R Coding Demonstration Week 9: Polling Errors and **Sampling from the Voter** File (Tidy)

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- Modern election forecasting usually takes polling averages + Monte Carlo simulation to simulate uncertainty about what exactly the final votes will be in each state
- Allows us to simulate different electoral vote outcomes in presidential races.
- But polling averages can be wrong! Let's use the 2020 results (so far!) to investigate how off the polling errors were.

library(tidyverse) polls_2020 <- read.csv("data/polls_2020.csv")</pre>

| Variable Name | Description |
|----------------------------|--|
| state | State (or district) name |
| biden_polls | Polling average for Biden |
| trump_polls | Polling average for Trump |
| <pre>biden_poll_lead</pre> | Biden's lead in the polling average |
| e_votes | Number of electoral votes for state/district |
| biden_pct | Preliminary percent of votes for Biden |
| trump_pct | Preliminary percent of votes for Trump |
| biden_lead | Preliminary lead for Biden |

Based on the final polling averages, calculate the number of electoral votes that Biden is predicted to win.

polls_2020 %>% mutate(biden_winning_shy = biden_poll_lead > 0) %>% summarize(total_ev = sum(e_votes[biden_winning_shy]))

total_ev
1 351

Suppose now that there are "Shy Trump" voters who refuse to answer the polls or give the wrong answer. Assume these result in a 4 point swing to Biden. Adjusting Biden's lead for this, how many electoral votes is he predicted to get?

polls_2020 %>% mutate(biden_winning_shy = biden_poll_lead - 4 > 0) %>% summarize(total_ev = sum(e_votes[biden_winning_shy]))

total_ev
1 279

How accurate have U.S. polls been?

Weighted-average error in polls in final 21 days of the campaign

| | PRESID | ENTIAL | STATE-LEVEL | | | |
|-----------|---------|---------|-------------|----------------|---------------|----------|
| CYCLE | PRIMARY | GENERAL | GOVERNOR | U.S. SENATE | U.S. HOUSE | COMBINED |
| 2017-18 | _ | - | 5.2 | 6.0 | 4.1 | 5.1 |
| 2015-16 | 10.1 | 4.8 | 5.4 | 5.0 | 5.5 | 6.8 |
| 2013-14 | - | - | 4.4 | 5.4 | 6.7 | 5.4 |
| 2011-12 | 8.9 | 3.6 | 4.8 | 4.7 | 4.7 | 5.1 |
| 2009-10 | - | - | 4.9 | 4.8 | 6.9 | 5.7 |
| 2007-08 | 7.4 | 3.6 | 4.1 | 4.7 | 5.7 | 5.4 |
| 2005-06 | - | - | 5.0 | 4.2 | 6.5 | 5.3 |
| 2003-04 | 7.1 | 3.2 | 6.1 | 5.6 | 5.4 | 4.8 |
| 2001-02 | - | - | 5.2 | 4.9 | 5.4 | 5.2 |
| 1999-2000 | 7.6 | 4.4 | 4.9 | 6.1 | 4.4 | 5.5 |
| 1998 | - | _ | 8.1 | 7.4 | 6.8 | 7.5 |
| All years | 8.7 | 4.0 | 5.4 | 5.4 | 6.2 | 5.9 |

Pollsters that are banned by FiveThirtyEight because we know or suspect that they faked their data are not included in the averages. Averages are weighted based on the number of polls a particular firm conducted. Specifically, the weights are based on the square root of the number of polls in a particular category that each

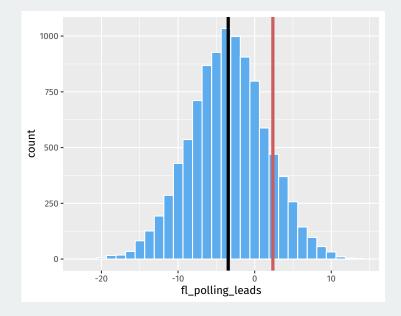
Let's use random variables to simulate polling errors and compare them to the actual polling error. Assume that the polling error for each state is distributed normally with mean 0 and standard deviation 5. Conduct 10,000 simulations of that polling error and add it to the Biden lead in Florida to get simulations of different possible polling averages.

Plot the distribution of the simulated polling average leads for Biden and calculate what proportion of these leads are bigger in magnitude than the true polling error.

Answer 3

```
n sims <- 10000
polling noise <- rnorm(n = n sims, mean = 0, sd = 5)
fl 2020 <- polls 2020 %>%
  filter(state == "Florida") %>%
  pull(biden lead)
fl 2020 polls <- polls 2020 %>%
  filter(state == "Florida") %>%
  pull(biden poll lead)
fl polling leads <- fl 2020 + polling noise
mean(abs(polling_noise) >= abs(fl_2020 - fl_2020_polls))
```

Answer 3 (cont'd)



Let's use random variables to simulate polling errors and compare them to the actual polling error. Assume that the polling error for each state is distributed normally with mean 0 and standard deviation 5. Conduct 10,000 simulations of that polling error and add it to the Biden lead in Wisconsin to get simulations of different possible polling averages.

Plot the distribution of the simulated polling average leads for Biden and calculate what proportion of these leads are bigger in magnitude than the true polling error.

