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

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Statistical inference **via** data science…

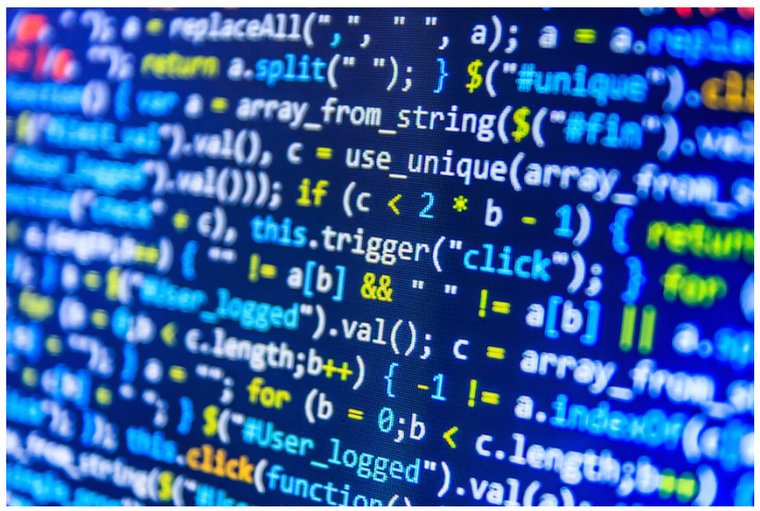
Guiding paper

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

- Minimize prerequisites to research
- Substitute "mathematics" with "computation" as the *engine of statistics*

$$t = \frac{(\overline{X}_1 - \overline{X}_2) - (\mu_1 - \mu_2)}{S_{\overline{X}_1 - \overline{X}_2}} = \frac{\overline{X}_1 - \overline{X}_2}{S_{\overline{X}_1 - \overline{X}_2}}$$

$$S_{\overline{X}_1 - \overline{X}_2} = \sqrt{\frac{(N_1 - 1)s_1^2 + (N_2 - 1)s_2^2}{N_1 + N_2 - 2}\left[\frac{1}{N_1} + \frac{1}{N_2}\right]}$$



My proposed path for intro stats students

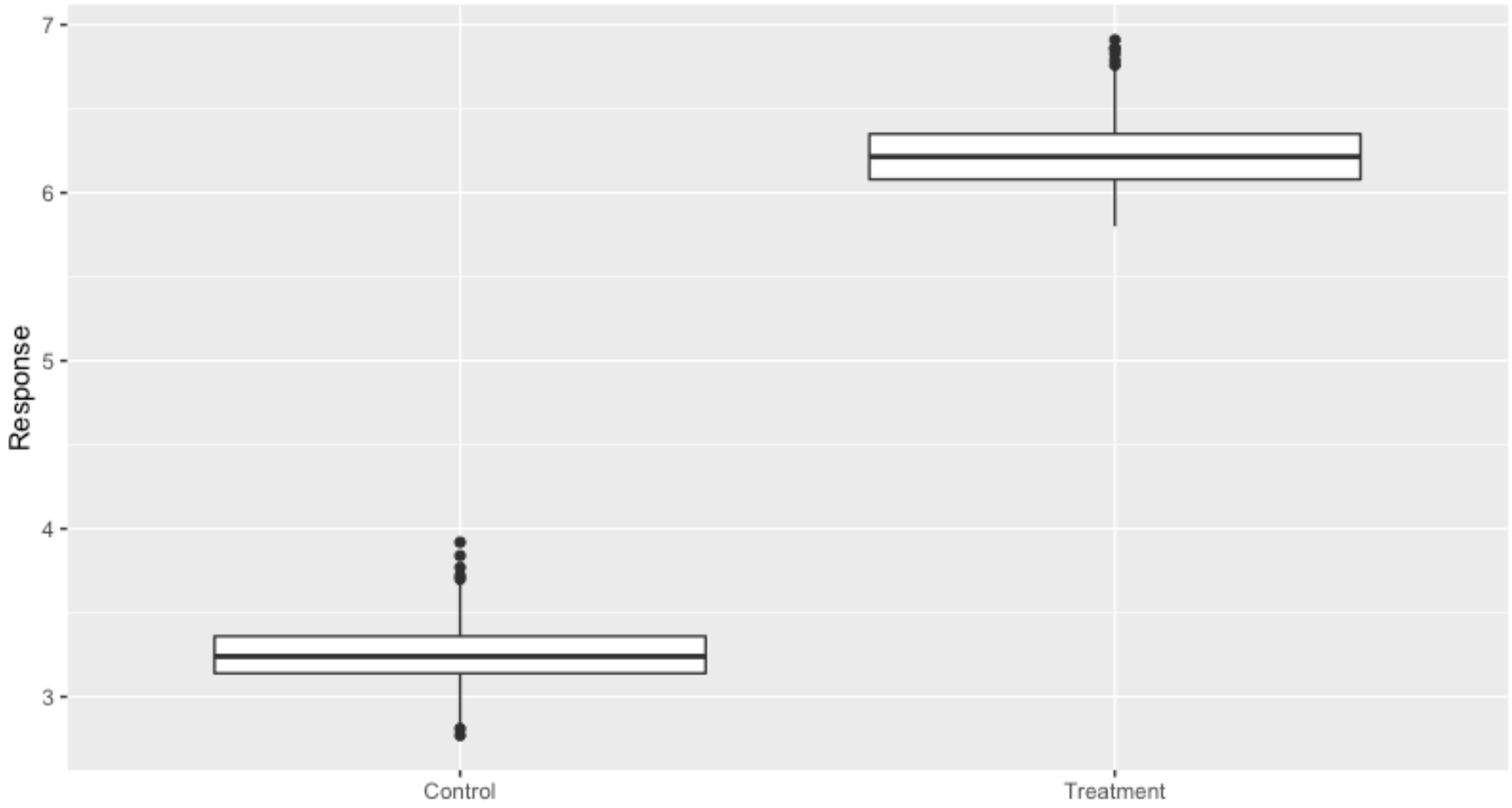
Have them:

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

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?



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

Ch2,4,5 Data Wrangling, Importing, "Tidy"

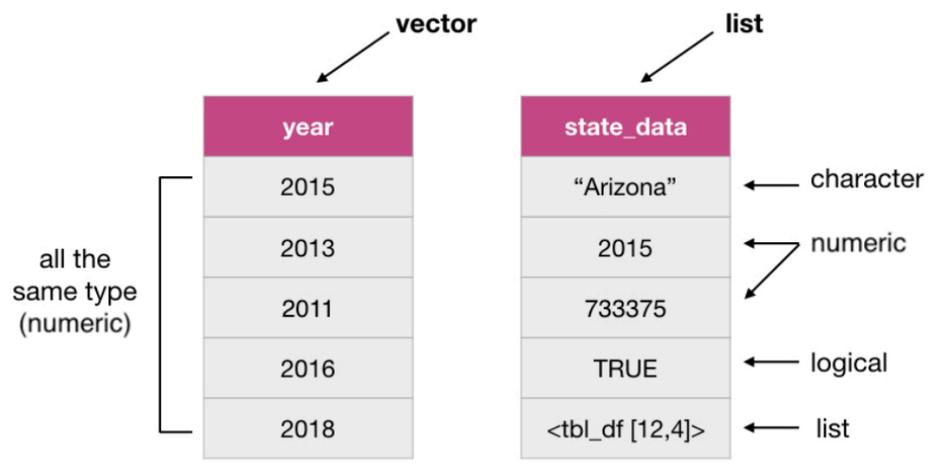
Have students practice:

