Gov 50: 12. Prediction and Iteration

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Roadmap

1. Prediction

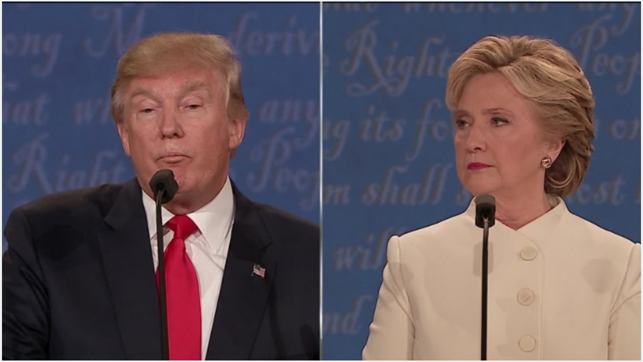
2. Loops

3. Evaluating the predictions

4. Time-series plot

1/ Prediction

2016 US Presidential Election



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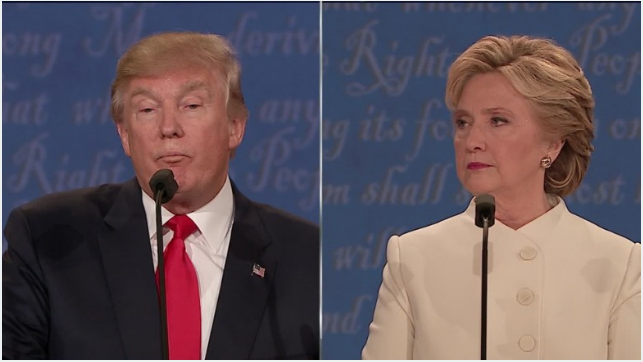

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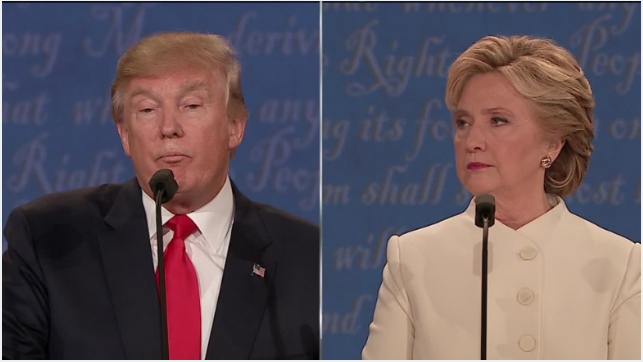

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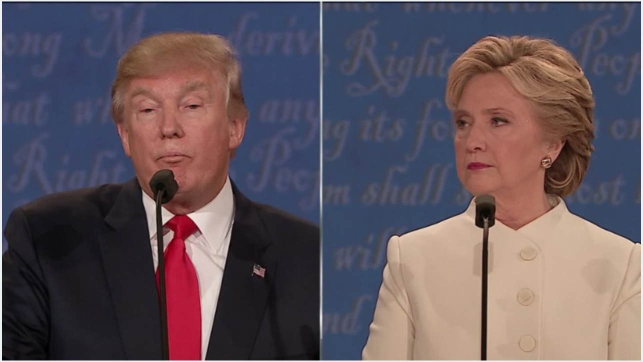

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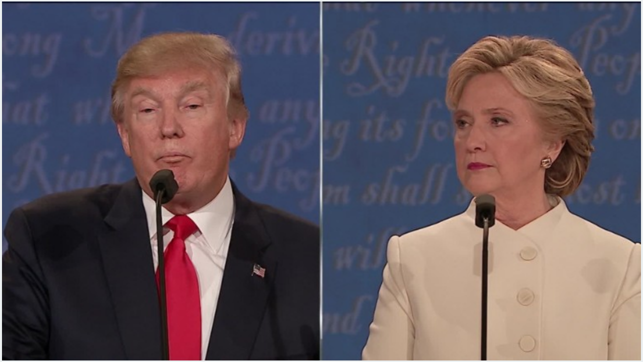

