Multivariate Analysis

Part 2: Visualizations

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Agenda

1. Finish up last lecture
2. Rules of visualization
3. Overtime Polls + `weighted.mean()`
4. Predicting winner with Electoral College Votes

Conditional Analysis of Polls

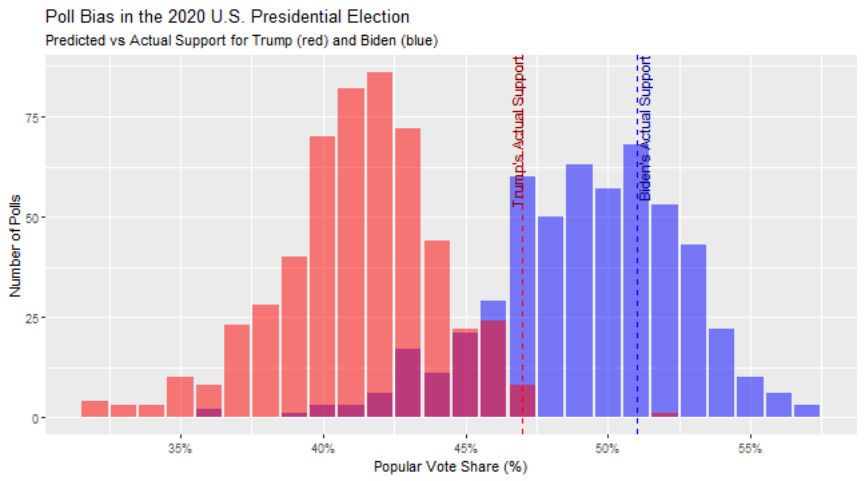
```
require(tidyverse)
poll <- readRDS('../data/Pres2020_PV.Rds')

poll <- poll %>%
  mutate(Trump = Trump/100,
         Biden = Biden/100,
         margin = round(Biden - Trump,2))
```

The Research Question

```
pRQ <- poll %>%
  ggplot() +
  geom_bar(aes(x = Biden*100),fill = 'blue',alpha = .5) +
  geom_bar(aes(x = Trump*100),fill = 'red',alpha = .5) +
  geom_vline(xintercept = 47,linetype = 'dashed',color= 'red') +
  geom_vline(xintercept = 51,linetype = 'dashed',color= 'blue')+
  annotate(geom = 'text',x = c(47),y = Inf,angle = 90,hjust = 1,vjust = 0,label = c("Trump's Actual
Support"),color = 'darkred') +
  annotate(geom = 'text',x = c(51),y = Inf,angle = 90,hjust = 1,vjust = 1,label = c("Biden's Actual
Support"),color = 'darkblue') +
  labs(title = 'Poll Bias in the 2020 U.S. Presidential Election',
       subtitle = 'Predicted vs Actual Support for Trump (red) and Biden (blue)',
       x = 'Popular Vote Share (%)',
       y = 'Number of Polls') +
  scale_x_continuous(breaks = seq(30,60,by = 5),labels = function(x) paste0(x,'%'))
```

The Research Question

pRQ



The Research Question

```
poll %>% # Proportion that under-predict
  summarise(propBidenUP = mean(Biden < .51),
            propTrumpUP = mean(Trump < .47))
```

```
## # A tibble: 1 × 2
##   propBidenUP propTrumpUP
##         <dbl>       <dbl>
## 1       0.612       0.983
```

```
poll %>% # Average under-prediction
  summarise(avgBidenErr = mean(.51 - Biden),
            avgTrumpErr = mean(.47 - Trump))
```

```
## # A tibble: 1 × 2
##   avgBidenErr avgTrumpErr
##         <dbl>       <dbl>
## 1      0.0175      0.0577
```

Theorizing

- Research Question: Why do polls under-predict Trump more than Biden?
    1. Unrepresentative samples (how were respondents contacted?)
    2. Small samples (how many respondents?)
    3. Shy Trump Voters / trolls (lying respondents)
    4. Timing (closer to the election → less biased)

Theorizing

- A fifth explanation?
- Anti-Trump media!

Theorizing

- Theory #1: Does the "mode" of the survey matter?
  - I.e., if you only call people on landlines, who do you reach?
  - And how might they differ from the general population?
- Assumption 1: Younger people do not use landlines, meaning that surveys which rely on **r**andom **d**igit **d**ialing (RDD) will get disproportionately older respondents.
- Assumption 2: Younger voters are more progressive, making them less likely to support Trump.
- Theory: Surveys that use RDD will find more support for Trump than Biden.

Analyzing

- Plot the Biden-Trump vote margin by mode type

```
poll %>%
  count(Mode)
```

```
## # A tibble: 9 × 2
##   Mode                n
##   <chr>           <int>
## 1 IVR                 1
## 2 IVR/Online         47
## 3 Live phone - RBS    13
## 4 Live phone - RDD    51
## 5 Online             366
## 6 Online/Text         1
## 7 Phone - unknown     1
## 8 Phone/Online       19
## 9 <NA>               29
```

- So many modes of interviewing people!

(Soft) Rules of Visualization

- Variable `type` informs visualization

1. Univariate
    - Categorical data: `geom_bar()`
    - Continuous data: `geom_histogram()` or `geom_density()`
2. Bivariate
    - Categorical X Categorical: `geom_bar()`
    - Binary X Continuous: `geom_histogram()` or `geom_density()`
    - Categorical X Continuous: `geom_boxplot()` or `geom_violin()`
    - Continuous X Continuous: `geom_point()`

Beyond Bivariate

1. Trivariate
    - Categorical X Categorical X Continuous: `geom_tile()`
    - Continuous X Continuous X Categorical: `geom_point()` + `color`
    - Continuous X Continuous X Continuous: `geom_point()` + `color`/`size`
    - Latitude X Longitude X Categorical / Continuous: Maps!
    - Var X Var X Time: Animated!
    - (Beyond the scope of this course, but get creative!)

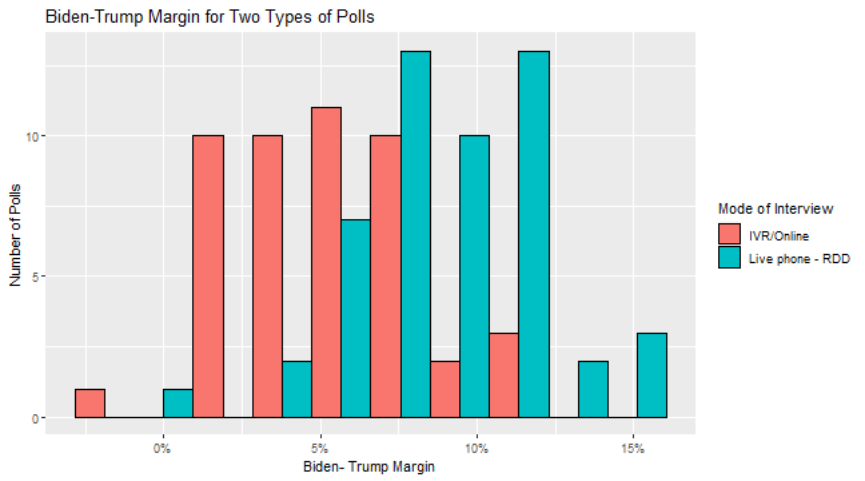
Analyzing

- For now, just focus on `IRV/Online` versus `Live phone - RDD`
- Since `margin` is a continuous variable, use `geom_histogram`

```
pMode <- poll %>%
  filter(Mode == "IVR/Online" | Mode == "Live phone - RDD") %>%
    ggplot(aes(x= margin, fill = Mode)) +
  labs(y = "Number of Polls",
         x = "Biden- Trump Margin",
         title = "Biden-Trump Margin for Two Types of Polls",
        fill = "Mode of Interview") +
    geom_histogram(bins=10, color="black", position="dodge") +
    scale_x_continuous(breaks=seq(-.1,.2,by=.05),
                       labels= scales::percent_format(accuracy = 1))
```

Mode Matters!

```
pMode
```



- But results are **inconsistent** with our theory!

Visualization

- How can we improve this? Perhaps `geom_density()` and `geom_vline()`?

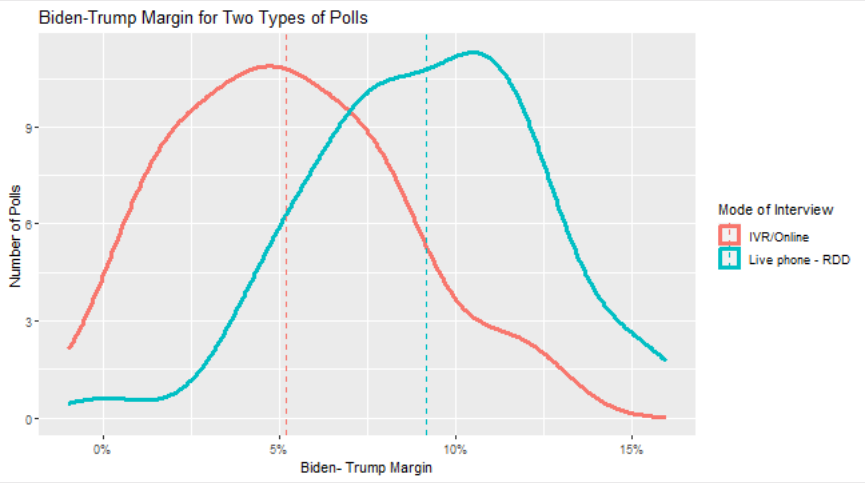
```
toplot <- poll %>%
  filter(Mode == "IVR/Online" | Mode == "Live phone - RDD")

pModeDens <- toplot %>%
  ggplot(aes(x= margin, color = Mode)) +
  labs(y = "Number of Polls",
       x = "Biden- Trump Margin",
       title = "Biden-Trump Margin for Two Types of Polls",
       color = "Mode of Interview") +
  geom_density(lwd = 1.2) +
  scale_x_continuous(breaks=seq(-.1,.2,by=.05),
                     labels= scales::percent_format(accuracy = 1)) +
  geom_vline(data = toplot %>%
               group_by(Mode) %>%
               summarise(margin = mean(margin)),aes(xintercept = margin,color = Mode),linetype = 'dashed')
```

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2
## 3.4.0.
## ℹ Please use `linewidth` instead.
```

Visualization

- How can we improve this? Perhaps `geom_density()` and `geom_vline()`?