- Looking at raw data values using `View()`
- Functional programming with the pipe %>%
  i.e. develop *algorithmic thinking*
- Thinking of data in terms of "tidy" *data frames* that can be transformed with `filter()`, `mutate()`, `group_by() %>% summarize()`

vector of type char | vector of type numeric | vector of type logical

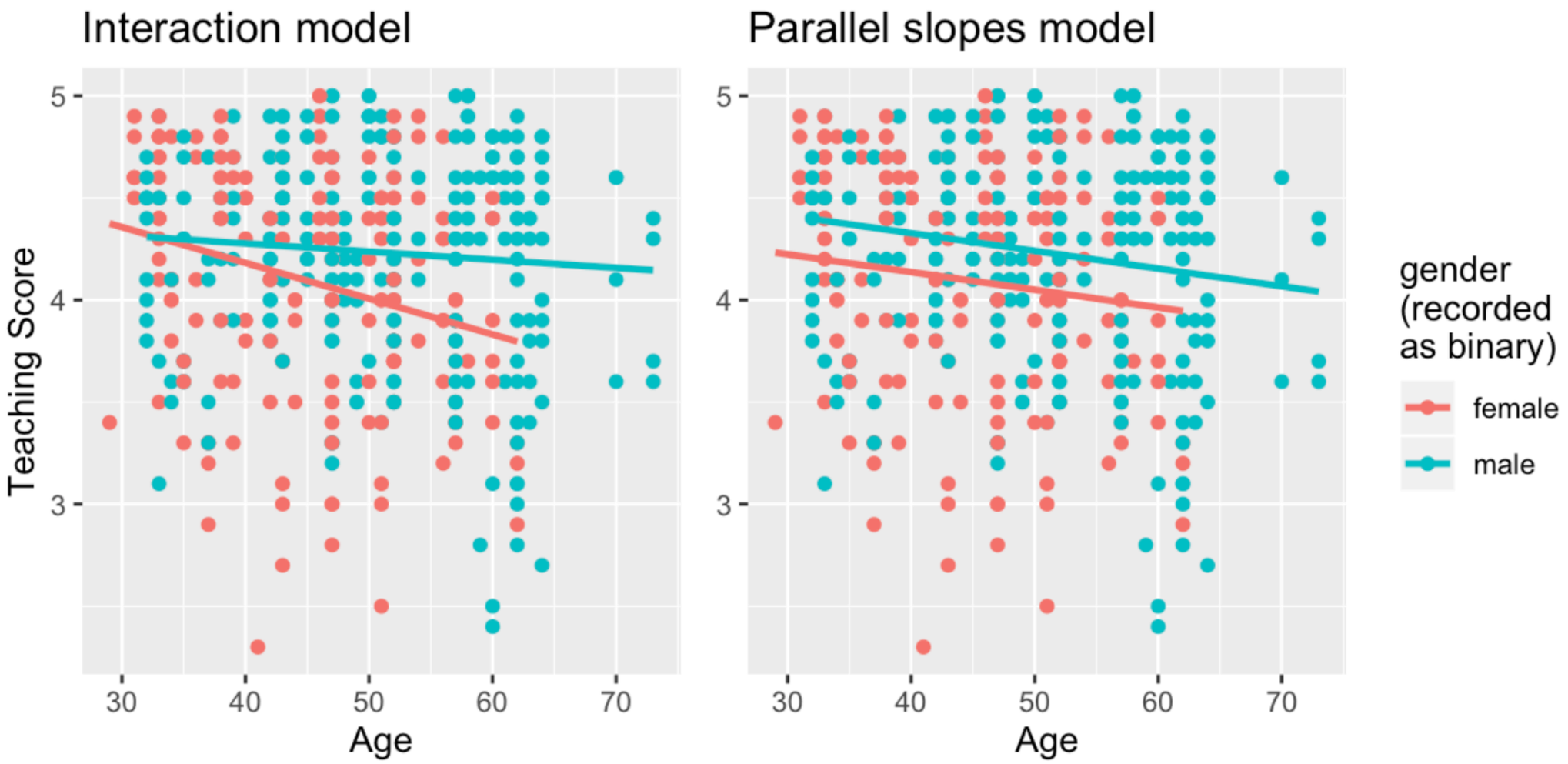
state	year	voted
AK	2016	TRUE
AL	2016	TRUE
AR	2016	TRUE
AZ	2016	TRUE
CA	2016	TRUE
CO	2016	TRUE
CT	2016	TRUE
DC	2016	TRUE
DE	2016	TRUE
FL	2016	TRUE
GA	2016	TRUE
HI	2016	TRUE
IA	2016	TRUE

VS



An aside: Ch6,7 Linear Regression

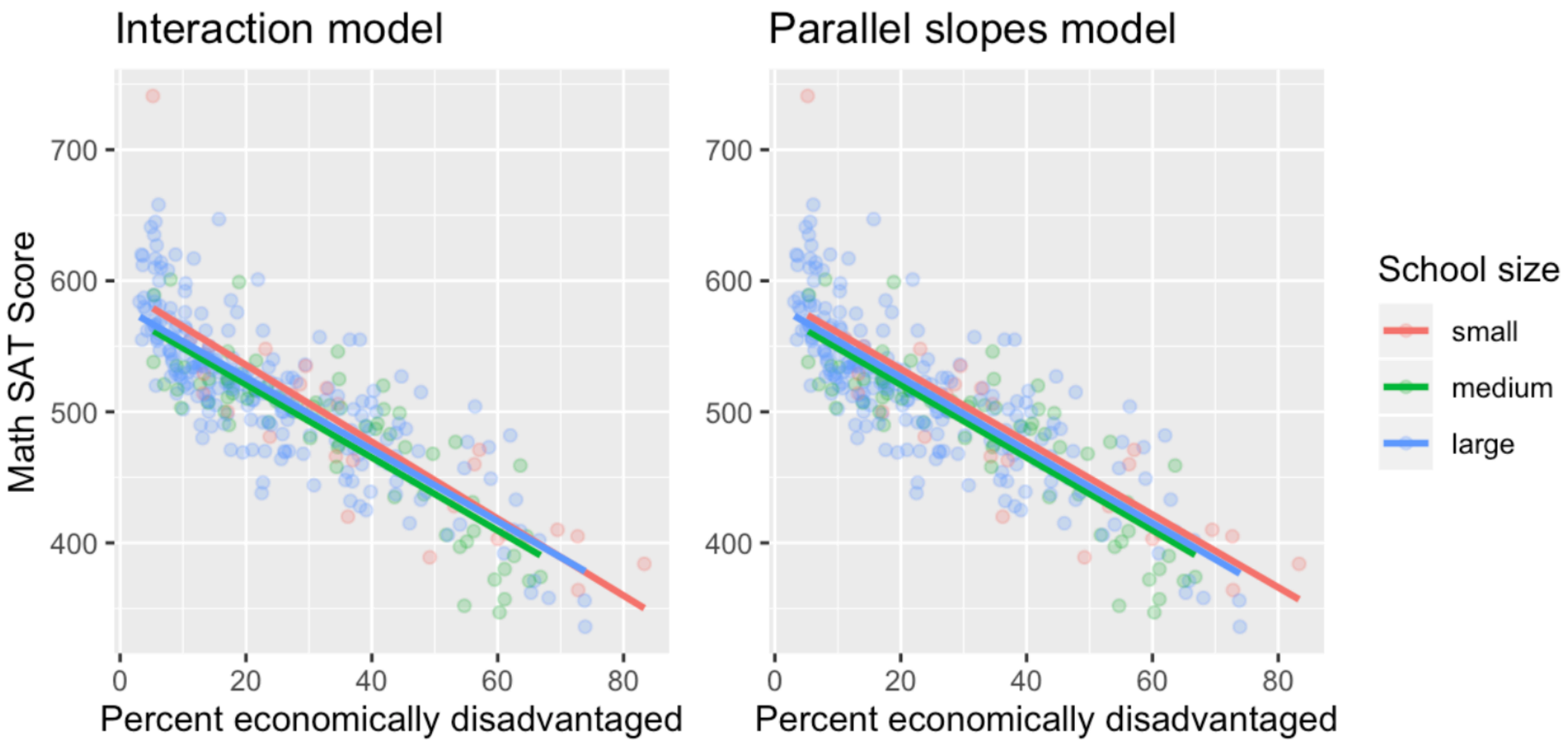
“Visual” model selection using teaching evals data



