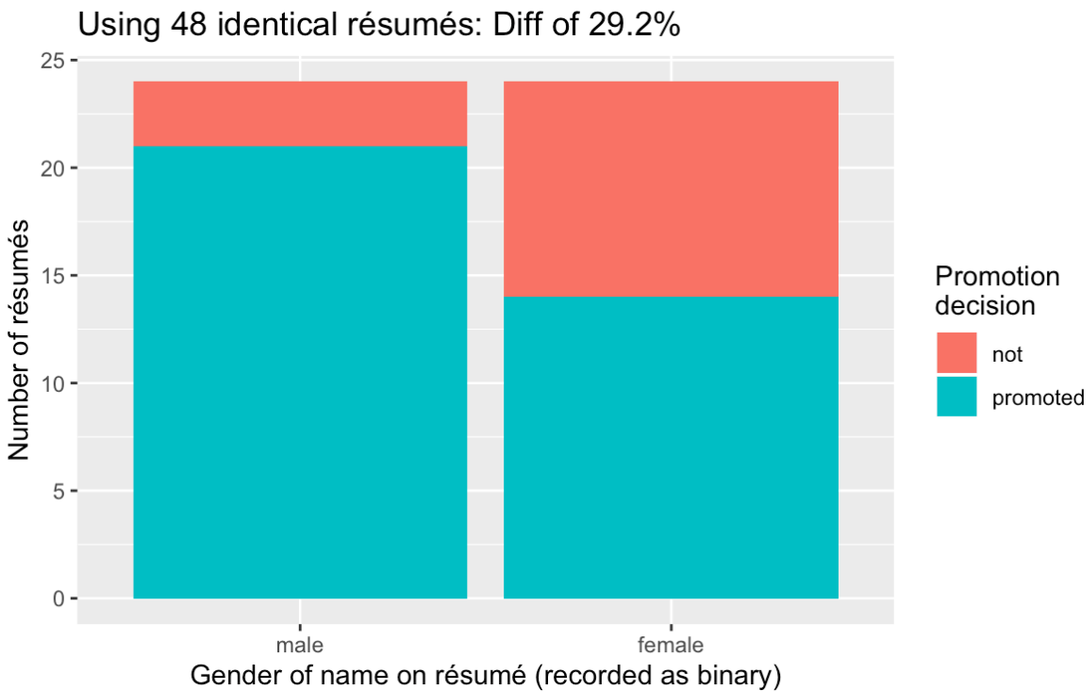


From: OpenIntro

Ch9 Does gender affect promotions at banks?