```
pModeDens
```



More Modes

- `geom_histogram()` and `geom_density()` less useful for more comparisons
- First, let's drop modes that were hardly used

```
(toKeep <- poll %>%
  count(Mode) %>%
  filter(n > 5,
         !is.na(Mode)))
```

```
## # A tibble: 5 × 2
##   Mode                n
##   <chr>           <int>
## 1 IVR/Online         47
## 2 Live phone - RBS    13
## 3 Live phone - RDD    51
## 4 Online            366
## 5 Phone/Online        19
```

```
toplot <- poll %>% filter(Mode %in% toKeep$Mode)
```

More Modes

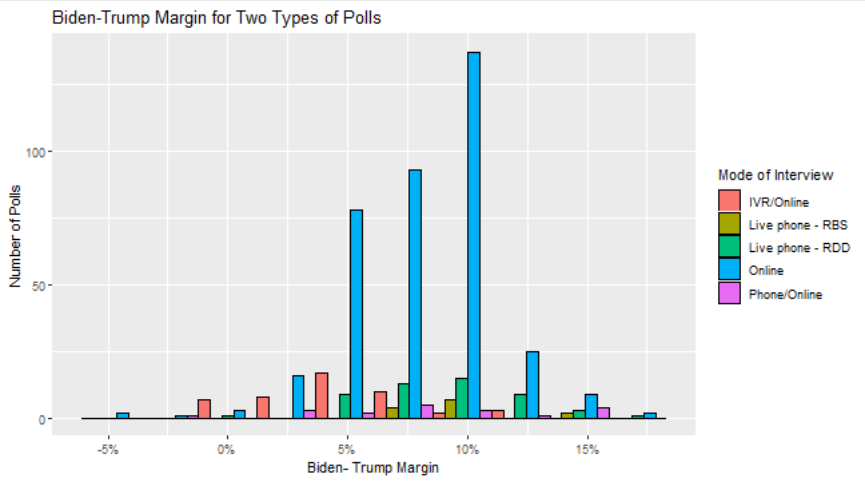
- How hard is `geom_histogram()` with more categories?

```
pModeHist <- toplot %>%
  ggplot(aes(x= margin, fill = Mode)) +
  labs(y = "Number of Polls",
       x = "Biden- Trump Margin",
       title = "Biden-Trump Margin for Two Types of Polls",
       fill = "Mode of Interview") +
  geom_histogram(color = 'black',position = 'dodge',bins = 10) +
  scale_x_continuous(breaks=seq(-.1,.2,by=.05),
                     labels= scales::percent_format(accuracy = 1))
```

More Modes

- How hard is `geom_histogram()` with more categories?

```
pModeHist
```



More Modes

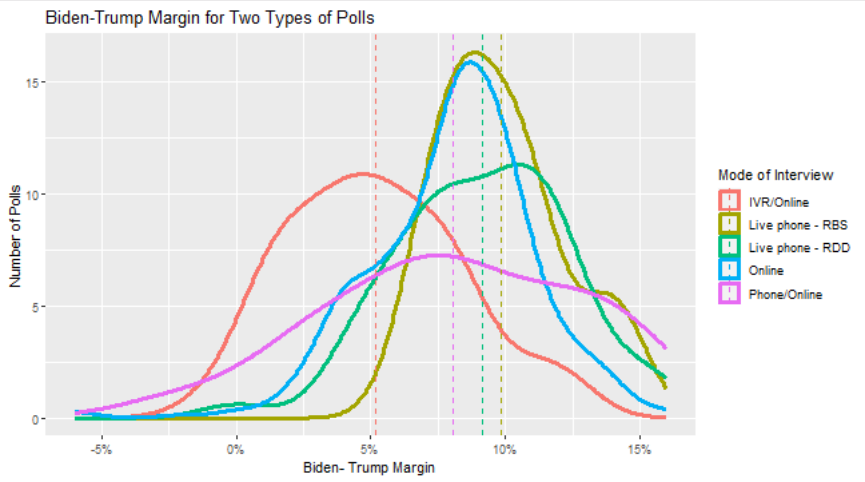
- How hard is `geom_density()` with more categories?

```
pModeDens <- toplot %>%
  ggplot(aes(x= margin, color = Mode)) +
  labs(y = "Number of Polls",
       x = "Biden- Trump Margin",
       title = "Biden-Trump Margin for Two Types of Polls",
       color = "Mode of Interview") +
  geom_density(lwd = 1.2) +
  scale_x_continuous(breaks=seq(-.1,.2,by=.05),
                     labels= scales::percent_format(accuracy = 1)) +
  geom_vline(data = toplot %>%
               group_by(Mode) %>%
               summarise(margin = mean(margin)),aes(xintercept = margin,color = Mode),linetype = 'dashed')
```

More Modes

- How hard is `geom_density()` with more categories?

```
pModeDens
```



geom_boxplot()

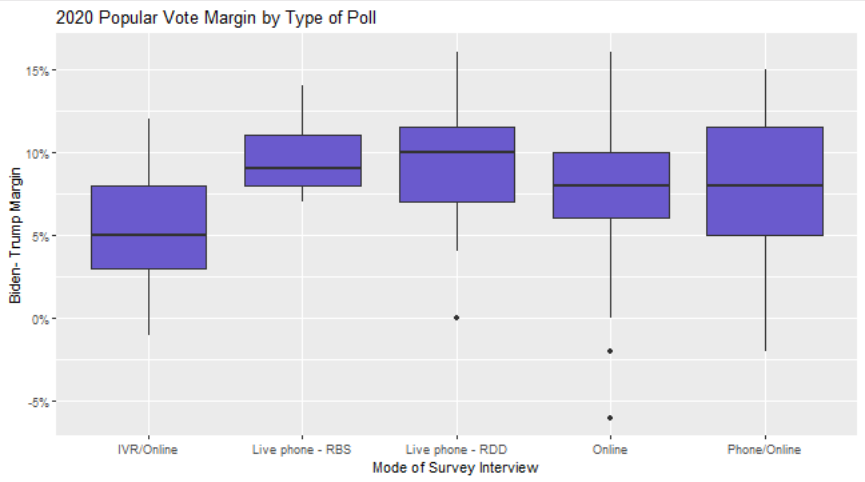
- More categories requires more compact ways of visualizing distributions

```
pModeBox <- toplot %>%
  ggplot(aes(x = Mode, y = margin)) +
    labs(x = "Mode of Survey Interview",
         y = "Biden- Trump Margin",
         title = "2020 Popular Vote Margin by Type of Poll") +
    geom_boxplot(fill = "slateblue") +
    scale_y_continuous(breaks=seq(-.1,.2,by=.05),
                       labels= scales::percent_format(accuracy = 1))
```

geom_boxplot()

- More categories requires more compact ways of visualizing distributions

```
pModeBox
```



Ordering Unordered Categories

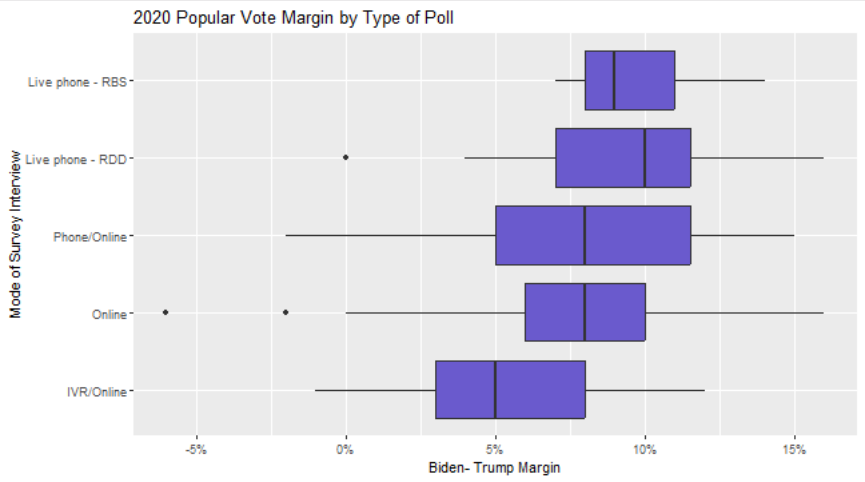
- We can use `reorder()` to arrange categories by the data

```
pModeBox <- toplot %>%
  ggplot(aes(x = reorder(Mode,margin), y = margin)) +
    labs(x = "Mode of Survey Interview",
         y = "Biden- Trump Margin",
         title = "2020 Popular Vote Margin by Type of Poll") +
    geom_boxplot(fill = "slateblue") +
    scale_y_continuous(breaks=seq(-.1,.2,by=.05),
                       labels= scales::percent_format(accuracy = 1))
```

Ordering Unordered Categories

- We can use `reorder()` to arrange categories by the data