From: OpenIntro

An aside: Ch6,7 Linear Regression

“Visual” model selection using 2017 MA Public HS Data

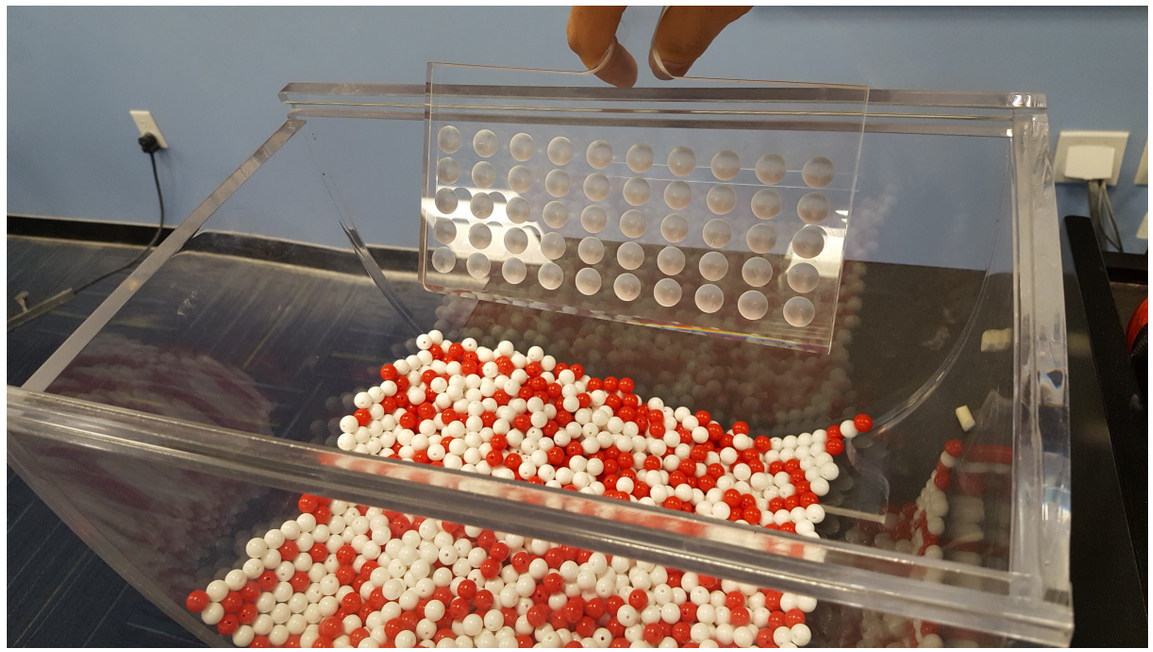


My proposed path for intro stats students

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

Ch7 What proportion of bowl's balls are red?



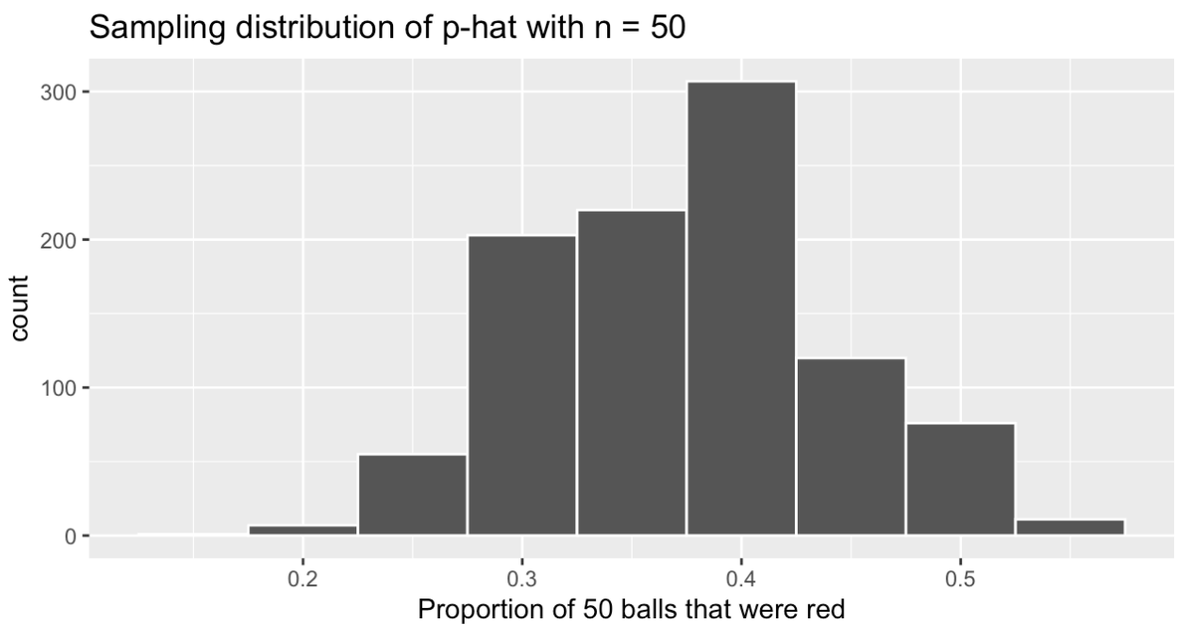
```
> library(moderndive)
> bowl
# A tibble: 2,400 x 2
   ball_ID color
     <int> <chr>
 1       1 white
 2       2 white
 3       3 white
 4       4 red
 5       5 white
 6       6 white
 7       7 red
 8       8 white
 9       9 red
10      10 white
# … with 2,390 more rows
```

```
> # 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
 4         2    1641 red
 5         3    1783 red
 6         3    1036 white
 7         4    1242 red
 8         4     745 white
 9         5    1836 white
10         5     771 white
```