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# … with 38 more rows
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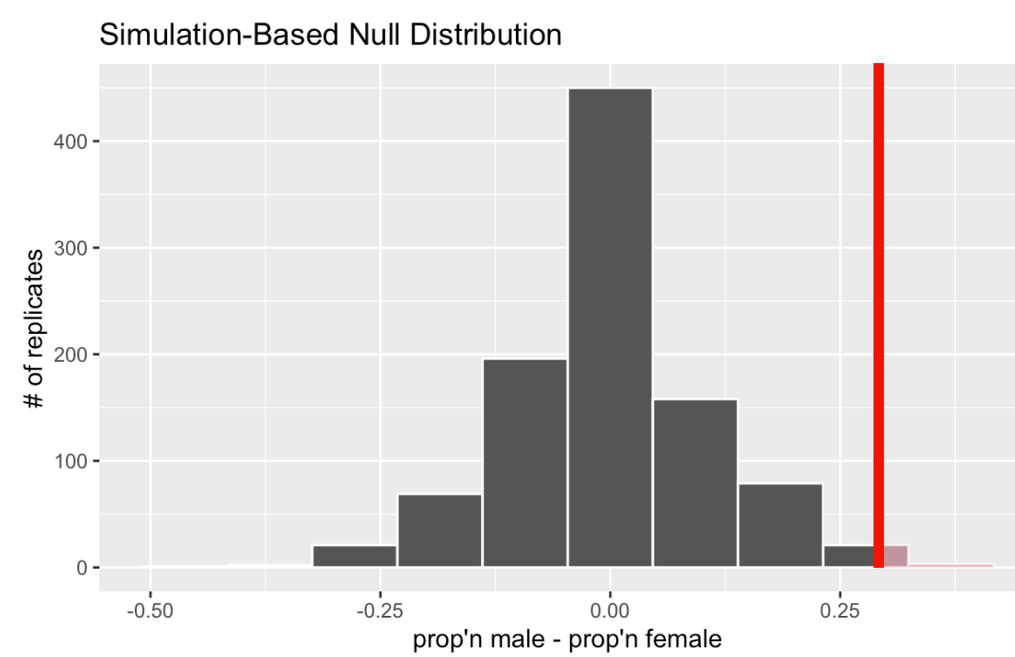
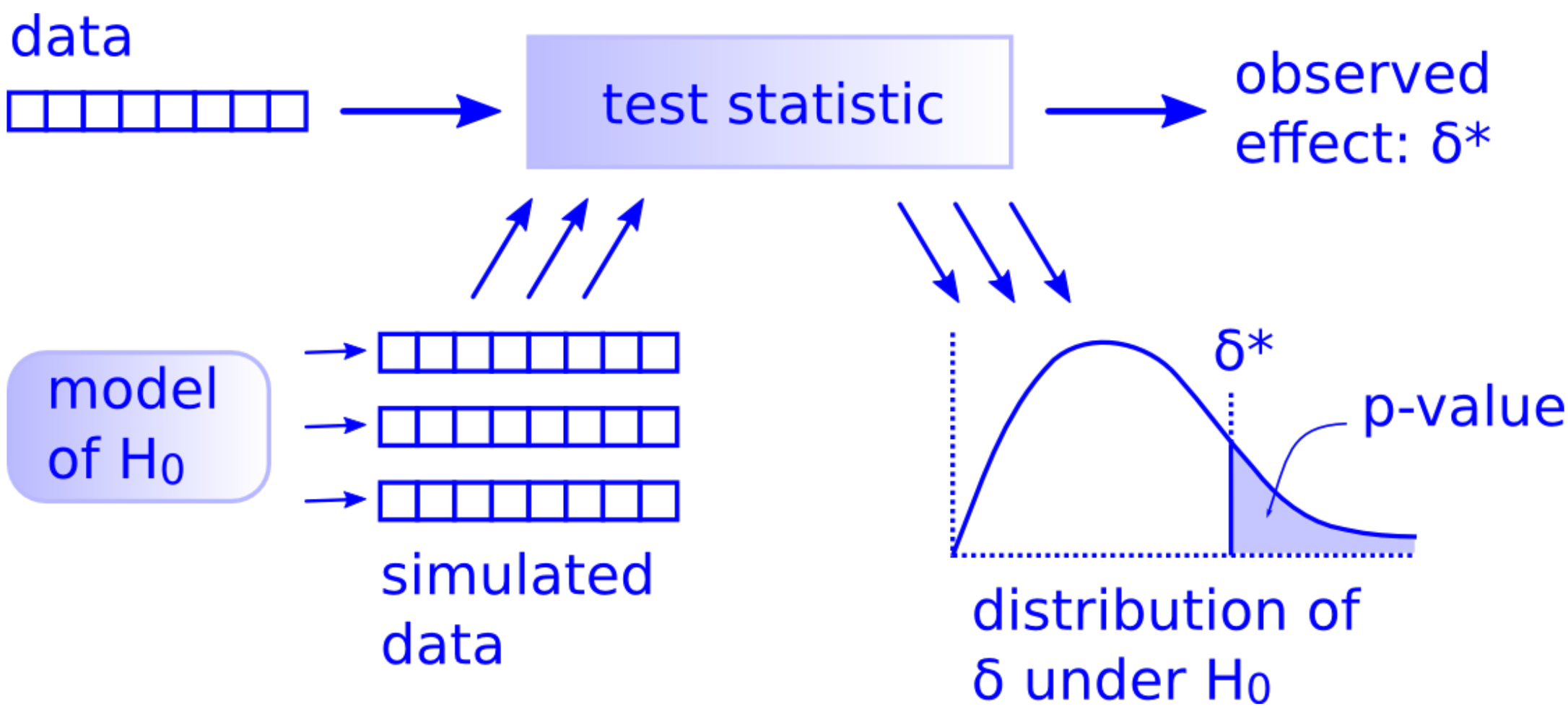
Using permutation “shuffling” assuming H_0 is true:

```
# Diff args given that variables are binary:
promotions %>%
  specify(formula = decision ~ gender,
          success = "promoted") %>%
  hypothesize(null = "independence") %>%
  generate(reps = 1000, type = "permute") %>%
  calculate(stat = "diff in props”,
            order = c(“male”, “female"))
```