```
pModeBox + coord_flip()
```



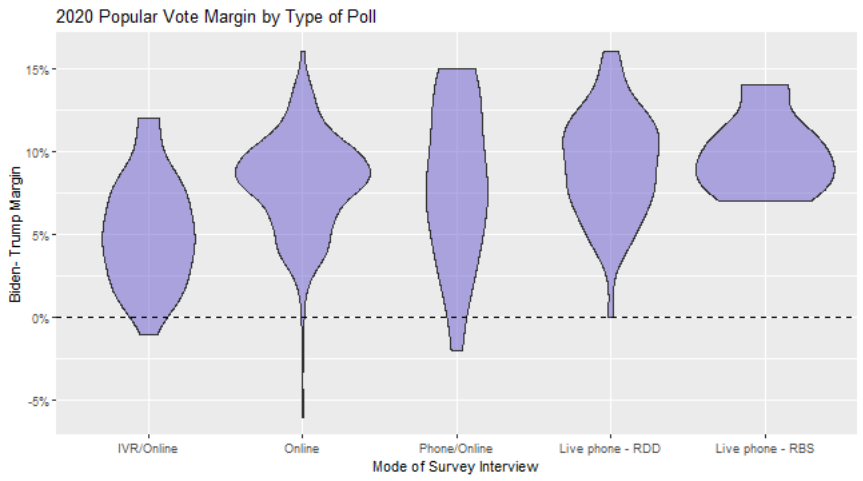
geom_violin()

- Boxplots are cleaner than densities and histograms for multiple categories
- But we lose ability to see distributions within the 80% box

```
pModeViol <- toplot %>%
  ggplot(aes(x = reorder(Mode,margin), y = margin)) +
    labs(x = "Mode of Survey Interview",
         y = "Biden- Trump Margin",
         title = "2020 Popular Vote Margin by Type of Poll") +
    geom_violin(fill = "slateblue",alpha = .5) +
    scale_y_continuous(breaks=seq(-.1,.2,by=.05),
                       labels= scales::percent_format(accuracy = 1))
```

geom_violin()

```
pModeViol + geom_hline(yintercept = 0,linetype = 'dashed')
```



Continuous by Continuous

- For conditional relationships between two continuous variables, use `geom_point()`
- Theory: Are polls politically biased?
  - I.e., a Biden-friendly poll might **under**predict Trump support and **over**predict Biden support
- Data: Trump support conditional on Biden support

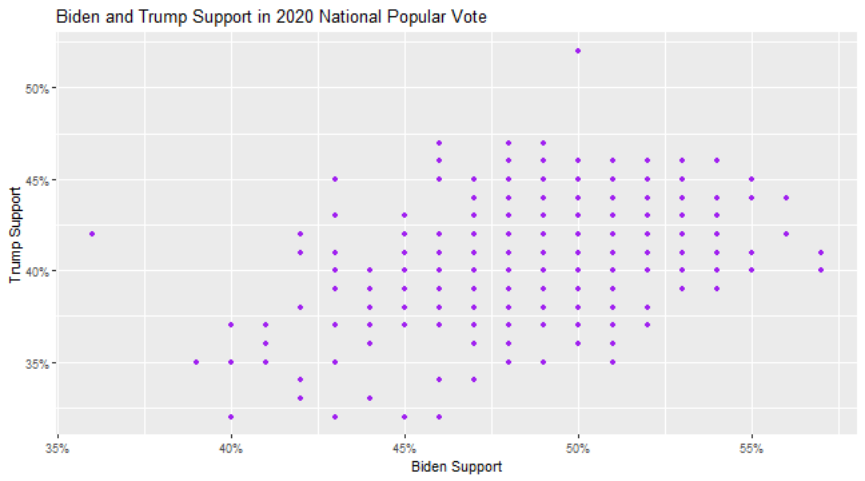
Analysis

- Plot Trump support versus Biden support

```
pSupp <- poll %>%
  ggplot(aes(x = Biden, y = Trump)) +
  labs(title="Biden and Trump Support in 2020 National Popular Vote",
       y = "Trump Support",
       x = "Biden Support") +
  geom_point(color="purple") +
    scale_y_continuous(breaks=seq(0,1,by=.05),
                       labels= scales::percent_format(accuracy = 1)) +
  scale_x_continuous(breaks=seq(0,1,by=.05),
                       labels= scales::percent_format(accuracy = 1))
```

geom_scatter()

```
pSupp
```



- How many observations are at each point?

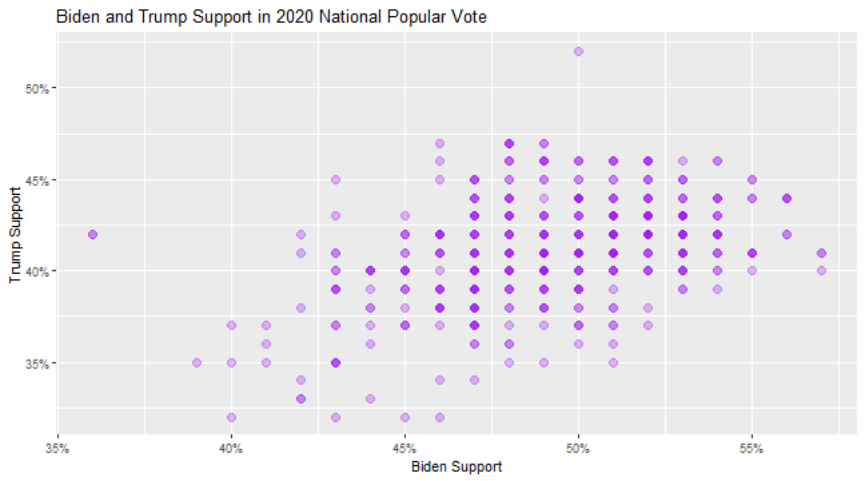
Tweaking `alpha`

- We can set the transparency of each point such that multiple points will show up darker
  - I.e., `alpha=.3` means that a single point will be 70% transparent, but 3 points on top of each other will be 10% transparent

```
pSupp <- poll %>%
  ggplot(aes(x = Biden, y = Trump)) +
  labs(title="Biden and Trump Support in 2020 National Popular Vote",
       y = "Trump Support",
       x = "Biden Support") +
  geom_point(color="purple",alpha = .3,size = 3) +
    scale_y_continuous(breaks=seq(0,1,by=.05),
                       labels= scales::percent_format(accuracy = 1)) +
  scale_x_continuous(breaks=seq(0,1,by=.05),
                       labels= scales::percent_format(accuracy = 1))
```

Tweaking `alpha`

```
pSupp
```



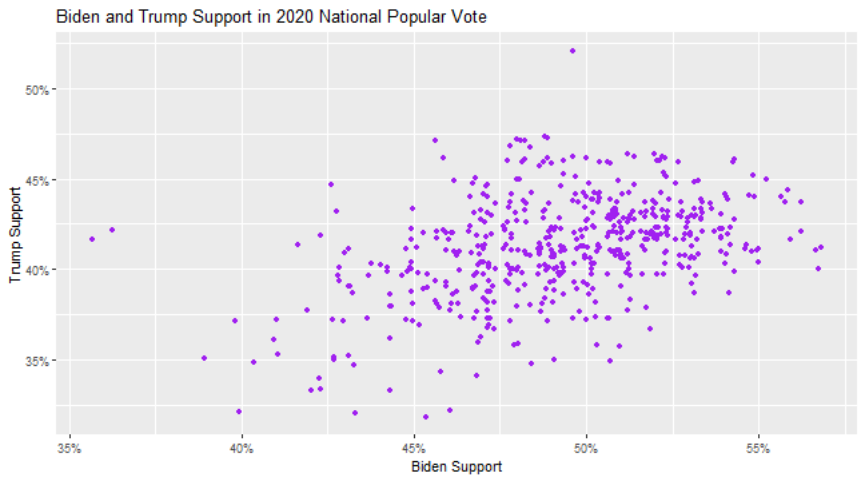
geom_jitter()

- Instead, we could "jitter" the points
    - This adds some random noise to each point to shake them off each other

```
pSupp <- poll %>%
  ggplot(aes(x = Biden, y = Trump)) +
  labs(title="Biden and Trump Support in 2020 National Popular Vote",
       y = "Trump Support",
       x = "Biden Support") +
  geom_jitter(color="purple") +
    scale_y_continuous(breaks=seq(0,1,by=.05),
                       labels= scales::percent_format(accuracy = 1)) +
  scale_x_continuous(breaks=seq(0,1,by=.05),
                       labels= scales::percent_format(accuracy = 1))
```

geom_jitter()

```
pSupp
```



size

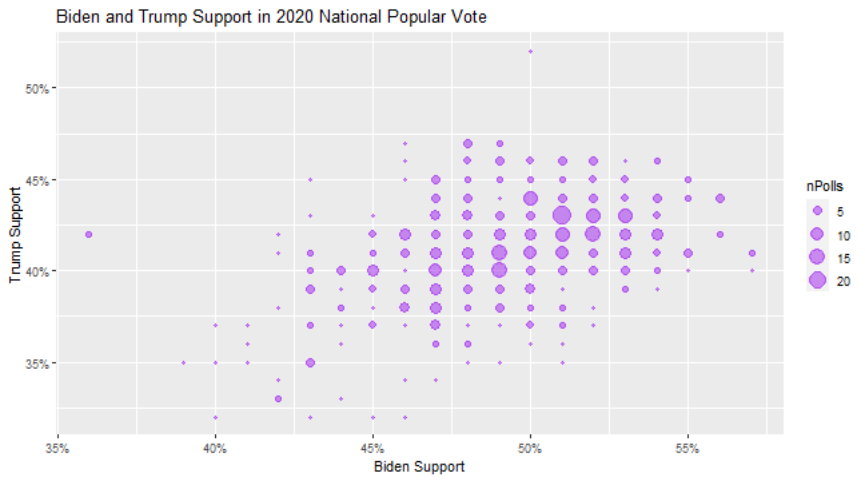
- Finally, we could simply count the number of polls at each x,y coordinate
  - Then size the points by the number of polls