Simulating repeated sampling:

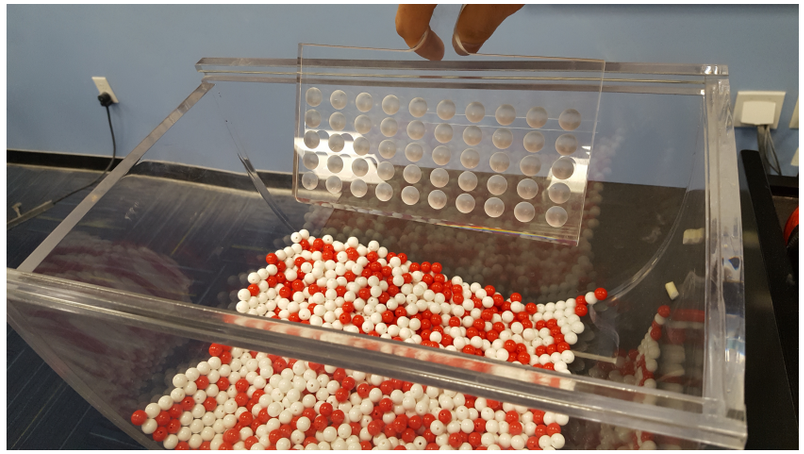
```
library(tidyverse)
library(moderndive)

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



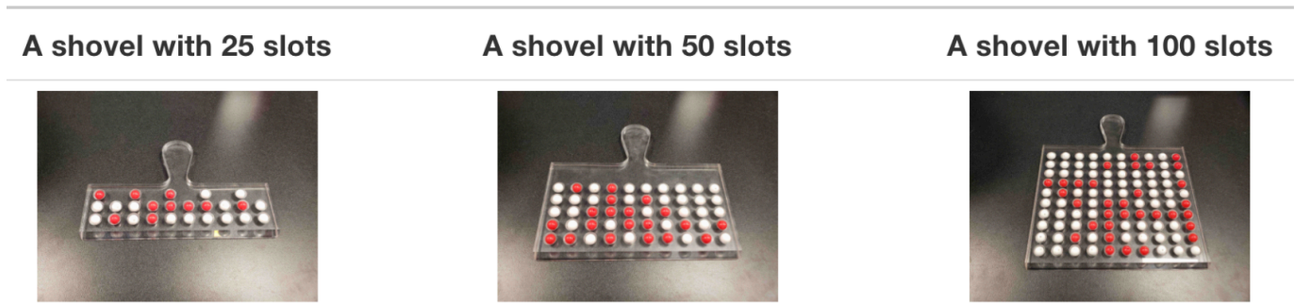
Read: [Do things by hand first! Hancock & Rummerfield (2020)]

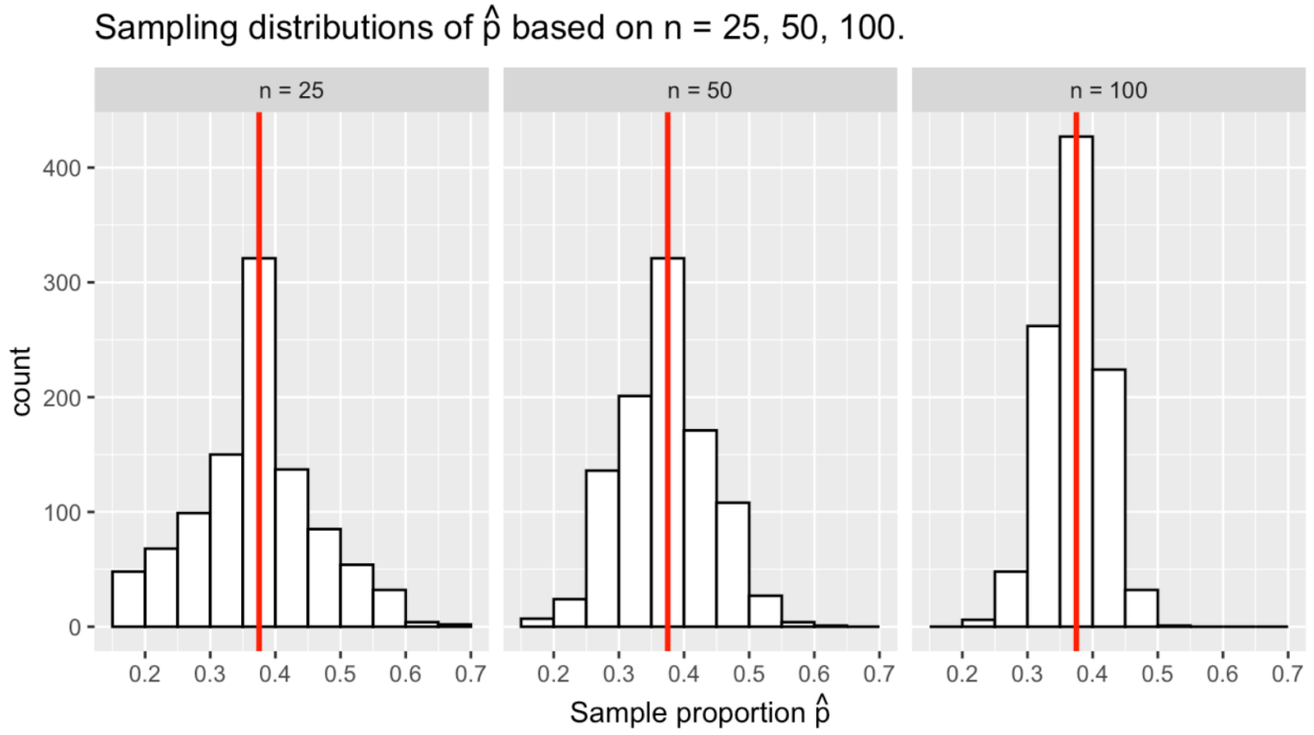
Ch7 Sampling



Two goals of this sampling simulation:

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



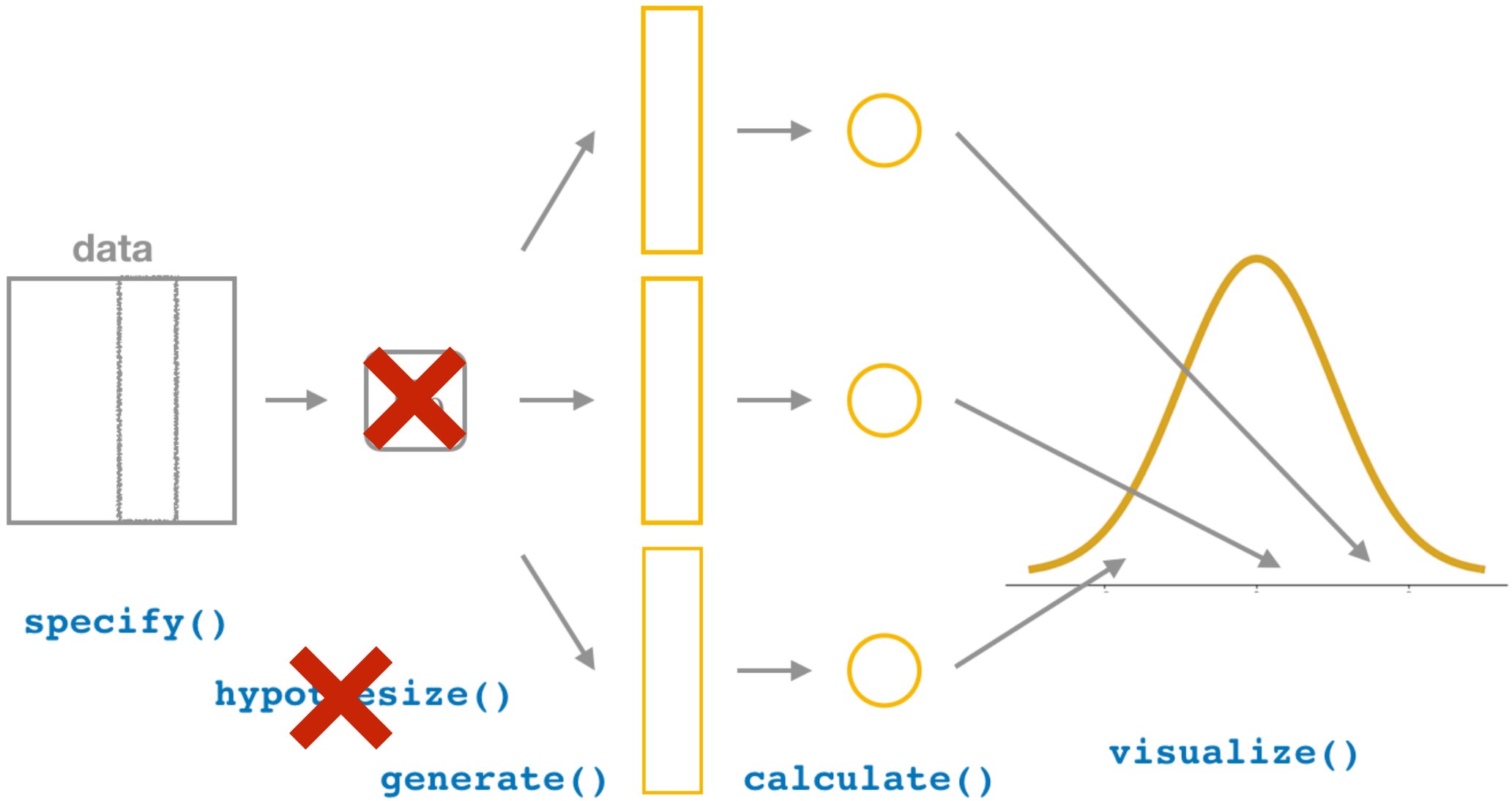


Sampling scenarios covered in ModernDive

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



Skip this step for confidence intervals

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

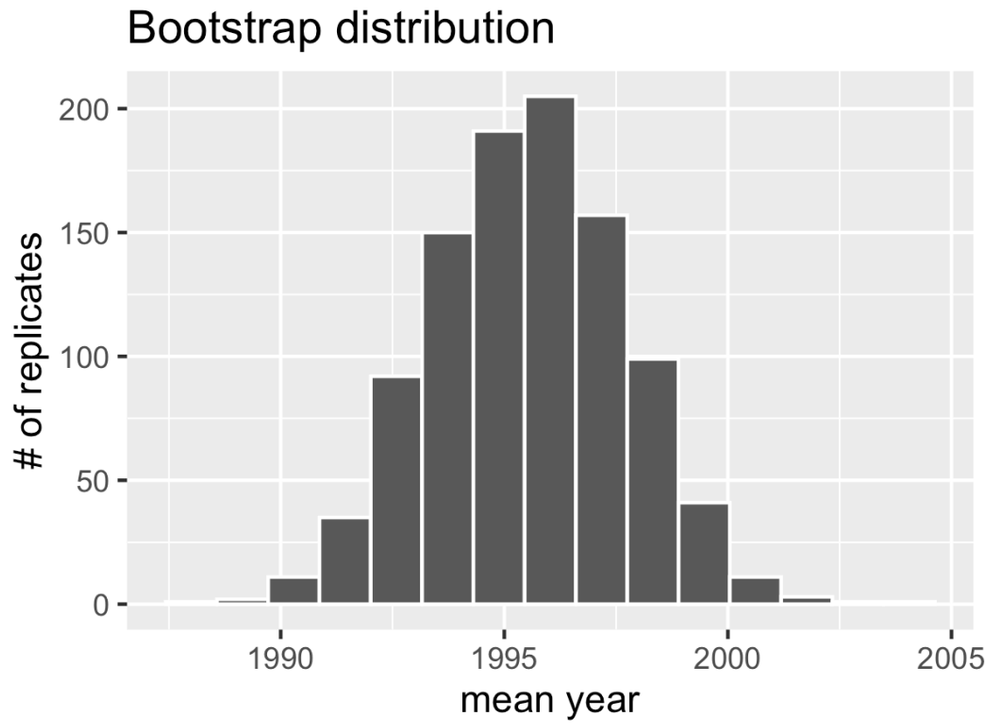
Ch8 What is mean year of all 🇺🇸 pennies?