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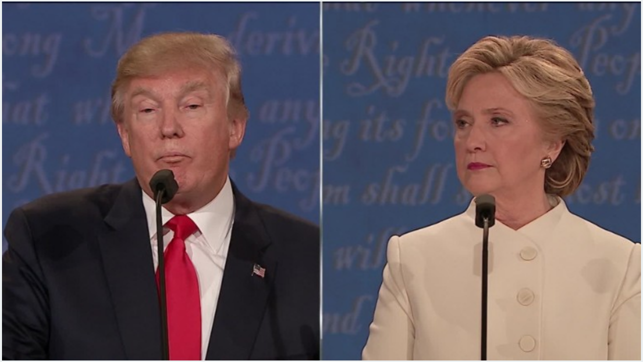

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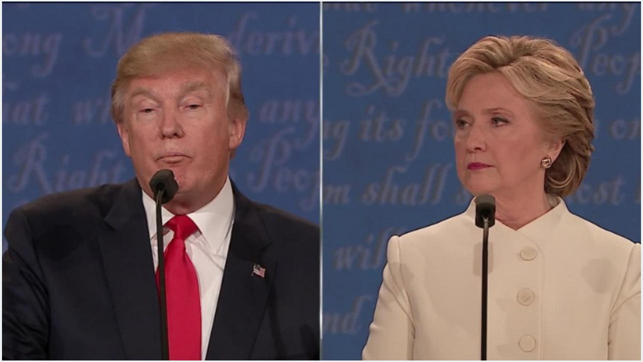

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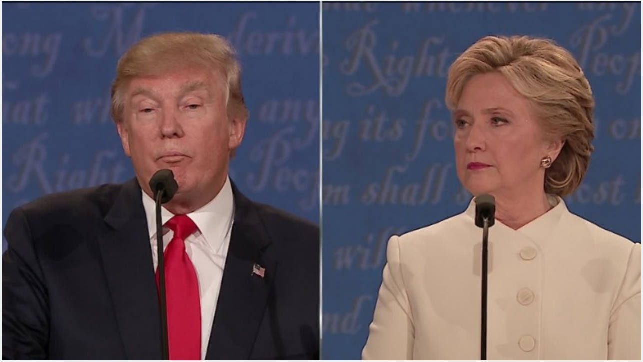

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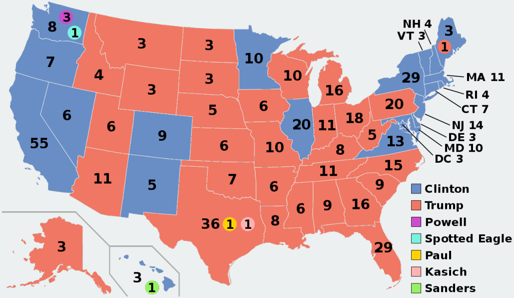
- Election determined by 77,744 votes (margins in WI, MI, and PA)
    - 0.056% of the electorate (~136 million)

Predicting US Presidential Elections



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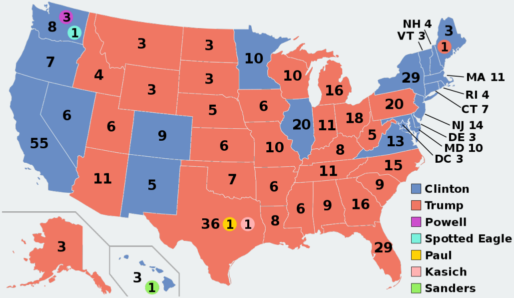