```
pSupp <- poll %>%
  group_by(Biden,Trump) %>%
  summarise(nPolls = n()) %>%
  ggplot(aes(x = Biden, y = Trump,size = nPolls)) +
  labs(title="Biden and Trump Support in 2020 National Popular Vote",
       y = "Trump Support",
       x = "Biden Support") +
  geom_point(color="purple",alpha = .5) +
    scale_y_continuous(breaks=seq(0,1,by=.05),
                       labels= scales::percent_format(accuracy = 1)) +
  scale_x_continuous(breaks=seq(0,1,by=.05),
                       labels= scales::percent_format(accuracy = 1))
```

```
## `summarise()` has grouped output by 'Biden'. You can
## override using the `.groups` argument.
```

size

pSupp


Biden and Trump Support in 2020 National Popular Vote
Trump Support
50%
45%
40%
35%
35%
40%
45%
50%
55%
Biden Support
nPolls
5
10
15
20

Theory

- These results indicate that polls which predict greater support for Biden **also** predict greater support for Trump
  - Is this consistent with the theory?
  - Recall that **Biden-biased** polls should underpredict Trump support and overpredict Biden support
  - In the data, this would suggest a **negative** relationship
  - But we find a **positive** relationship
- **Inconsistent** with the theory, but raises another puzzle
- Why do polls that underpredict support for Biden also underpredict support for Trump?
  - Third party bias? Polls bias against 3rd party candidates
  - Timing of poll? Fewer uncertain responses closer to election

Dates and More Dimensions

- To test the timing of polls theory, let's look at how predicted support varies over time

```
poll %>%
  select(StartDate,EndDate,DaysinField)
```

```
## # A tibble: 528 × 3
##    StartDate  EndDate   DaysinField
##    <chr>      <chr>           <dbl>
##  1 10/31/2020 11/2/2020           3
##  2 10/31/2020 11/2/2020           3
##  3 10/29/2020 11/2/2020           5
##  4 11/1/2020  11/1/2020           1
##  5 11/1/2020  11/1/2020           1
##  6 10/30/2020 11/1/2020           3
##  7 10/31/2020 11/2/2020           3
##  8 10/30/2020 11/1/2020           3
##  9 10/29/2020 11/1/2020           4
## 10 10/29/2020 11/1/2020           4
## # … with 518 more rows
```

Dates

- Need to convert `StartDate` and `EndDate` into `date` class

```
election.day <- as.Date("11/3/2020", "%m/%d/%Y")
election.day
```

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

```
election.day16 <- as.Date("11/8/2016", "%m/%d/%Y")
election.day16
```

```
## [1] "2016-11-08"
```

```
election.day - election.day16
```

```
## Time difference of 1456 days
```

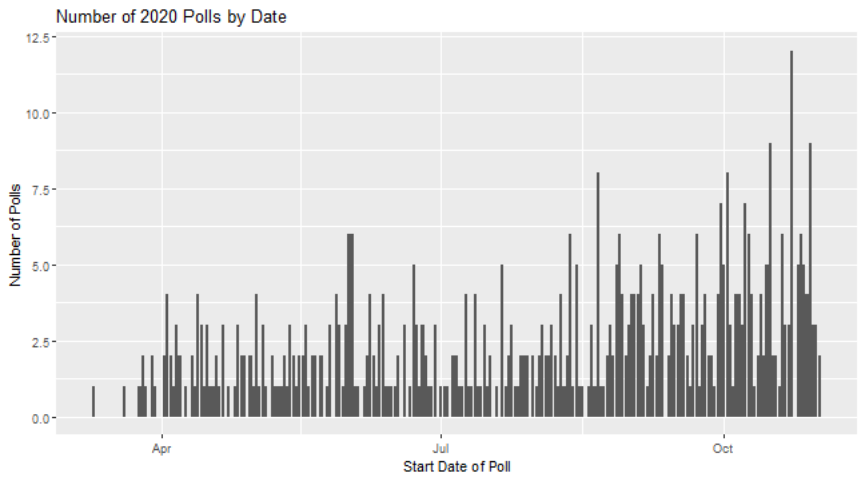
Wrangling

```
toplot <- poll %>%
                mutate(EndDate = as.Date(EndDate, "%m/%d/%Y"),
                       StartDate = as.Date(StartDate, "%m/%d/%Y"),
                       DaysToED = as.numeric(election.day - EndDate),
                       margin = Biden - Trump)
```

- How many polls were conducted over time?

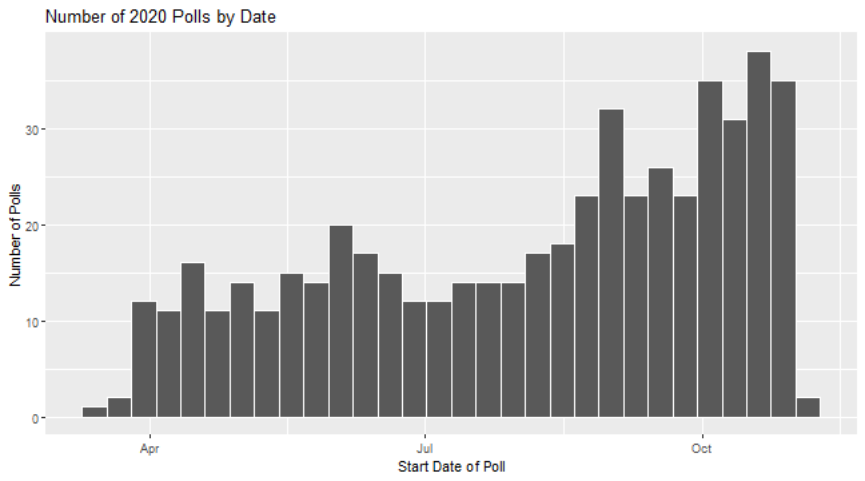
Polls by Date (geom_bar)

```
toplot %>%
  ggplot(aes(x = StartDate)) +
  geom_bar() + labs(title = 'Number of 2020 Polls by Date',x = 'Start Date of Poll',y = 'Number of Polls')
```



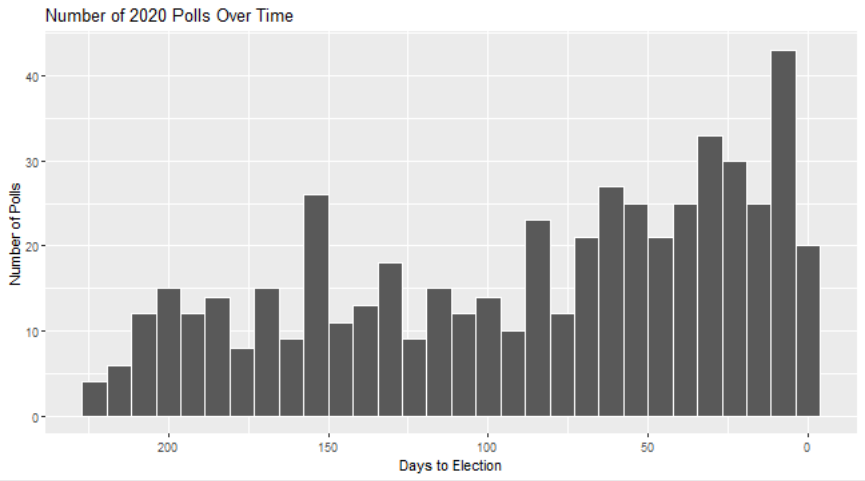
Polls by Date (geom_histogram)

```
toplot %>%
  ggplot(aes(x = StartDate)) +
  geom_histogram(bins = 30,color = 'white') + labs(title = 'Number of 2020 Polls by Date',x = 'Start Date of
Poll',y = 'Number of Polls')
```



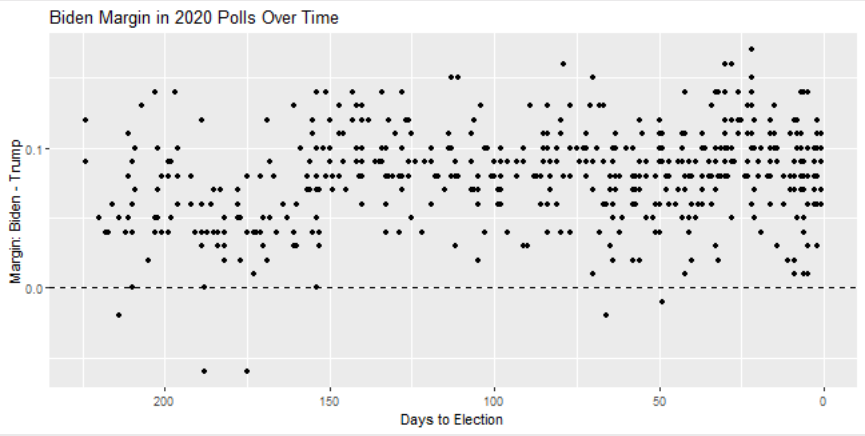
Polls by Time to Election