```
> 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
```

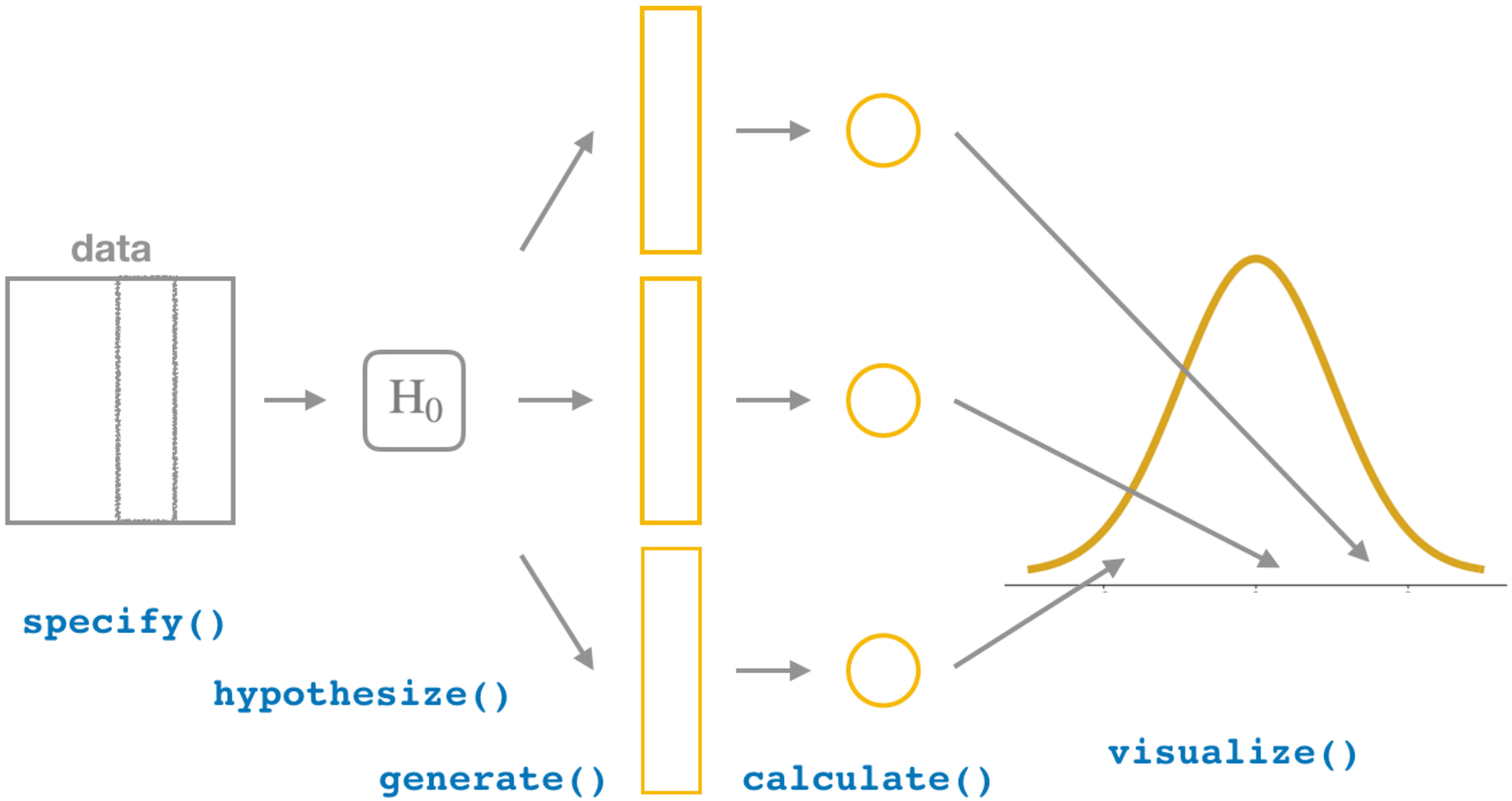
Using bootstrap resampling with replacement:

```
library(tidyverse)
library(infer)

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

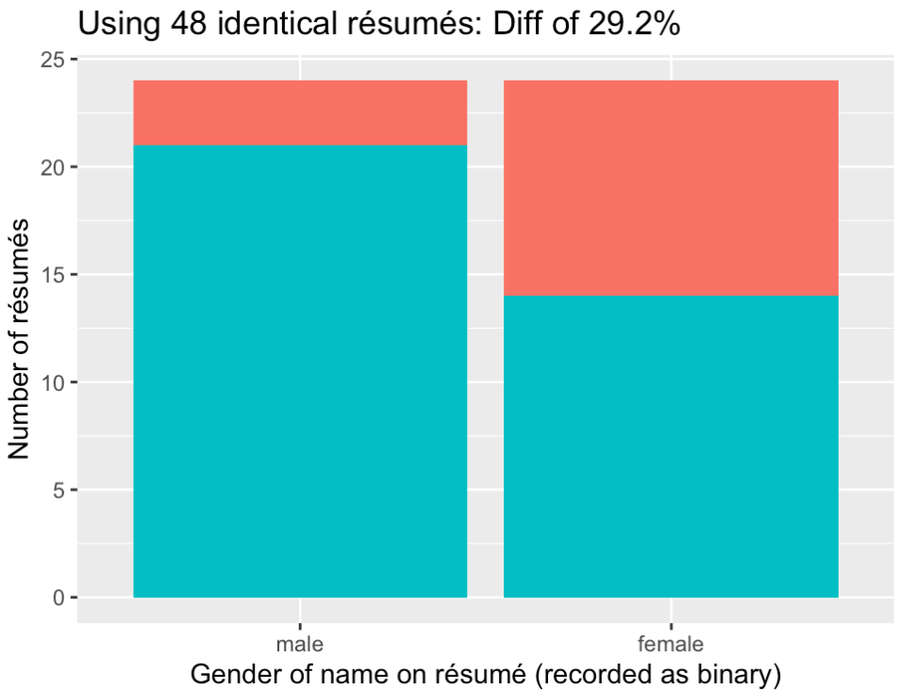


infer package for “tidy” statistical inference



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

Ch9 Does gender affect promotions at banks?

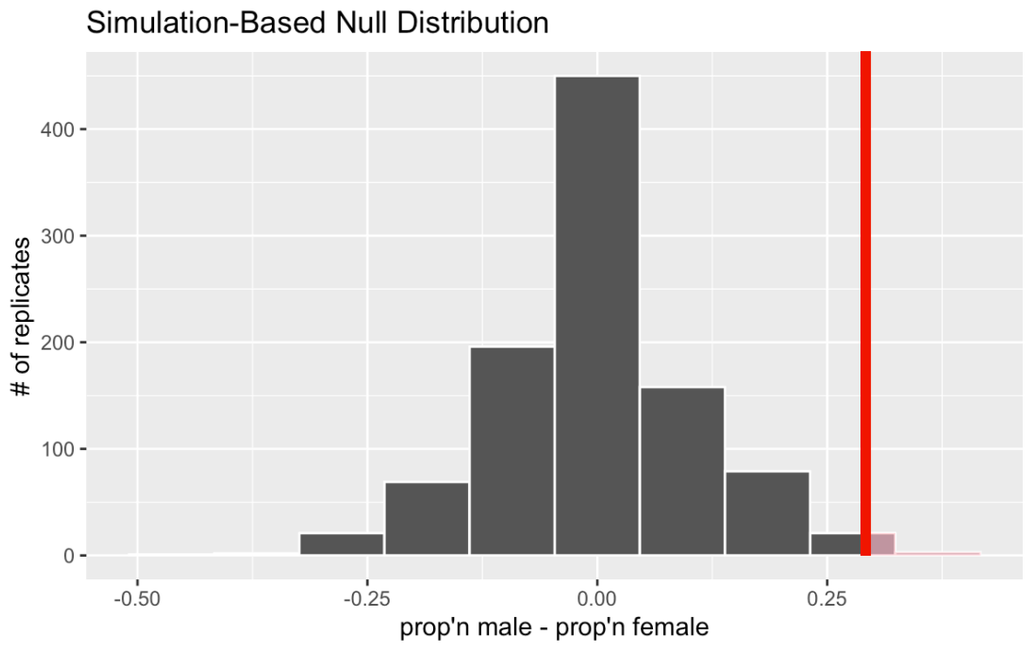



```
> library(moderndive)
> promotions
# A tibble: 48 x 3
      id decision gender
   <int> <fct>    <fct>
 1    11 promoted male
 2     3 promoted male
 3     7 promoted male
 4    44 not      female
 5    30 promoted female
 6    38 not      male
 7     2 promoted male
 8    24 promoted female
 9     1 promoted male
10    20 promoted male
# … with 38 more rows
```

```
> # Under H0: p_m - p_f = 0
> promotions
# A tibble: 48 x 4
      id decision gender gender_shuffle
   <int> <fct>    <fct>  <fct>
 1    11 promoted male   male
 2     3 promoted male   female
 3     7 promoted male   male
 4    44 not      female female
 5    30 promoted female male
 6    38 not      male   female
 7     2 promoted male   male
 8    24 promoted female male
 9     1 promoted male   male
10    20 promoted male   male
# … with 38 more rows
```