From: [OpenIntro]

“There is only one test”



From: [Downey blogpost]

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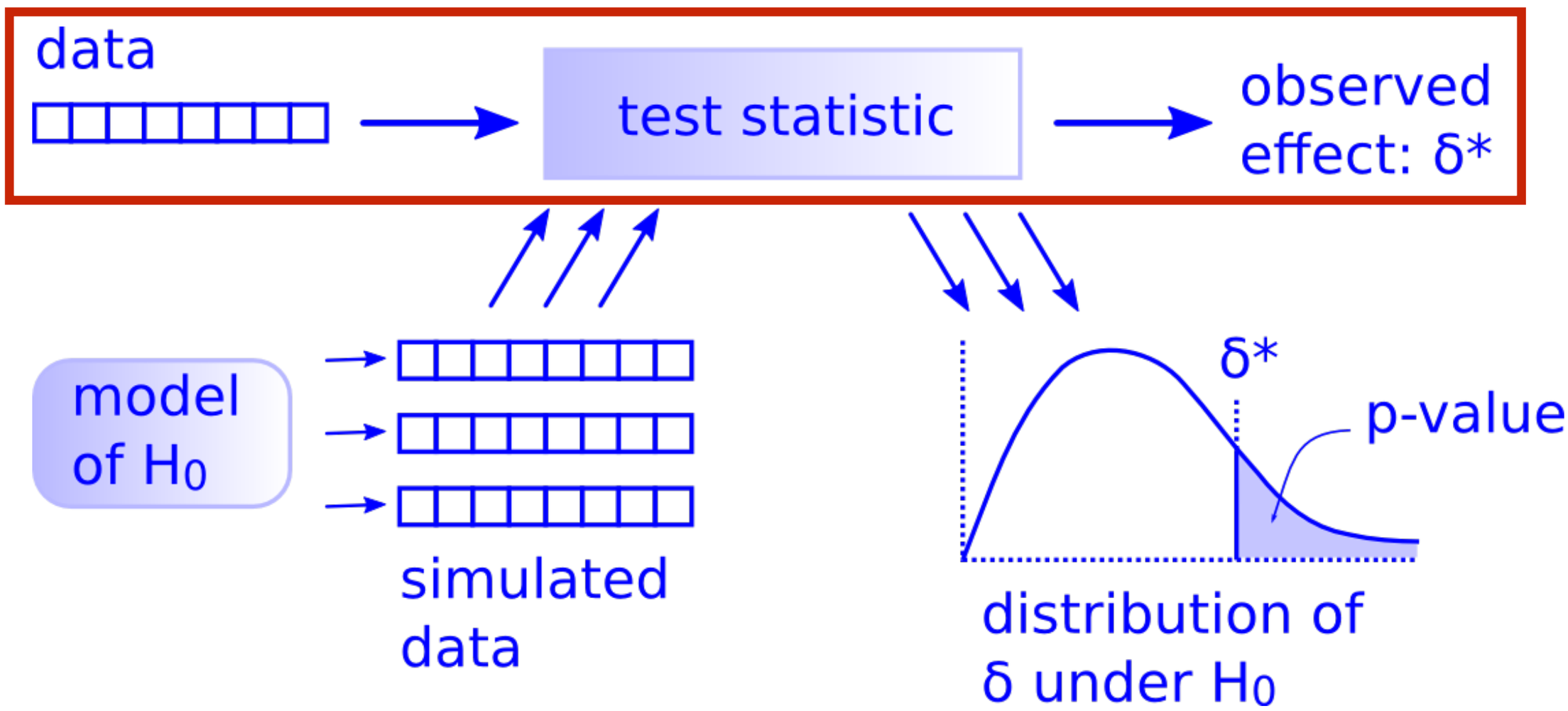