```
toplot %>%
  ggplot(aes(x = DaysToED)) +
  geom_histogram(bins = 30,color = 'white') + labs(title = 'Number of 2020 Polls Over Time',x = 'Days to
Election',y = 'Number of Polls') +
  scale_x_reverse()
```



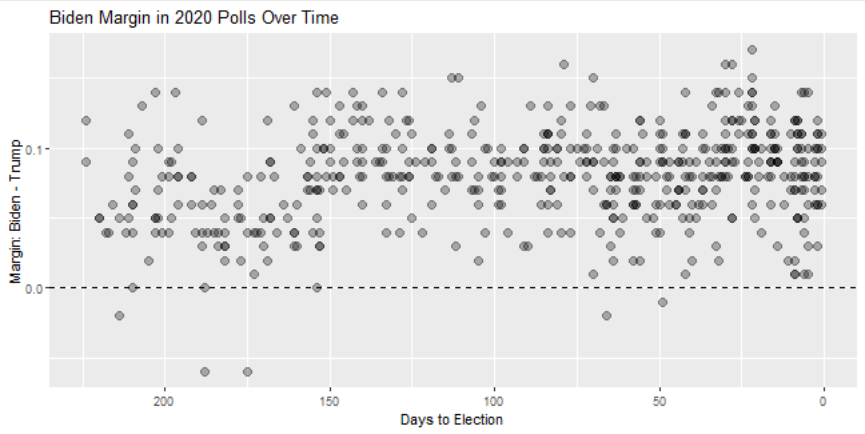
Margin by Time to Election

```
toplot %>%
  ggplot(aes(x = DaysToED,y = margin)) +
  geom_point() +
  labs(title = 'Biden Margin in 2020 Polls Over Time',
       x = 'Days to Election',y = 'Margin: Biden - Trump') +
  scale_x_reverse() + geom_hline(yintercept = 0,linetype = 'dashed')
```



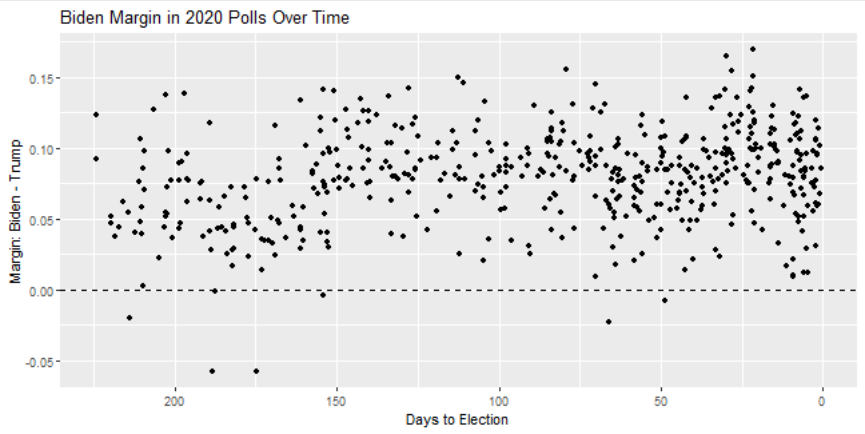
Margin by Time to Election

```
toplot %>%
  ggplot(aes(x = DaysToED,y = margin)) +
  geom_point(alpha = .3,size = 3) +
  labs(title = 'Biden Margin in 2020 Polls Over Time',
       x = 'Days to Election',y = 'Margin: Biden - Trump') +
  scale_x_reverse() + geom_hline(yintercept = 0,linetype = 'dashed')
```



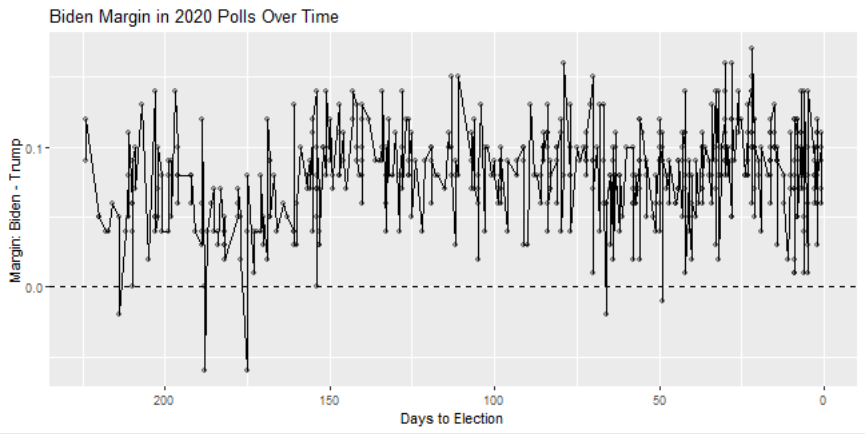
Margin by Time to Election

```
toplot %>%
  ggplot(aes(x = DaysToED,y = margin)) +
  geom_jitter(height = .005) +
  labs(title = 'Biden Margin in 2020 Polls Over Time',
       x = 'Days to Election',y = 'Margin: Biden - Trump') +
  scale_x_reverse() + geom_hline(yintercept = 0,linetype = 'dashed')
```



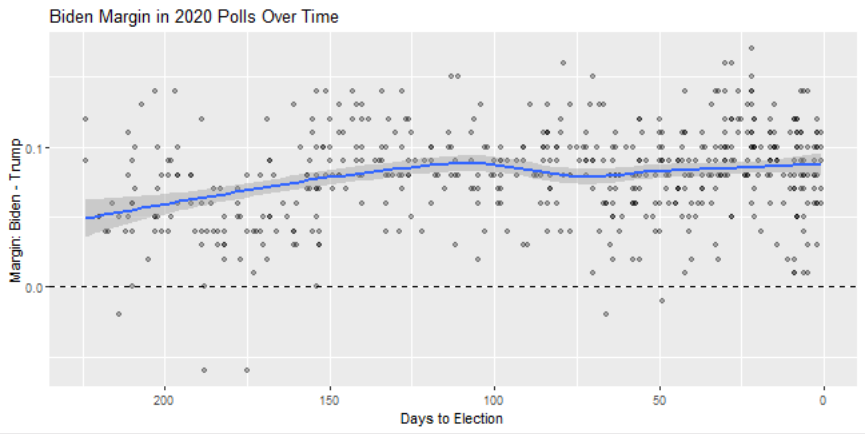
Highlight Trends

```
toplot %>%
  ggplot(aes(x = DaysToED,y = margin)) +
  geom_point(alpha = .3) +
  geom_line() +
  labs(title = 'Biden Margin in 2020 Polls Over Time',
       x = 'Days to Election',y = 'Margin: Biden - Trump') +
  scale_x_reverse() + geom_hline(yintercept = 0,linetype = 'dashed')
```



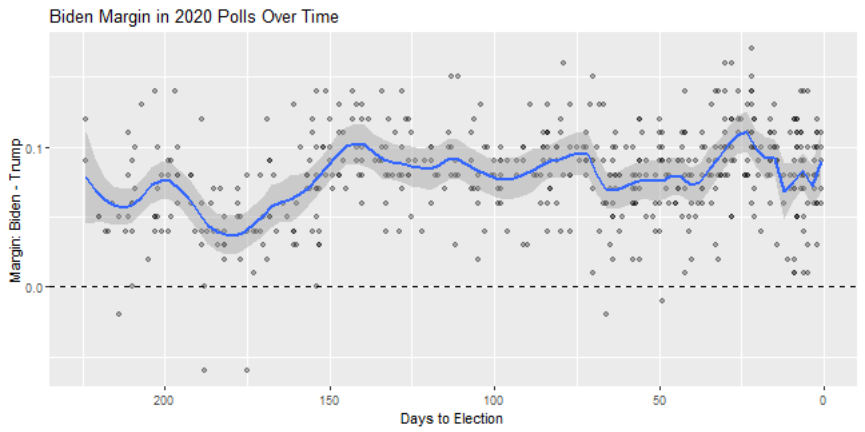
Highlight Trends

```
toplot %>%
  ggplot(aes(x = DaysToED,y = margin)) +
  geom_point(alpha = .3) +
  geom_smooth() +
  labs(title = 'Biden Margin in 2020 Polls Over Time',
       x = 'Days to Election',y = 'Margin: Biden - Trump') +
  scale_x_reverse() + geom_hline(yintercept = 0,linetype = 'dashed')
```



Highlight Trends

```
toplot %>%
  ggplot(aes(x = DaysToED,y = margin)) +
  geom_point(alpha = .3) +
  geom_smooth(span = .1) +
  labs(title = 'Biden Margin in 2020 Polls Over Time',
       x = 'Days to Election',y = 'Margin: Biden - Trump') +
  scale_x_reverse() + geom_hline(yintercept = 0,linetype = 'dashed')
```



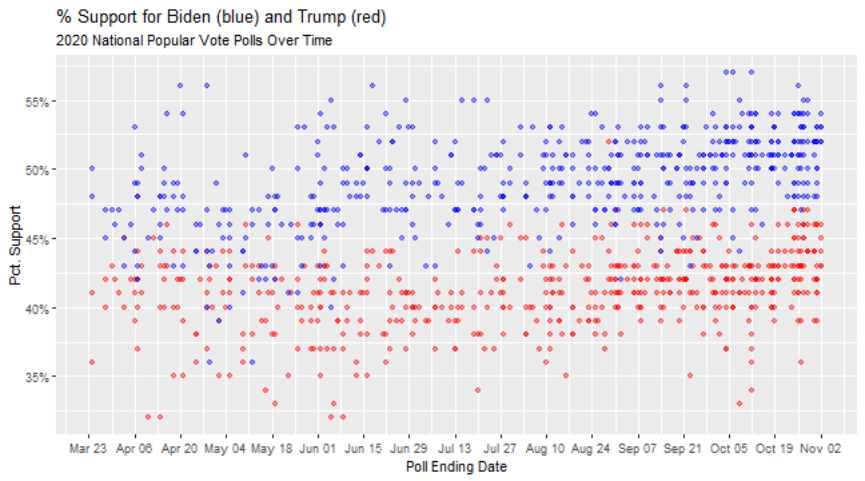
Multiple Variables over time

- We can look at multiple continuous variables at the same time
    - Use `color` or `fill` to distinguish