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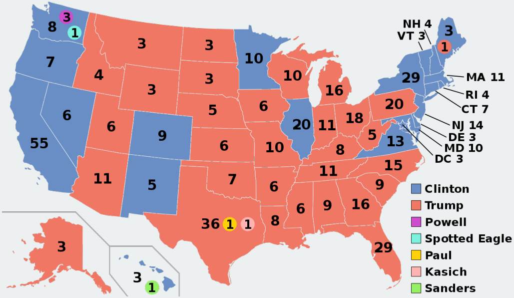

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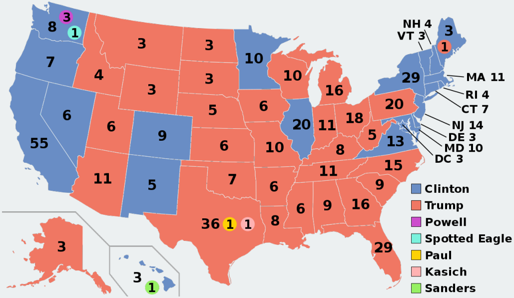

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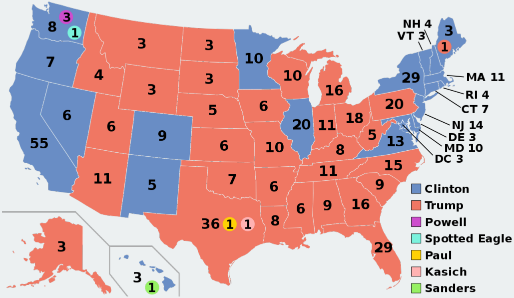

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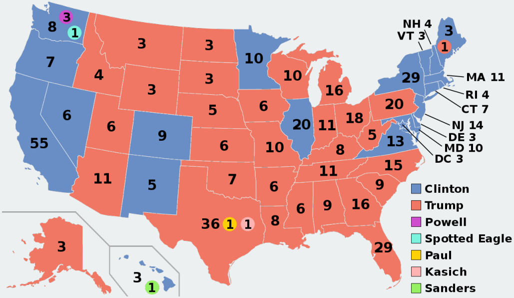

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  - Must win an absolute majority of 538 electoral votes
  - 538 = 435 (House of Representatives) + 100 (Senators) + 3 (DC)
  - Must win at least 270 votes
  - nobody wins an absolute majority ⇝ House vote
- Must predict winner of each state

Prediction strategy

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- Sounds like a lot of subsets, ugh...

2/ Loops

A simple example

What if we wanted to know the number of unique values of each column of the `cces_2020` data?

```r
library(gov50data)
cces_2020
```

```
## # A tibble: 51,551 x 6
##    gender race  educ                     pid3    turno~1 pres_~2
##    <fct>  <fct> <fct>                    <fct>     <dbl> <fct>
##  1 Male   White 2-year                   Republ~       1 Donald~
##  2 Female White Post-grad                Democr~      NA <NA>
##  3 Female White 4-year                   Indepe~       1 Joe Bi~
##  4 Female White 4-year                   Democr~       1 Joe Bi~
##  5 Male   White 4-year                   Indepe~       1 Other
##  6 Male   White Some college             Republ~       1 Donald~
##  7 Male   Black Some college             Not su~      NA <NA>
##  8 Female White Some college             Indepe~       1 Donald~
##  9 Female White High school graduate Republ~       1 Donald~
## 10 Female White 4-year                   Democr~       1 Joe Bi~
## # ... with 51,541 more rows, and abbreviated variable names
## #   1: turnout_self, 2: pres_vote
```

Manually changing values

```
length(unique(cces_2020$gender))
```

```
## [1] 2
```

```
length(unique(cces_2020$race))
```

```
## [1] 8
```

```
length(unique(cces_2020$educ))
```

```
## [1] 6
```

```
length(unique(cces_2020$pid3))
```

```
## [1] 5
```

```
length(unique(cces_2020$turnout_self))
```

```
## [1] 3
```

```
length(unique(cces_2020$pres_vote))
```

```
## [1] 7
```