Answer 4

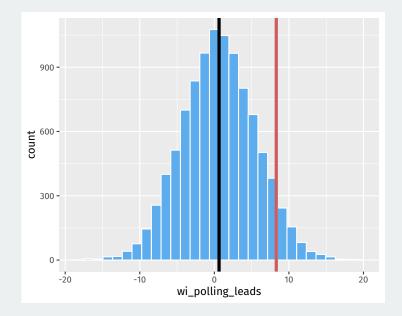
```
polling_noise <- rnorm(n = n_sims, mean = 0, sd = 5)</pre>
```

```
wi_2020 <- polls_2020 %>%
filter(state == "Wisconsin") %>%
pull(biden_lead)
```

```
wi_2020_polls <- polls_2020 %>%
filter(state == "Wisconsin") %>%
pull(biden poll lead)
```

wi_polling_leads <- wi_2020 + polling_noise mean(abs(polling_noise) >= abs(wi_2020 - wi_2020_polls))

Answer 4 (cont'd)



- A new way that some pollsters are polling for election is by sampling from the voter file directly.
- Voter files are really big, so we're going to work with one county in FL, Miami-Dade.
- We've stripped identifiable data, but the original had names, addresses, phone numbers, and email addresses.

load("data/dade_vf_2020.RData")

| Variable | Description |
|----------|---|
| voter_id | Voter ID number |
| city | City of residence |
| precinct | Precinct of residence |
| race | Race of registered voter |
| dem | 1=Democrat, 0=otherwise |
| rep | 1=Republican, 0=otherwise |
| female | 1=Female, 0=otherwise (Male/Unknown) |
| age | Registrant age |
| PPP_2016 | 1 = Voted in 2016 presidential primary, 0=didn't vote |
| PRI_2016 | 1 = Voted in 2016 state primary, 0=didn't vote |
| GEN_2016 | 1 = Voted in 2016 general election, 0=didn't vote |

What proportion of Miami-Dade County registered voters are registered as Democrats? Take a sample of size 100 and calculate the sample mean.

mean(dade\$dem)

[1] 0.407

dem_sample <- sample(dade\$dem, size = 100)
dem_sample</pre>

[1] 0 ## [33] 0 0 1 ## [65] 0 1 0 1 0 0 ## [97] 0 0 1 1

mean(dem_sample)

| dade %>% | | |
|--------------------------|------|-----|
| <pre>sample_n(size</pre> | 100) | %>% |
| pull(dem) %>% | | |
| mean() | | |

What is the average age of Miami-Dade County registered voters (that is, what is the population mean)? Take a sample of size 100 ages from the set of registered voters and calculate the sample mean.

mean(dade\$age, na.rm = TRUE)

[1] 50

age_sample <- sample(dade\$age, size = 100) age_sample

 ##
 [1]
 26
 23
 58
 35
 66
 35
 27
 23
 81
 72
 25
 47
 26
 20
 48
 47
 22
 75
 73
 19
 53

 ##
 [22]
 32
 58
 49
 30
 54
 24
 20
 36
 38
 52
 68
 60
 50
 21
 50
 85
 48
 52
 31
 56
 53

 ##
 [43]
 19
 28
 50
 84
 34
 63
 51
 68
 84
 87
 19
 72
 48
 65
 51
 54
 26
 66
 29
 20
 59

 ##
 [64]
 22
 33
 19
 28
 24
 28
 79
 20
 70
 49
 39
 25
 63
 36
 45
 26
 97
 33
 53
 43
 67
 59
 54
 36
 45
 26
 97
 33
 53
 43
 67
 59
 54
 36
 45
 26
 97
 33

mean(age_sample, na.rm = TRUE)

[1] 46.5

| dade %>% | | |
|--------------------------|------|-----|
| <pre>sample_n(size</pre> | 100) | %>% |
| pull(age) %>% | | |
| mean() | | |

[1] 49.1

Use a for loop to repeat the process of sampling the voter file 10,000 times. In each iteration, take a sample of 100 from dade\$dem and save the sample mean of that sample.

Compare the mean and standard deviation of the 10,000 sample means to the population mean and population standard deviation of dem. Draw a histogram of the means: what distribution do they follow?

Answer 7

n_sims <- 10000

```
samples <- data.frame(sample_means = rep(NA, times = n_sims))
for (i in 1:n_sims) {
   samples$sample_means[i] <- mean(sample(dade$dem, size = 100))
}
mean(samples$sample means)</pre>
```

[1] 0.406

mean(dade\$dem)

[1] 0.407

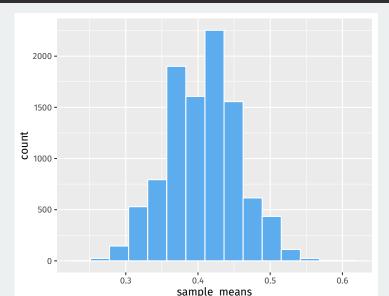
sd(samples\$sample_means)

[1] 0.0491

sd(dade\$dem) / sqrt(100)

Answer 7 (cont'd)

ggplot(samples, aes(x = sample_means)) +
 geom_histogram(fill = "steelblue2", color = "white", bins = 15)



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