```
BidenTrumpplot <- toplot %>%
  ggplot()  +
  geom_point(aes(x = EndDate, y = Trump),
             color = "red", alpha=.4)  +
  geom_point(aes(x = EndDate, y = Biden),
             color = "blue", alpha=.4) +
  labs(title="% Support for Biden (blue) and Trump (red)",
       subtitle = "2020 National Popular Vote Polls Over Time",
       y = "Pct. Support",
       x = "Poll Ending Date") +
  scale_x_date(date_breaks = "2 week", date_labels = "%b %d") +
  scale_y_continuous(breaks=seq(.3,.7,by=.05),
                     labels= scales::percent_format(accuracy = 1))
```

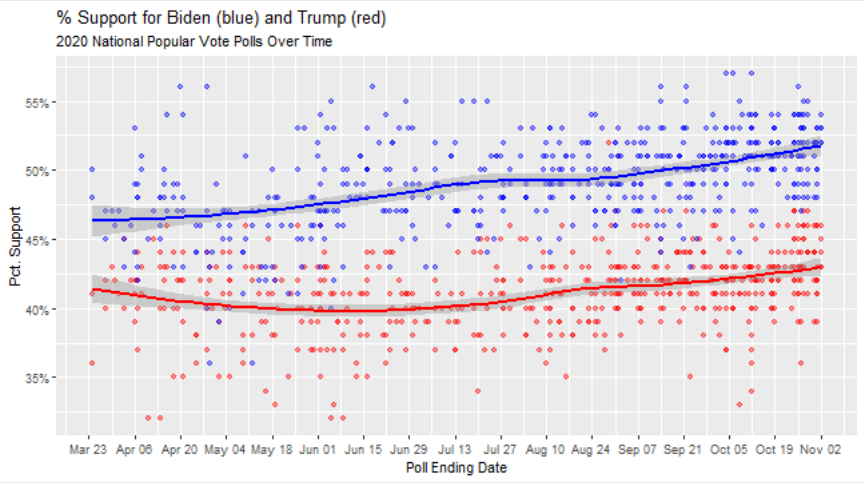
Multiple Variables over time

```
BidenTrumpplot
```



Highlighting Trends

```
BidenTrumpplot +
  geom_smooth(aes(x = EndDate, y = Trump),
              color = "red",se=T) +
  geom_smooth(aes(x = EndDate, y = Biden),
              color = "blue",se=T)
```



Typing back to theory

- Evidence of **both** Biden and Trump support increasing toward election
- Does this mean third party support waned?
- Does this mean that undecided voters made a decision?

2. Overtime Errors

- Wrangling to convert character dates to `date` class
- Plotting prediction errors over time

```
toplot <- poll %>%
  mutate(EndDate = as.Date(EndDate, "%m/%d/%Y"),
         StartDate = as.Date(StartDate, "%m/%d/%Y"),
         DaysToED = as.numeric(as.Date('11/3/2020',format = '%m/%d/%Y') - EndDate),
         margin = Biden - Trump,
         errDem = Biden - DemCertVote / 100,
         errRep = Trump - RepCertVote / 100)
```

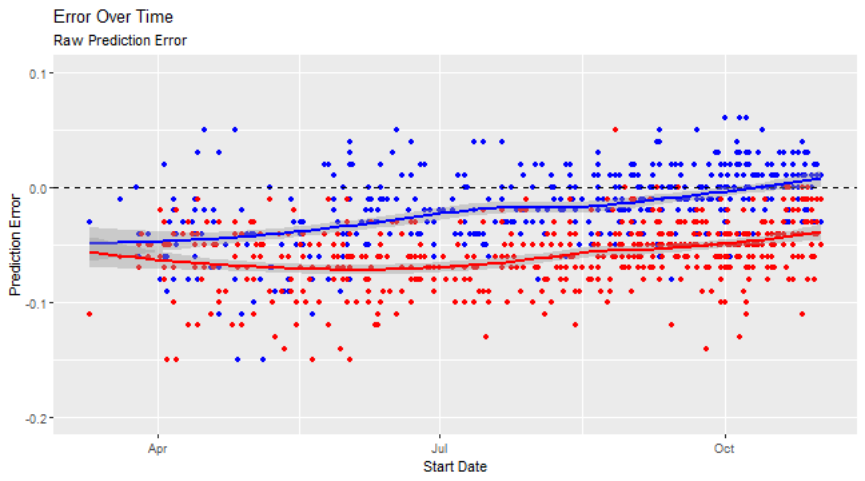
Overtime Errors

- Wrangling to convert character dates to `date` class
- Plotting prediction errors over time

```
pErrOverTime_Raw <- toplot  %>%
  ggplot(aes(x = StartDate)) +
  geom_point(aes(y = errDem),color = 'blue') +
  geom_point(aes(y = errRep),color = 'red') +
  geom_hline(yintercept = 0,linetype = 'dashed') +
  geom_smooth(aes(y = errDem),color = 'blue') +
  geom_smooth(aes(y = errRep),color = 'red') +
  labs(title = 'Error Over Time',subtitle = 'Raw Prediction Error',x = 'Start Date',y = 'Prediction Error') +
  ylim(c(-.2,.1))
```

Overtime Errors

```
pErrOverTime_Raw
```



Poll Quality

- Polls got better
  - ...but more for Biden than for Trump
- Poll quality:
  - Sample size
  - "Margin of Error" (`MoE`)

Weighting by Sample Size

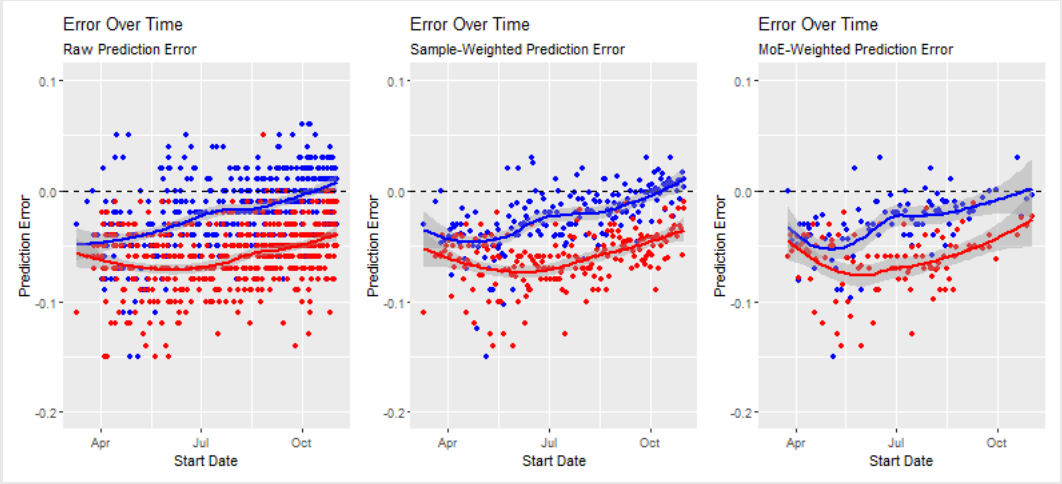
```
pErrOverTime_SampleSize <- toplot %>%
  group_by(StartDate) %>%
  summarise(errDem = weighted.mean(errDem,w = SampleSize),
            errRep = weighted.mean(errRep,w = SampleSize)) %>%
  ggplot(aes(x = StartDate)) +
  geom_point(aes(y = errDem),color = 'blue') +
  geom_point(aes(y = errRep),color = 'red') +
  geom_hline(yintercept = 0,linetype = 'dashed') +
  geom_smooth(aes(y = errDem),color = 'blue') +
  geom_smooth(aes(y = errRep),color = 'red') +
  labs(title = 'Error Over Time',subtitle = 'Sample-Weighted Prediction Error',x = 'Start Date',y =
'Prediction Error') +
  ylim(c(-.2,.1))
```

Weighting by Inverse of MoE

```
pErrOverTime_MoE <- toplot %>%
  group_by(StartDate) %>%
  summarise(errDem = weighted.mean(errDem,w = 1/MoE),
            errRep = weighted.mean(errRep,w = 1/MoE)) %>%
  ggplot(aes(x = StartDate)) +
  geom_point(aes(y = errDem),color = 'blue') +
  geom_point(aes(y = errRep),color = 'red') +
  geom_hline(yintercept = 0,linetype = 'dashed') +
  geom_smooth(aes(y = errDem),color = 'blue') +
  geom_smooth(aes(y = errRep),color = 'red') +
  labs(title = 'Error Over Time',subtitle = 'MoE-Weighted Prediction Error',x = 'Start Date',y = 'Prediction
Error') +
  ylim(c(-.2,.1))
```

Comparing