Subsetting with brackets

Note that we can also access variables with `[[]]`:

```
unique(cces_2020$gender)
```

```
## [1] Male   Female
## Levels: Male Female skipped not asked
```

```
unique(cces_2020[[1]])
```

```
## [1] Male   Female
## Levels: Male Female skipped not asked
```

```
unique(cces_2020$pid3)
```

```
## [1] Republican  Democrat    Independent Not sure
## [5] Other
## 7 Levels: Democrat Republican Independent ... not asked
```

```
unique(cces_2020[[4]])
```

```
## [1] Republican  Democrat    Independent Not sure
## [5] Other
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```

Manually changing values, alternative

```
length(unique(cces_2020[[1]]))
```

```
## [1] 2
```

```
length(unique(cces_2020[[2]]))
```

```
## [1] 8
```

```
length(unique(cces_2020[[3]]))
```

```
## [1] 6
```

```
length(unique(cces_2020[[4]]))
```

```
## [1] 5
```

```
length(unique(cces_2020[[5]]))
```

```
## [1] 3
```

```
length(unique(cces_2020[[6]]))
```

```
## [1] 7
```

Recognizing the template

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Can we give R this template and a set of column numbers have it do our task repeatedly?

Loops in R

for loop provide a way to execute these templates multiple times:

```
output <- rep(NA, times = ncol(cces_2020))     # 1. output
for (i in seq_along(cces_2020)) {              # 2. sequence
  output[i] <- length(unique(cces_2020[[i]]))  # 3. body
}
output
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## [1] 2 8 6 5 3 7
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- Elements of a loop:

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  5. `{}`: curly braces to define beginning and end of the loop.
- Indentation is important for readability of the code.

2020 polling prediction

Election data: `pres20`

Name	Description
`state`	abbreviated name of state
`biden`	Biden's vote share (percentage)
`trump`	Trump's vote share (percentage)
`ev`	number of electoral college votes for the state

Polling data `polls20`:

Name	Description
`state`	state in which poll was conducted
`end_date`	end date the period when poll was conducted
`daysleft`	number of days between end date and election day
`pollster`	name of organization conducting poll
`sample_size`	name of organization conducting poll
`biden`	predicted support for Biden (percentage)
`trump`	predicted support for Trump (percentage)

Some preprocessing

```r
library(gov50data)

# calculate Trump's margin of victory
polls20 <- polls20 |>
  mutate(margin = biden - trump)
pres20 <- pres20 |>
  mutate(margin = biden - trump)

glimpse(polls20)
```

```
## Rows: 2,445
## Columns: 8
## $ end_date    <date> 2020-11-02, 2020-11-02, 2020-11-02, 2~
## $ state       <chr> "FL", "PA", "FL", "FL", "NV", "GA", "S~
## $ days_left   <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
## $ pollster    <chr> "The Political Matrix/The Listener Gro~
## $ sample_size <dbl> 966, 499, 400, 1054, 1024, 1041, 817, ~
## $ biden       <dbl> 44.2, 48.4, 47.0, 47.3, 48.4, 45.4, 39~
## $ trump       <dbl> 48.0, 49.2, 48.2, 49.4, 49.1, 49.7, 51~
## $ margin      <dbl> -3.8, -0.8, -1.2, -2.1, -0.7, -4.3, -1~
```

Reminder of our goal

- Coding strategy:
    1. For each state, subset to polls within that state.
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    3. Average the latest polls to estimate support for each candidate
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Poll prediction for each state

```r
poll_pred <- rep(NA, 51) # place holder

# get list of unique state names to iterate over
state_names <- sort(unique(polls20$state))

# add labels to holder
names(poll_pred) <- state_names

for (i in 1:51) {
  state_data <- subset(polls20, subset = (state == state_names[i]))

  latest <- state_data$days_left == min(state_data$days_left)

  poll_pred[i] <- mean(state_data$margin[latest])
}

head(poll_pred)
```

```
##      AK     AL     AR     AZ     CA     CO
##   -9.00 -26.00 -23.00   4.25  26.00  11.00
```