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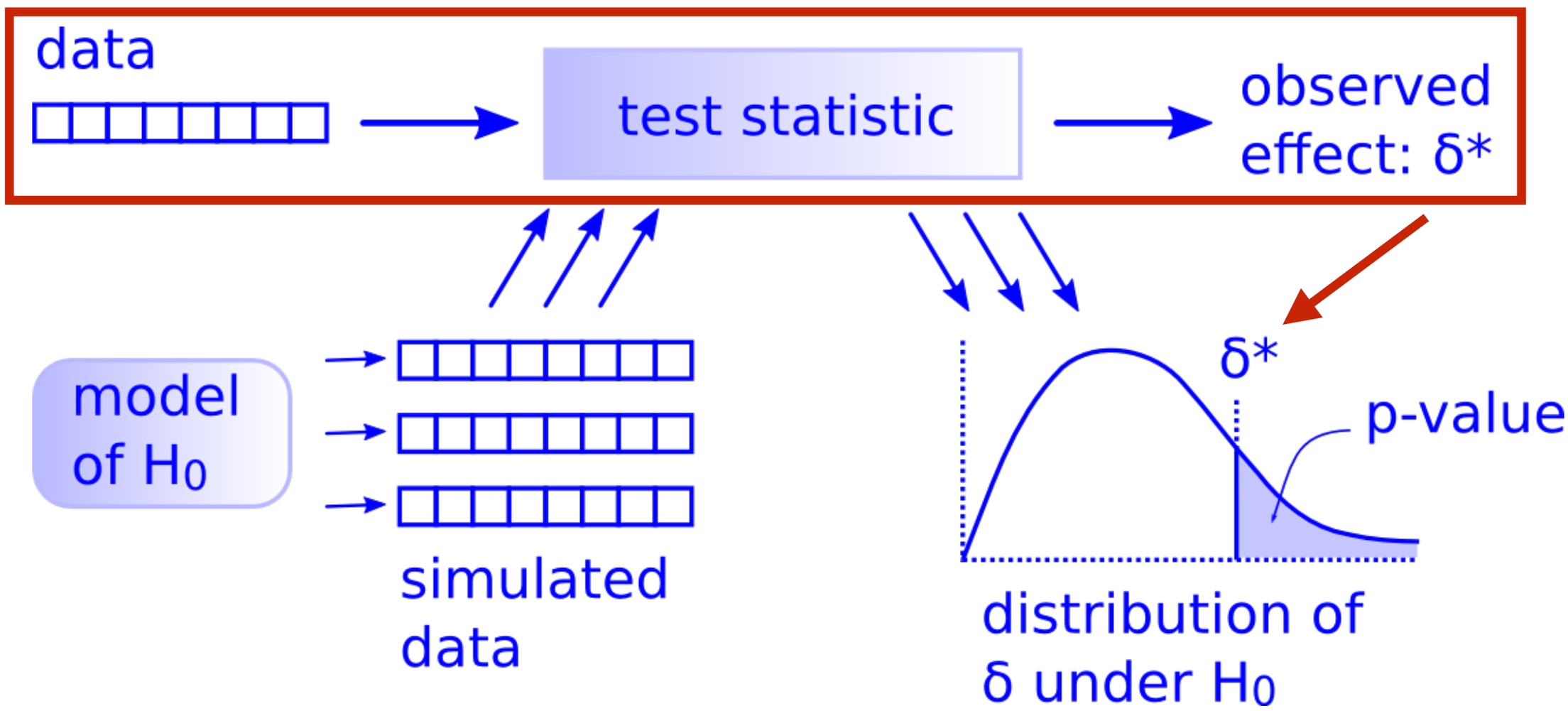