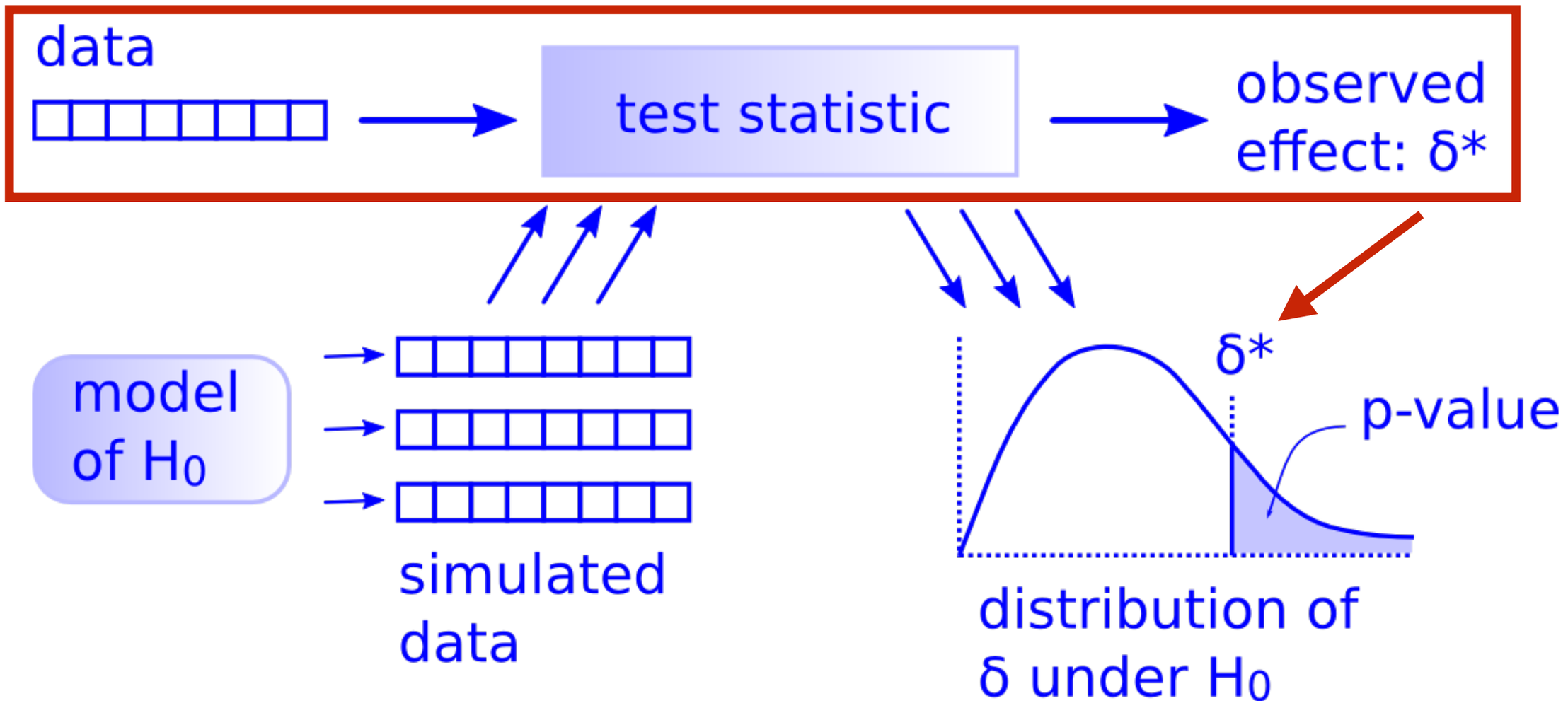
Using permutation “shuffling” assuming H_0 is true:

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



From: OpenIntro

“There is only one test”



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

$$H_0 : \beta_1 = 0$$
$$\text{vs } H_A : \beta_1 \neq 0.$$

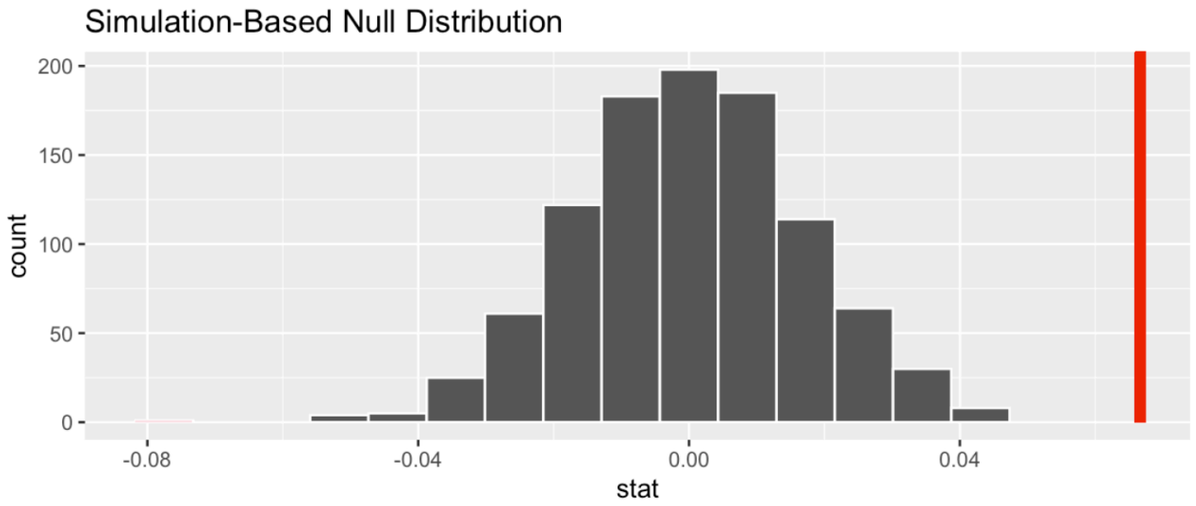


FIGURE 10.11: Null distribution and p-value.