Tidyverse alternative version

```
poll_pred <- polls20 |>
  group_by(state) |>
  filter(days_left == min(days_left)) |>
  summarize(margin_pred = mean(margin))
poll_pred
```

```
## # A tibble: 51 x 2
##    state margin_pred
##    <chr>       <dbl>
##  1 AK         -9
##  2 AL        -26
##  3 AR        -23
##  4 AZ          4.25
##  5 CA         26
##  6 CO         11
##  7 CT         22
##  8 DC         89
##  9 DE         22
## 10 FL          0.0800
## # ... with 41 more rows
```

3/ Evaluating the predictions

Polling errors

Prediction error = actual outcome − predicted outcome

```
poll_pred <- poll_pred |>
  left_join(pres20) |>
  mutate(errors = margin - margin_pred)
poll_pred
```

```
## # A tibble: 51 x 8
##    state margin_pred    ev biden trump  other  margin errors
##    <chr>       <dbl> <dbl> <dbl> <dbl>  <dbl>   <dbl>  <dbl>
##  1 AK         -9         3  42.8 52.8  0.732  -10.1   -1.06
##  2 AL        -26         9  36.6 62.0  0.699  -25.5    0.538
##  3 AR        -23         6  34.8 62.4  0.257  -27.6   -4.62
##  4 AZ          4.25     11  49.4 49.1  0.263    0.309 -3.94
##  5 CA         26        55  63.5 34.3  0.244   29.2    3.16
##  6 CO         11         9  55.0 41.6  0.161   13.4    2.41
##  7 CT         22         7  59.3 39.2  0.129   20.1   -1.93
##  8 DC         89         3  92.1  5.40 0.491   86.8   -2.25
##  9 DE         22         3  58.7 39.8  0.0780  19.0   -3.03
## 10 FL          0.0800   29  47.9 51.2  0.0835  -3.36  -3.44
## # ... with 41 more rows
```

Assessing the prediction error

Bias: average prediction error

```
mean(poll_pred$errors)
```

```
## [1] -3.98
```

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```
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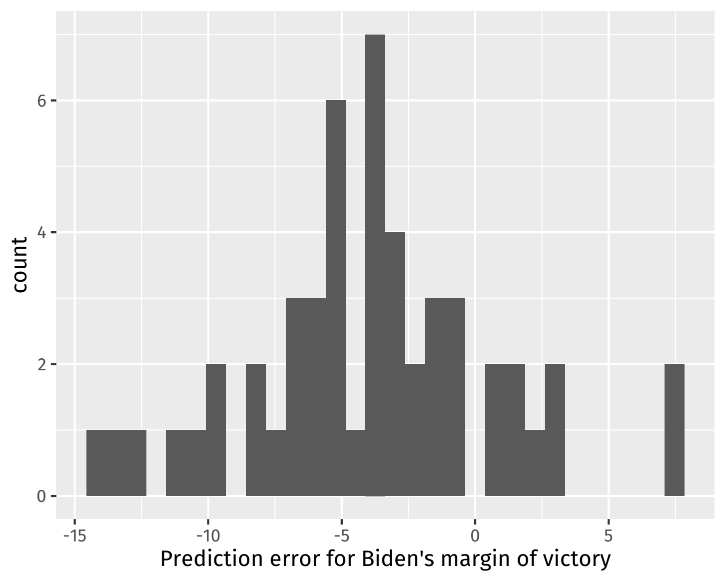
Root mean-square error: average magnitude of the prediction error

```r
sqrt(mean(poll_pred$errors^2))
```

```
## [1] 6.07
```