From: [Downey blogpost]

Ch10 Revisit Regression

TABLE 10.1: Previously seen linear regression table

term	estimate	std_error	statistic	p_value	lower_ci	upper_ci
intercept	3.880	0.076	50.96	0	3.731	4.030
bty_avg	0.067	0.016	4.09	0	0.035	0.099

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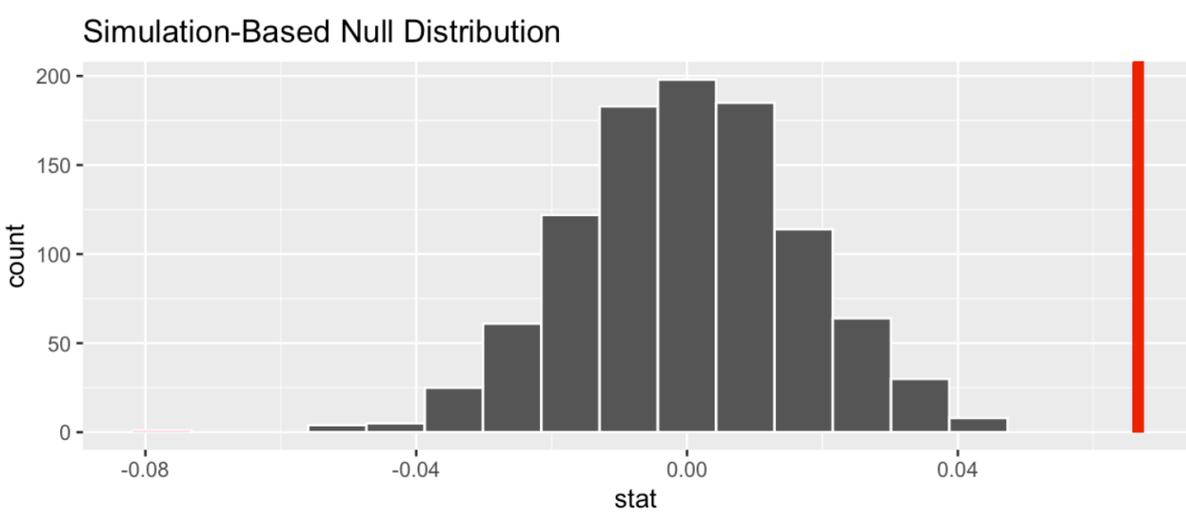

FIGURE 10.11: Null distribution and p-value.

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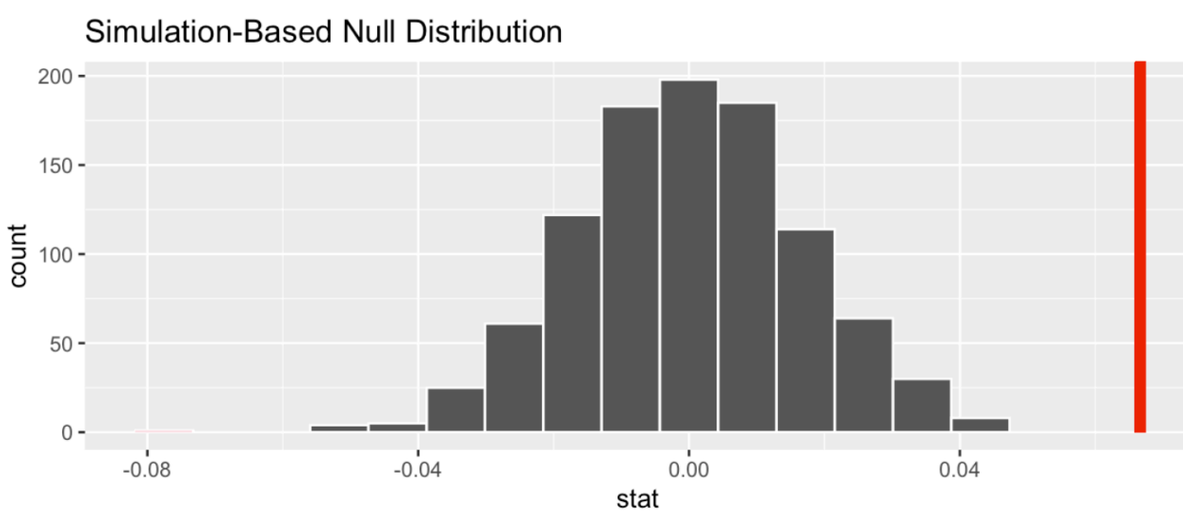