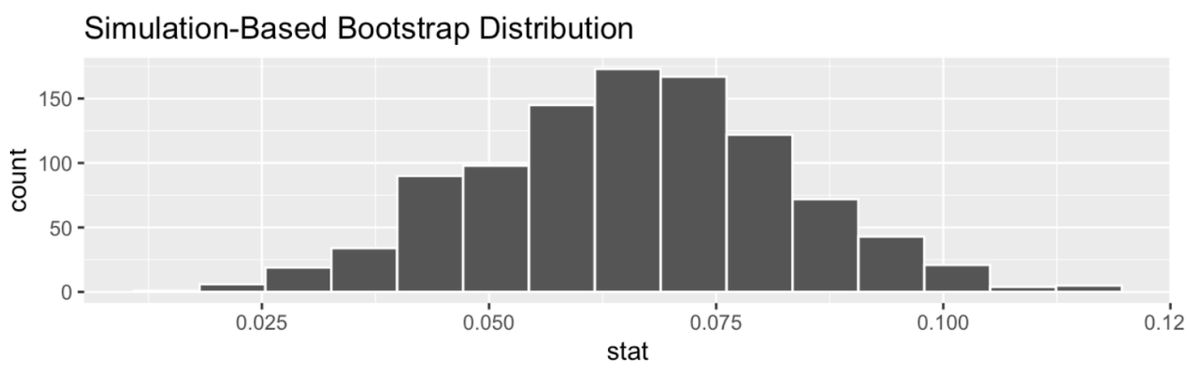


FIGURE 10.8: Bootstrap distribution of slope.

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How to make room for data science

In a single term course:

1. Drop all probability theory
2. Drop asymptotic theory in favor of simulation based inference
3. Introduce the “There is only one test” framework and tell students it’s true
4. De-emphasize χ^2 tests & ANOVA

When you have room for data science

In a multi-term sequence of courses:

1. ***Cover* probability theory: distributions, z-scores**
2. ***Make explicit connections* between asymptotic theory & simulation based inference**
3. ***Repeatedly go thru* "There is only one test" framework & *convince* students it's true**
4. ***Cover* χ^2 tests & ANOVA as *case studies***

#3 “Bridging the Gap”: Currently in ModernDive

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

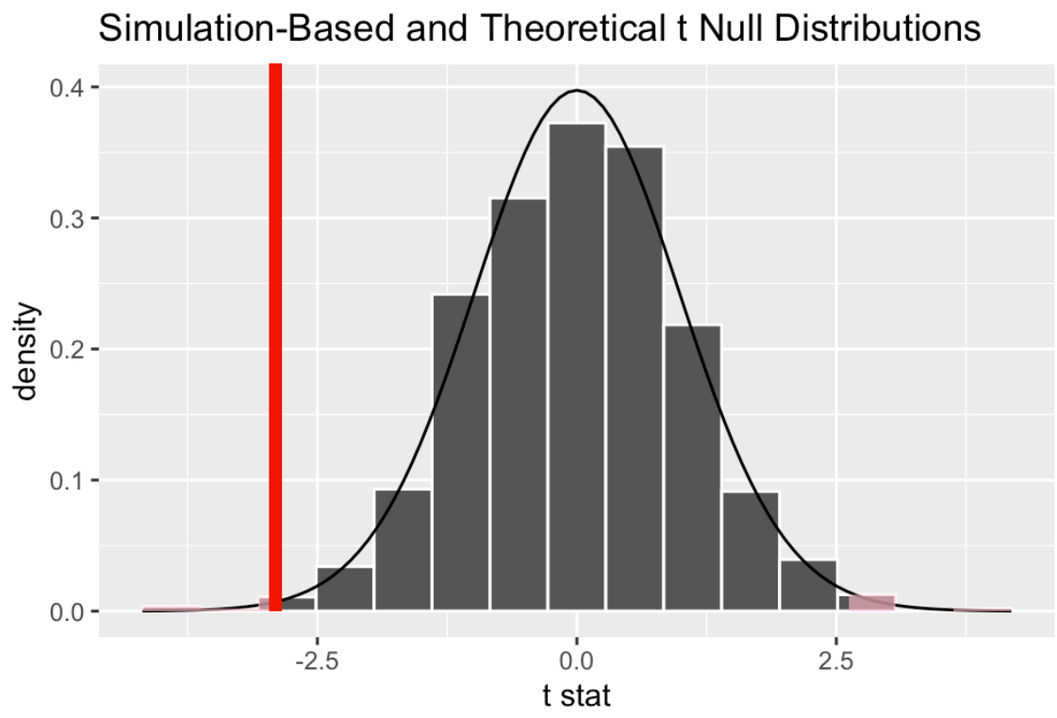
- 7.5.2 Central Limit Theorem (to be moved up)
- 8.7.2 Theory-based confidence intervals
- 9.6.1 Theory-based hypothesis tests
- 10.5.1 Theory-based inference for regression

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:

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



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

I'm curious!

1. Develop a minimally viable "data science" toolbox
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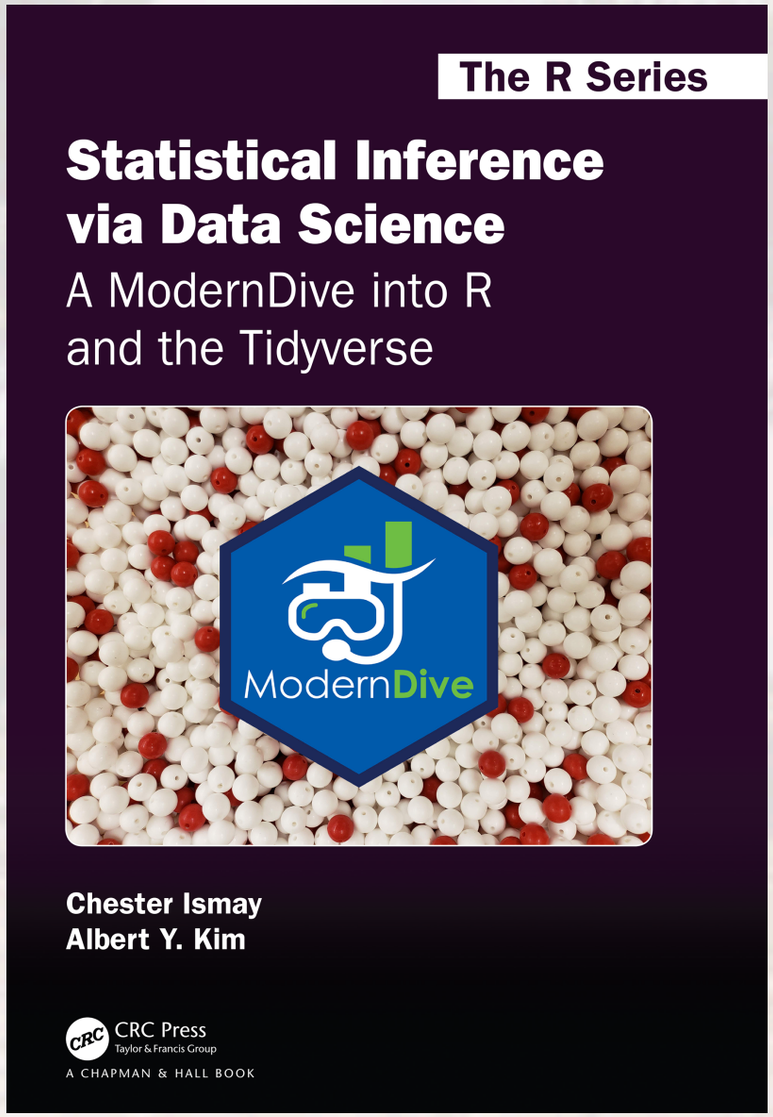
For more info check out:



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