```
require(patchwork)
pErrOverTime_Raw + pErrOverTime_SampleSize + pErrOverTime_MoE
```



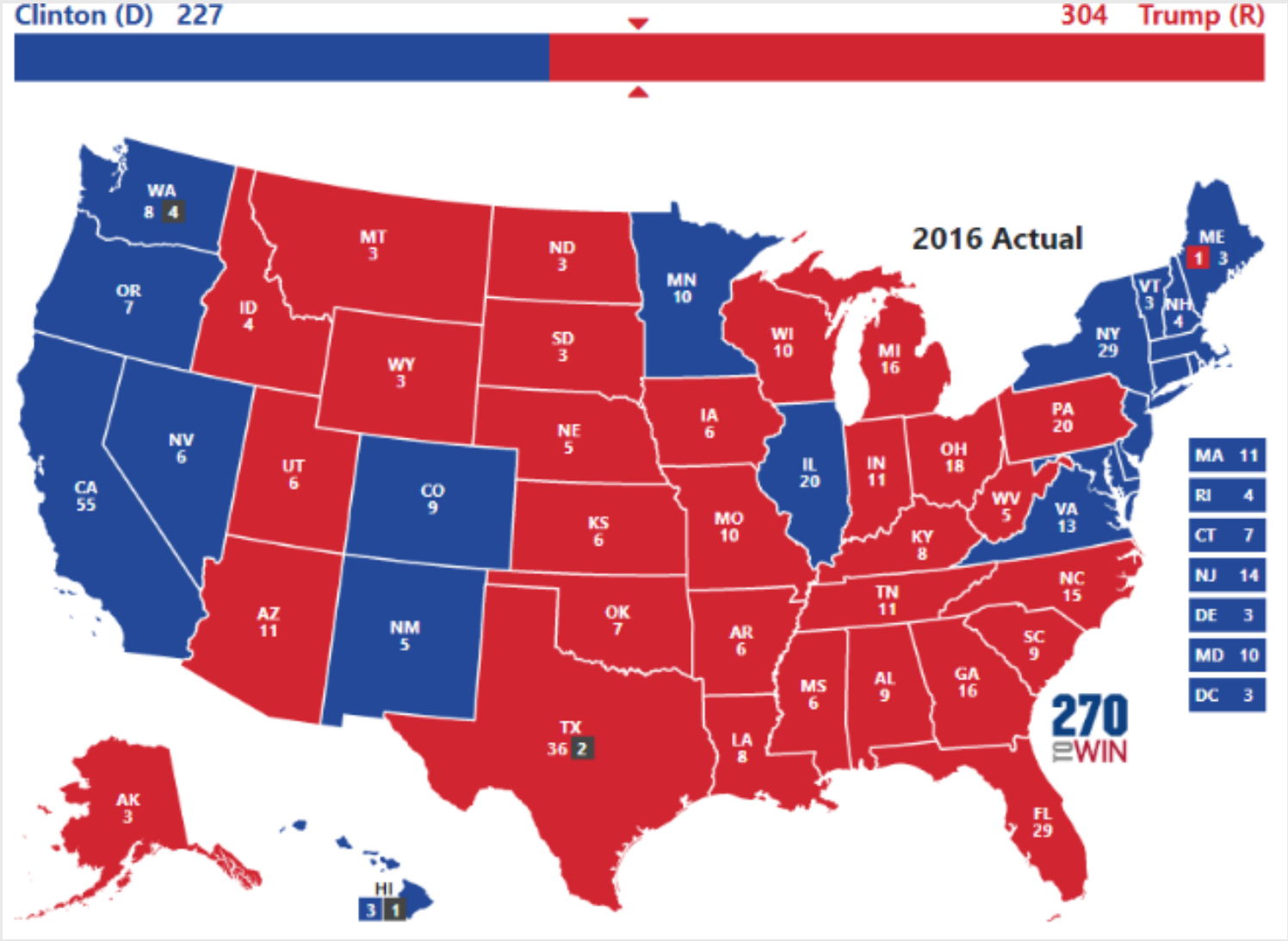
3. The Electoral College

- U.S. presidents determined by the **Electoral College** (EC)
  - Each state allocated votes equal to their "congressional delegation"
  - One vote per Senator + one vote per **M**ember **o**f **t**he **H**ouse (MotH)
  - 100 Senators + 435 MotHs + 3 votes for DC = 538 total votes
  - To win the presidency, you need at least 270 EC votes
- What does this mean for representation?
  - Population divided equally* across 435 MotHs
  - In 2020, each MotH represented 761,179 people
  - Geographic distribution of this population is **non-uniform**

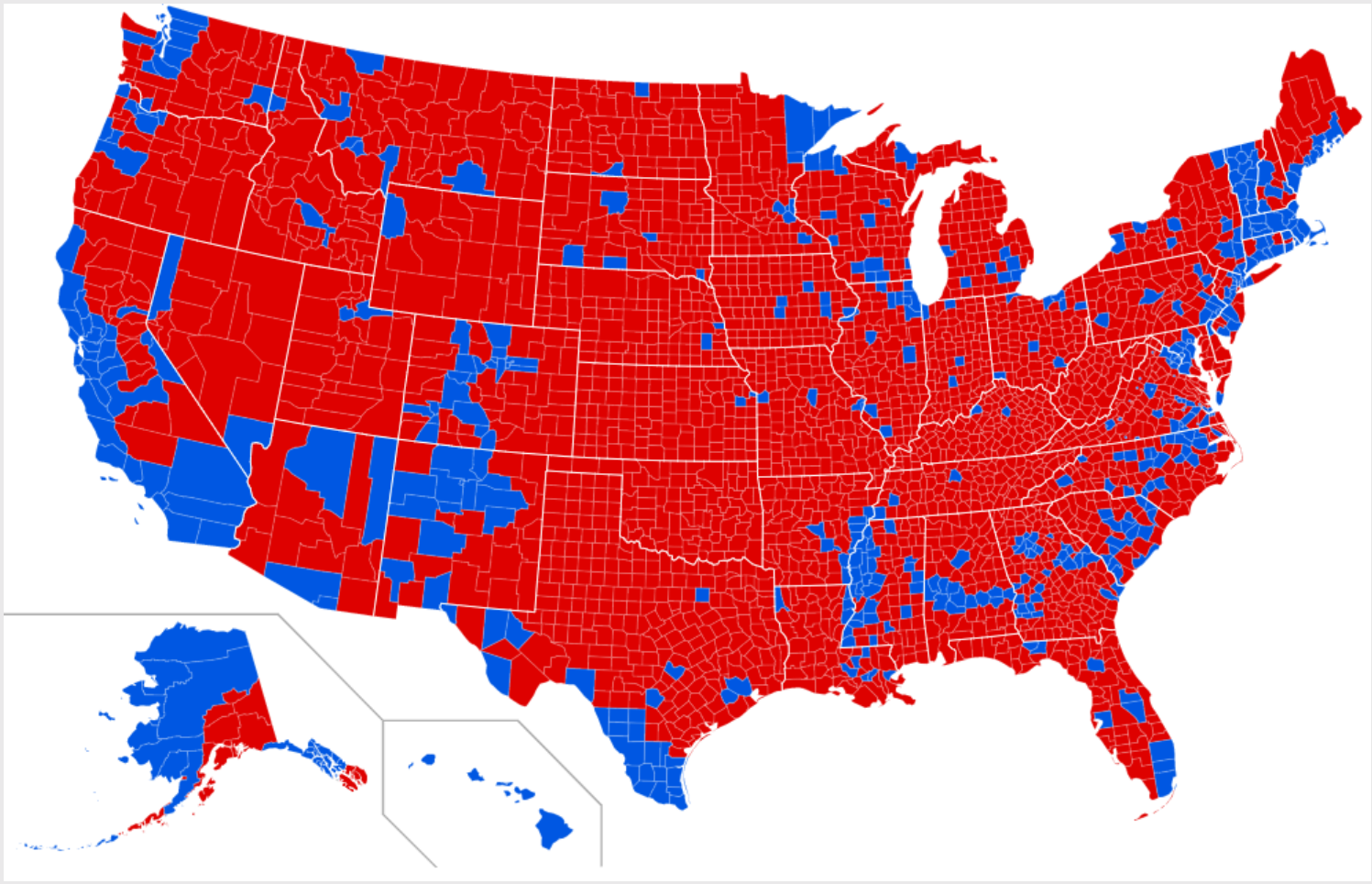