FIGURE 10.11: Null distribution and p-value.

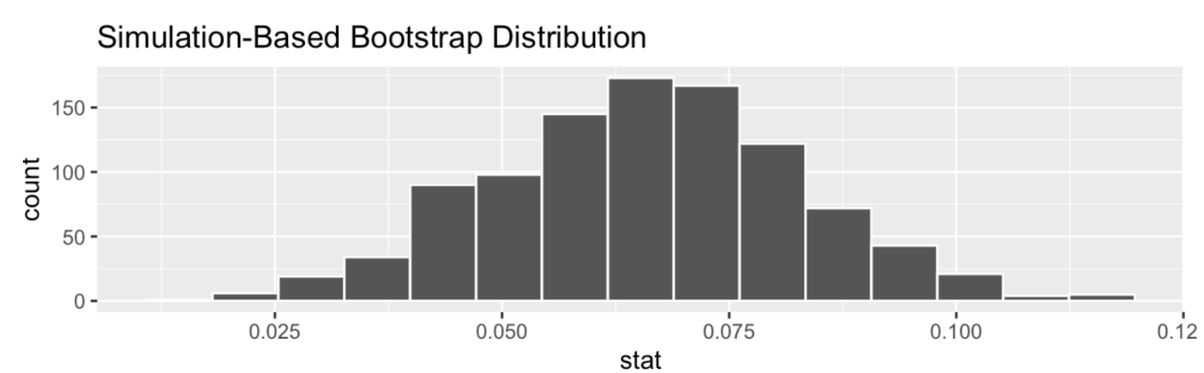

FIGURE 10.8: Bootstrap distribution of slope.

My proposed path for intro stats students

Have them:

1. Develop a minimally viable “data science” toolbox
2. Build intuition for statistical inference by *implementing* simulation-based methods using these tools
3. **Bridge the gap between simulation-based & traditional asymptotic-based inference**

How to make room for data science

In a single term course:

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In a single term course:

1. Drop all probability theory

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In a multi-term sequence of courses:

1. ***Cover* probability theory: distributions, z-scores**
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When you have room for data science

In a multi-term sequence of courses:

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#3 “Bridging the Gap”: Currently in ModernDive

Unspoken assumption of use in single term course, thus material is relegated to end of Chapters:

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TABLE 8.6: Comparing standard errors

Distribution type	Standard error
Sampling distribution	0.067
Bootstrap distribution	0.071
Formula approximation	0.070

Going back to Yohan and Ilyas’ sample proportion of $\hat{p}$ of 21/50 = 0.42, say this were based on a sample of size n = 100 instead of 50. Then the standard error would be:

$$\text{SE}_{\hat{p}} \approx \sqrt{\frac{0.42(1-0.42)}{100}} = \sqrt{0.002436} = 0.0494$$