Histogram of the errors

```r
ggplot(poll_pred, aes(x = errors)) +
  geom_histogram() +
  labs(
    x = "Prediction error for Biden's margin of victory"
  )
```



count
6
4
2
0
-15
-10
-5
0
5
Prediction error for Biden's margin of victory

Comparing polls to outcome

Sometimes we want plot text labels instead of point and we use `geom_text` and the `label` aesthetic:

```
## merge the actual results
ggplot(poll_pred, aes(x = margin_pred, y = margin)) +
  geom_text(aes(label = state)) +
  geom_abline(xintercept = 0, slope = 1, linetype = 2) +
  geom_hline(yintercept = 0, color = "grey50") +
  geom_vline(xintercept = 0, color = "grey50")
```

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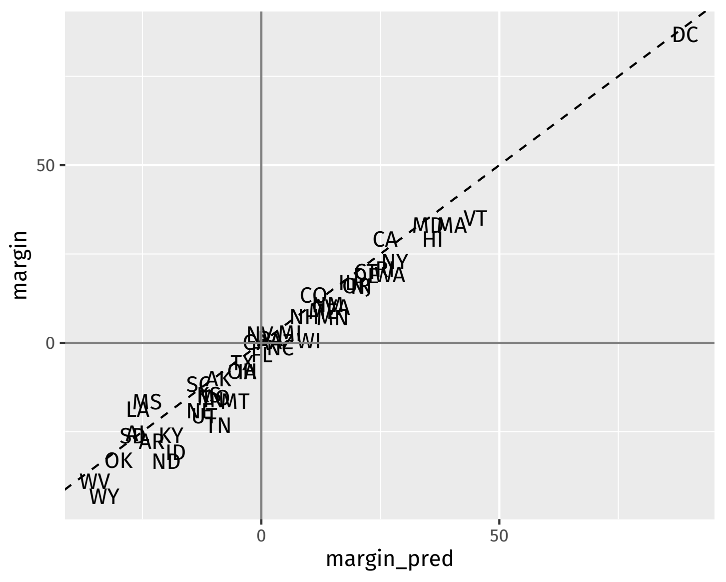

Classification

Election prediction: need to predict winner in each state:

```
poll_pred |>
  filter(margin > 0) |>
  summarize(sum(ev)) |> pull()
```

```
## [1] 306
```

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poll_pred |>
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```
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- Wrong prediction $\rightsquigarrow$ misclassification

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- Prediction of binary outcome variable = **classification problem**
- Wrong prediction $\rightsquigarrow$ misclassification
  1. **true positive**: predict Trump wins when he actually wins.

Classification

Election prediction: need to predict winner in each state:

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  filter(margin > 0) |>
  summarize(sum(ev)) |> pull()
```

```
## [1] 306
```

```r
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```

```
## [1] 328
```

- Prediction of binary outcome variable = **classification problem**
- Wrong prediction $\rightsquigarrow$ misclassification
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  3. **true negative**: predict Trump loses when he actually loses.
  4. **false negative**: predict Trump loses when he actually wins.
- Sometimes false negatives are more/less important: e.g., civil war.

Classification based on polls

Accuracy: `sign()` returns 1 for a positive number, `-1` for a negative number, and `0` for 0.

```
poll_pred |>
  summarize(prop_correct = mean(sign(margin_pred) == sign(margin))) |>
  pull()
```

```
## [1] 0.922
```

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  pull()
```

```
## [1] 0.922
```

Which states did polls call wrong?