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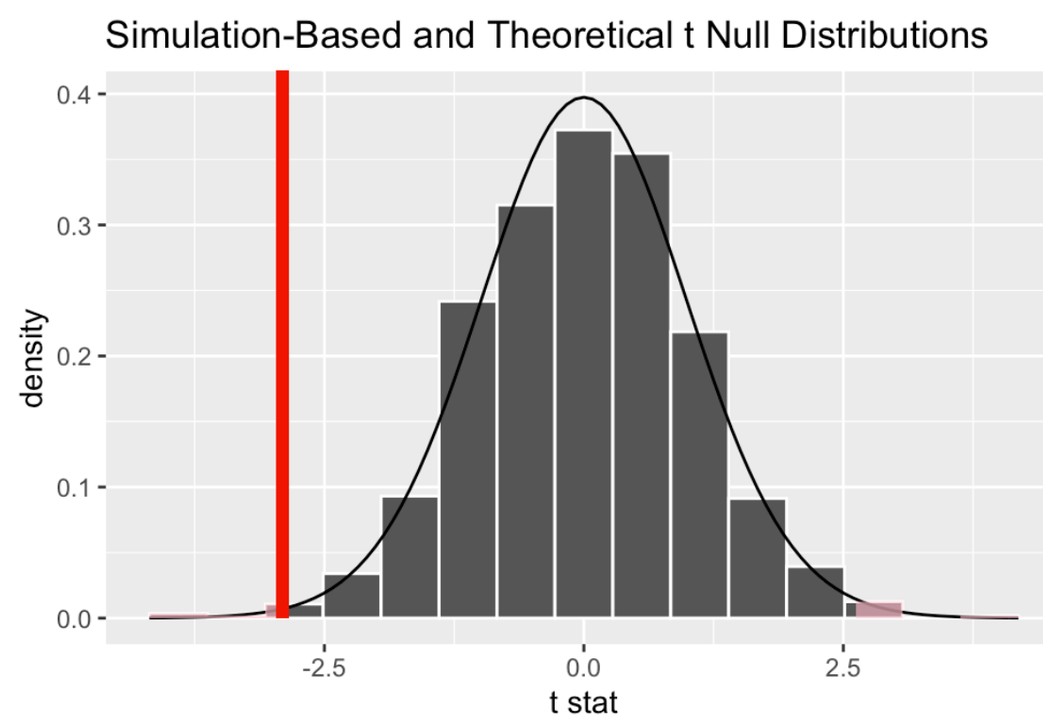

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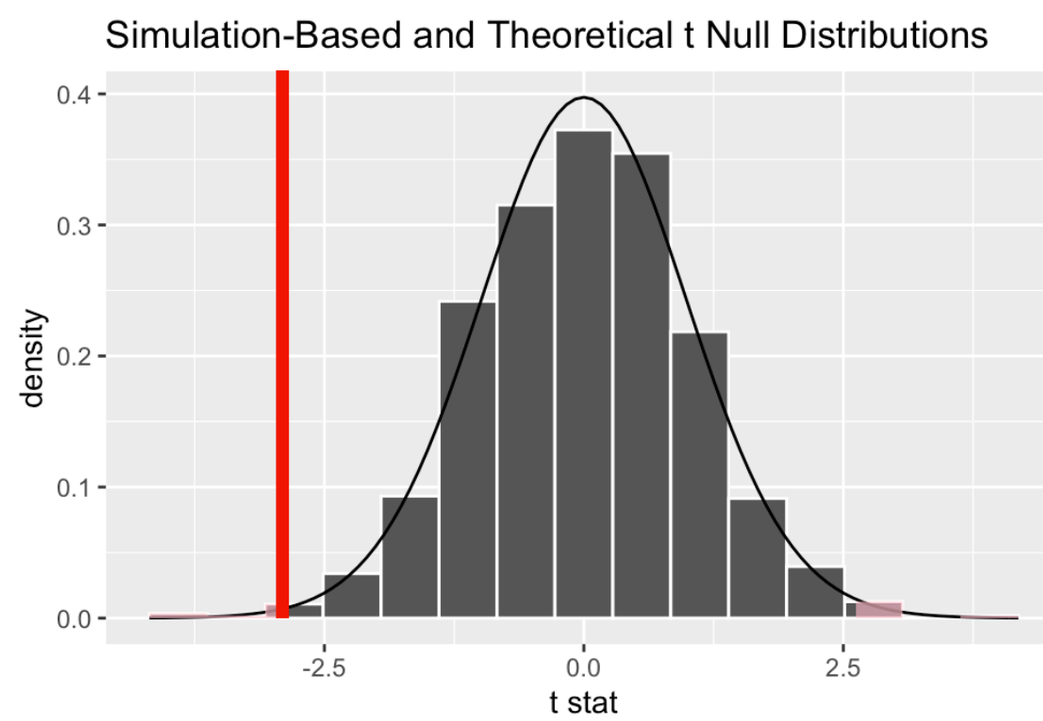

Can be improved! Read: Connecting simulation w/ traditional Lock^3 (2018)

I'm curious!