```
poll_pred |>
  filter(sign(margin_pred) != sign(margin))
```

```
## # A tibble: 4 x 8
##   state margin_pred    ev biden trump  other margin errors
##   <chr>       <dbl> <dbl> <dbl> <dbl>  <dbl>  <dbl>  <dbl>
## 1 FL         0.0800    29  47.9  51.2 0.0835 -3.36   -3.44
## 2 GA        -1.15      16  49.5  49.2 0.0759  0.236   1.39
## 3 NC         3.95      15  48.6  49.9 0.296  -1.35   -5.30
## 4 NV        -0.350      6  50.1  47.7 0.759   2.39    2.74
```

4/ Time-series plot

National polls

We often want to show a time series of the national-level polls to get a sense of the popular vote:

```
national_polls20
```

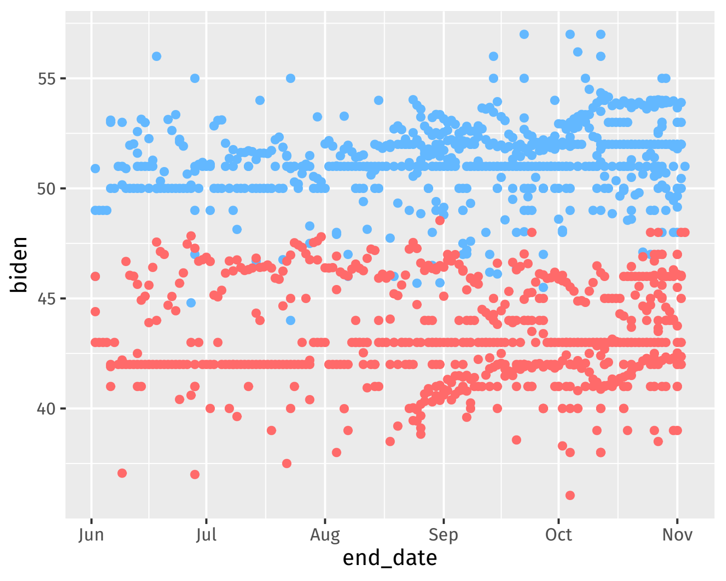
```
## # A tibble: 654 x 5
##    end_date   pollster                          sampl~1 biden trump
##    <date>     <chr>                               <dbl> <dbl> <dbl>
##  1 2020-11-03 Lake Research                        2400  51    48  
##  2 2020-11-02 Research Co.                         1025  50    42  
##  3 2020-11-02 YouGov                               1363  53    43  
##  4 2020-11-02 Ipsos                                 914  52    45  
##  5 2020-11-02 SurveyMonkey                        28240  52    46  
##  6 2020-11-02 HarrisX                              2297  52    48  
##  7 2020-11-02 TIPP                                 1212  50.4  46.0
##  8 2020-11-02 USC Dornsife                         5423  53.9  42.4
##  9 2020-11-01 John Zogby Strategies/EMI~           1008  49.6  43.8
## 10 2020-11-01 Swayable                             5174  51.8  46.1
## # ... with 644 more rows, and abbreviated variable name
## #   1: sample_size
```

Plotting the raw results

```r
national_polls20 |>
  ggplot(aes(x = end_date)) +
  geom_point(aes(y = biden), color = "steelblue1") +
  geom_point(aes(y = trump), color = "indianred1")
```

Plotting the raw results

Fairly messy:



Clean the mess by taking moving averages

Goal: plot the average of polls in the last 7 days (very difficult with `dplyr`).

Loop over each day in the data and do:

1. Subset to all polls in the previous 7 days of that day.

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1. Subset to all polls in the previous 7 days of that day.
2. Calculate the average of these polls for Biden and Trump.
3. Save the result as a 1-row tibble.

Dates in R

You can get R to properly understand dates and do arithmetic with them:

```
head(national_polls20$end_date)
```

```
## [1] "2020-11-03" "2020-11-02" "2020-11-02" "2020-11-02"
## [5] "2020-11-02" "2020-11-02"
```

```
head(national_polls20$end_date + 3)
```

```
## [1] "2020-11-06" "2020-11-05" "2020-11-05" "2020-11-05"
## [5] "2020-11-05" "2020-11-05"
```

Lubridate to create dates

We can covert a string to a date using the `lubridate` package:

```
"2020-11-03" + 3  ## R doesn't know this is a date yet!
```

```
## Error in "2020-11-03" + 3: non-numeric argument to binary operator
```

```
lubridate::ymd("2020-11-03") + 3
```

```
## [1] "2020-11-06"
```

```
lubridate::mdy("11/03/2020") + 3
```

```
## [1] "2020-11-06"
```

Getting a vector of dates

Setup the vector of dates to cover:

```
election_day <- lubridate::ymd("2020-11-03")
all_dates <- seq(from = min(national_polls20$end_date) + 1,
                 to = election_day,
                 by = "days")
head(all_dates)
```

```
## [1] "2020-06-03" "2020-06-04" "2020-06-05" "2020-06-06"
## [5] "2020-06-07" "2020-06-08"
```

Moving window loop

```r
output <- vector("list", length = length(all_dates))

for (i in seq_along(all_dates)) {
  this_date <- all_dates[[i]]

  this_week <- national_polls20 |>
    filter(
      this_date - end_date >= 0,      # this_date is after end_date
      this_date - end_date < 7       # within a week
    )

  output[[i]] <- this_week |>
    summarize(
      date = this_date,
      biden = mean(biden, na.rm = TRUE),
      trump = mean(trump, na.rm = TRUE)
    )
}
output <- bind_rows(output)
```

Result

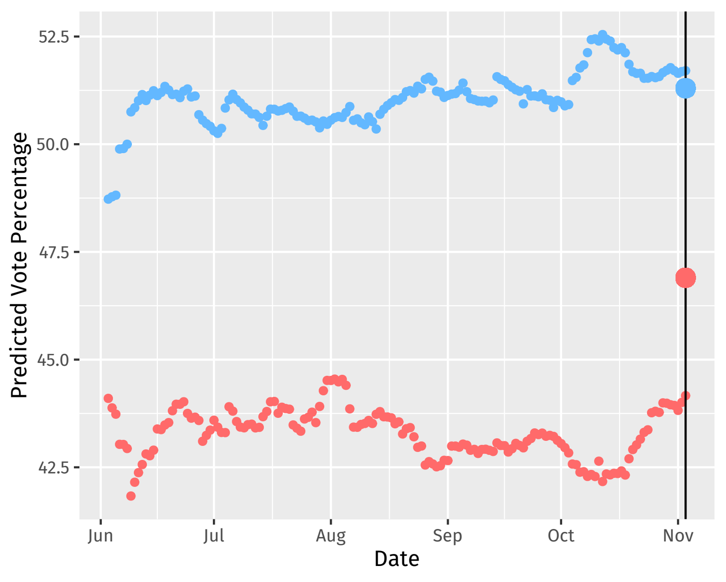
```
output
```

```
## # A tibble: 154 x 3
##    date       biden trump
##    <date>     <dbl> <dbl>
##  1 2020-06-03  48.7  44.1
##  2 2020-06-04  48.8  43.9
##  3 2020-06-05  48.8  43.7
##  4 2020-06-06  49.9  43.0
##  5 2020-06-07  49.9  43.0
##  6 2020-06-08  50    42.9
##  7 2020-06-09  50.8  41.8
##  8 2020-06-10  50.8  42.2
##  9 2020-06-11  51.0  42.4
## 10 2020-06-12  51.2  42.6
## # ... with 144 more rows
```

Let's plot

```
output |>
  ggplot(aes(x = date)) +
  geom_point(aes(y = biden), color = "steelblue1") +
  geom_point(aes(y = trump), color = "indianred1") +
  geom_vline(xintercept = election_day) +
  geom_point(aes(x = election_day, y = 51.3), color = "steelblue1", size =
  geom_point(aes(x = election_day, y = 46.9), color = "indianred1", size =
  labs(
    x = "Date",
    y = "Predicted Vote Percentage"
  )
```

Let’s plot


52.5
50.0
47.5
45.0
42.5
Predicted Vote Percentage
Jun
Jul
Aug
Sep
Oct
Nov
Date