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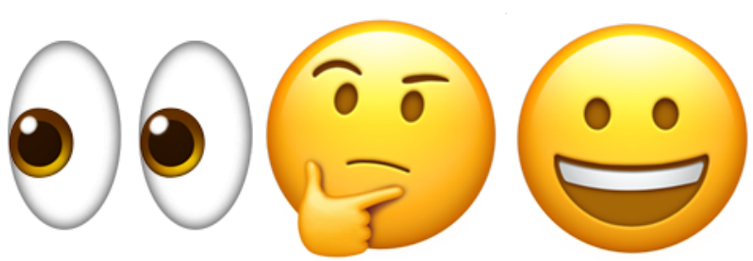
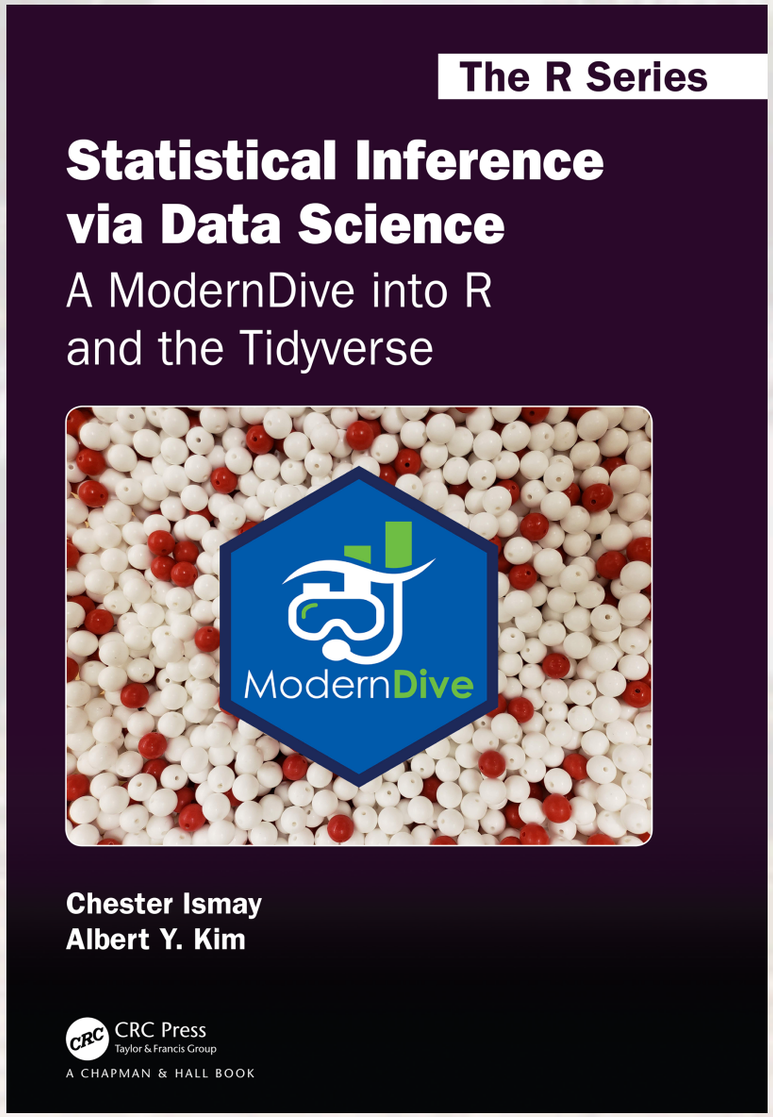


For more info check out:



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