Assigning Districts

- Every 10 years, U.S. takes a census of its population
- Based on these results, congressional districts are reapportioned
- In 2010, Florida's pop. was ~19m & average pop. per MotH was ~710k
  - How many MotHs? `ceiling(19000000 / 710000)` = `27`
  - Every state has 2 senators, so FL had 27 + 2 = 29 EC votes
  - In 2020, FL pop. was 21m → each resident had 0.00000137 of a vote
- What about Vermont?
  - 3 EC votes / 624,340 residents = 0.00000481
- Vermonters have roughly 3.5 times the influence of Floridians!

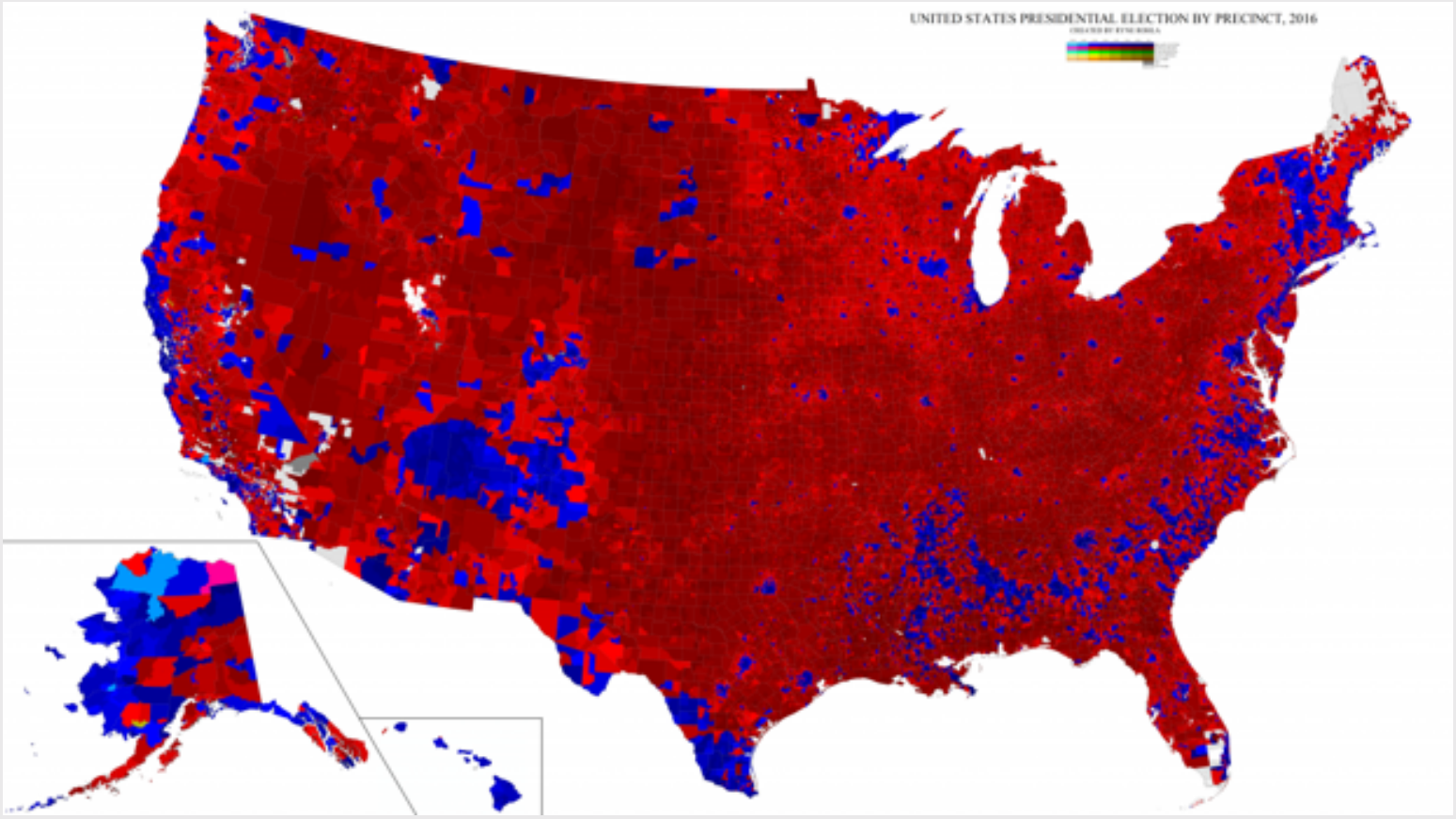
Data Viz Misleads!



Data Viz Misleads!

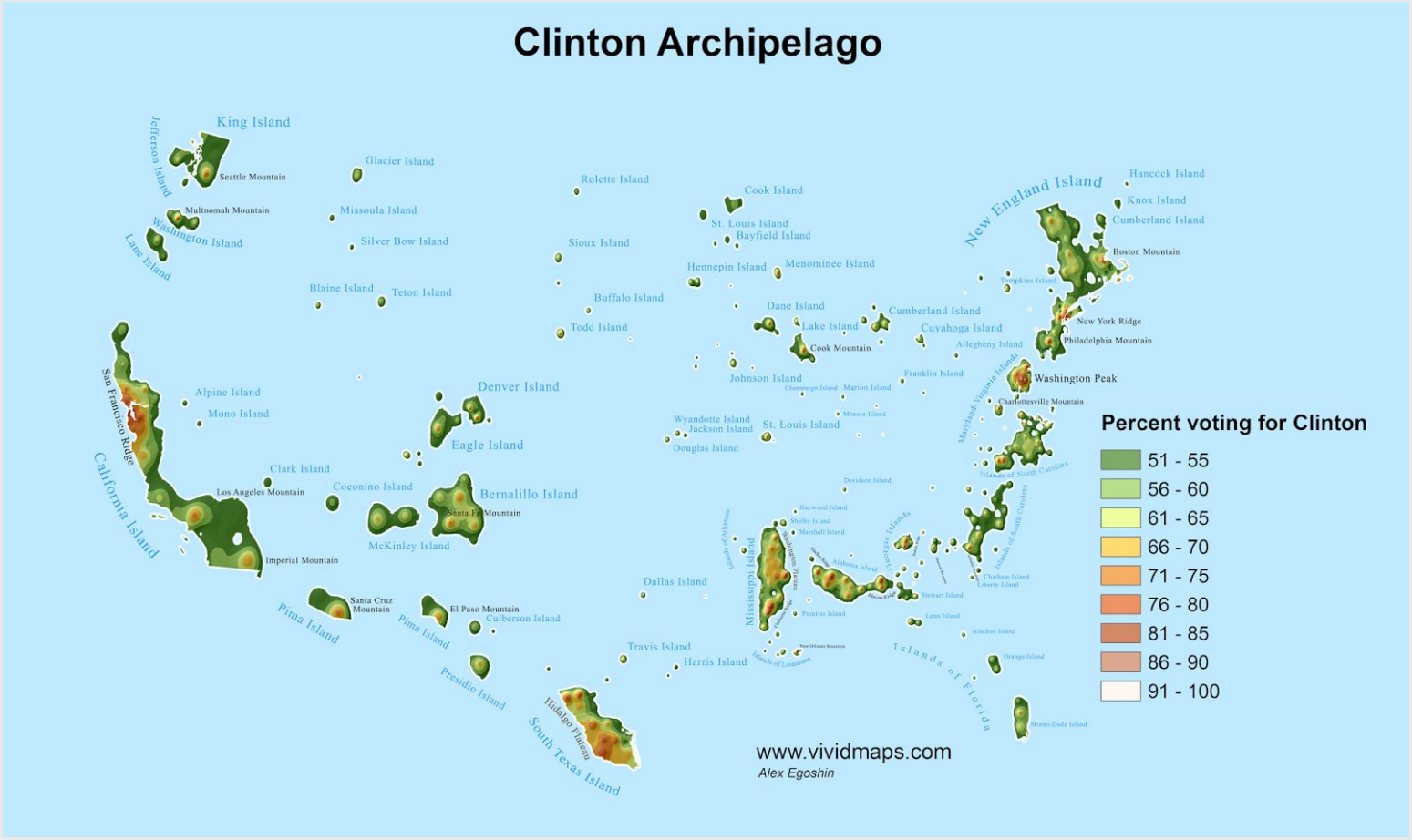


Data Viz Misleads!



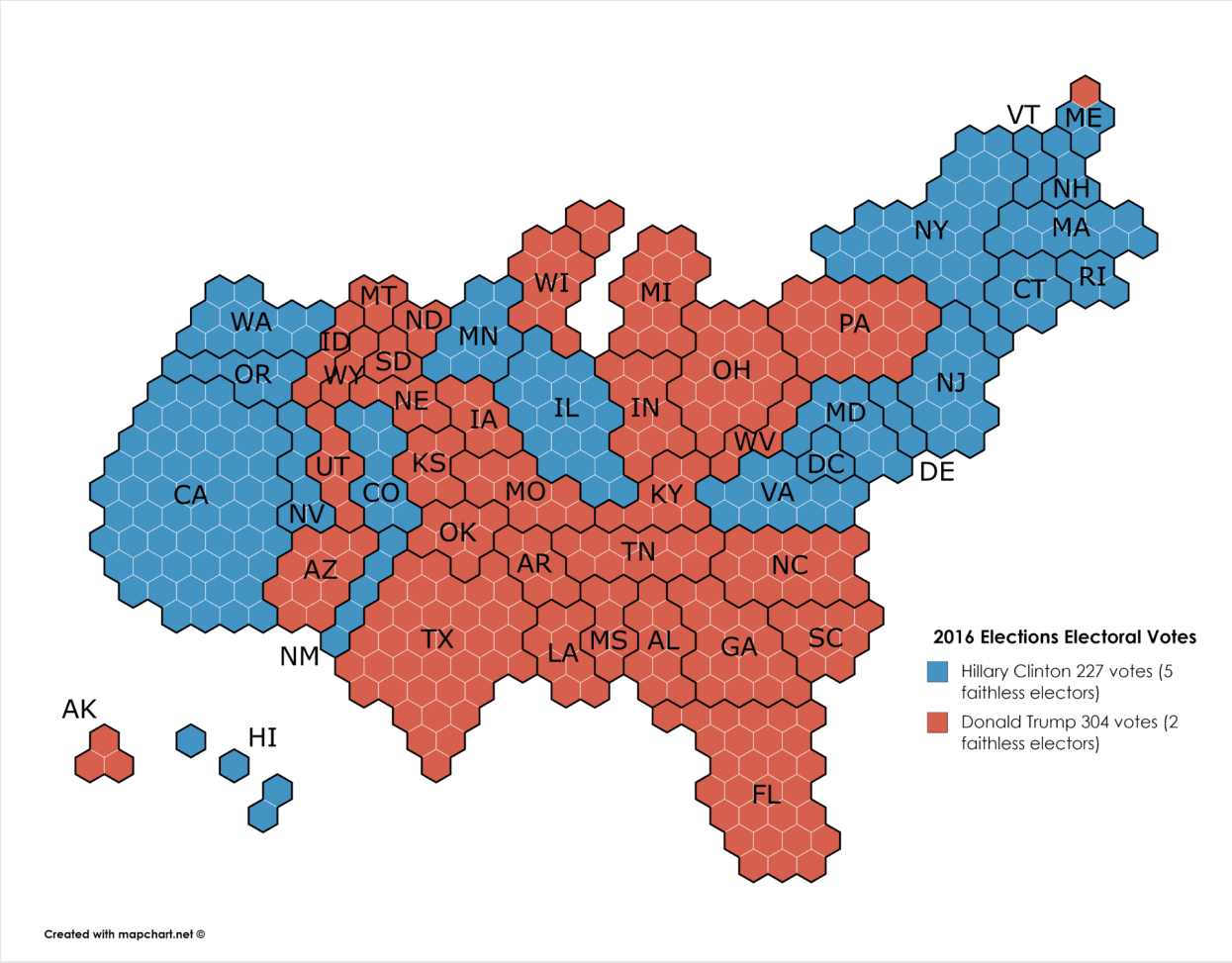
Data Viz Misleads!

Data Viz Misleads!



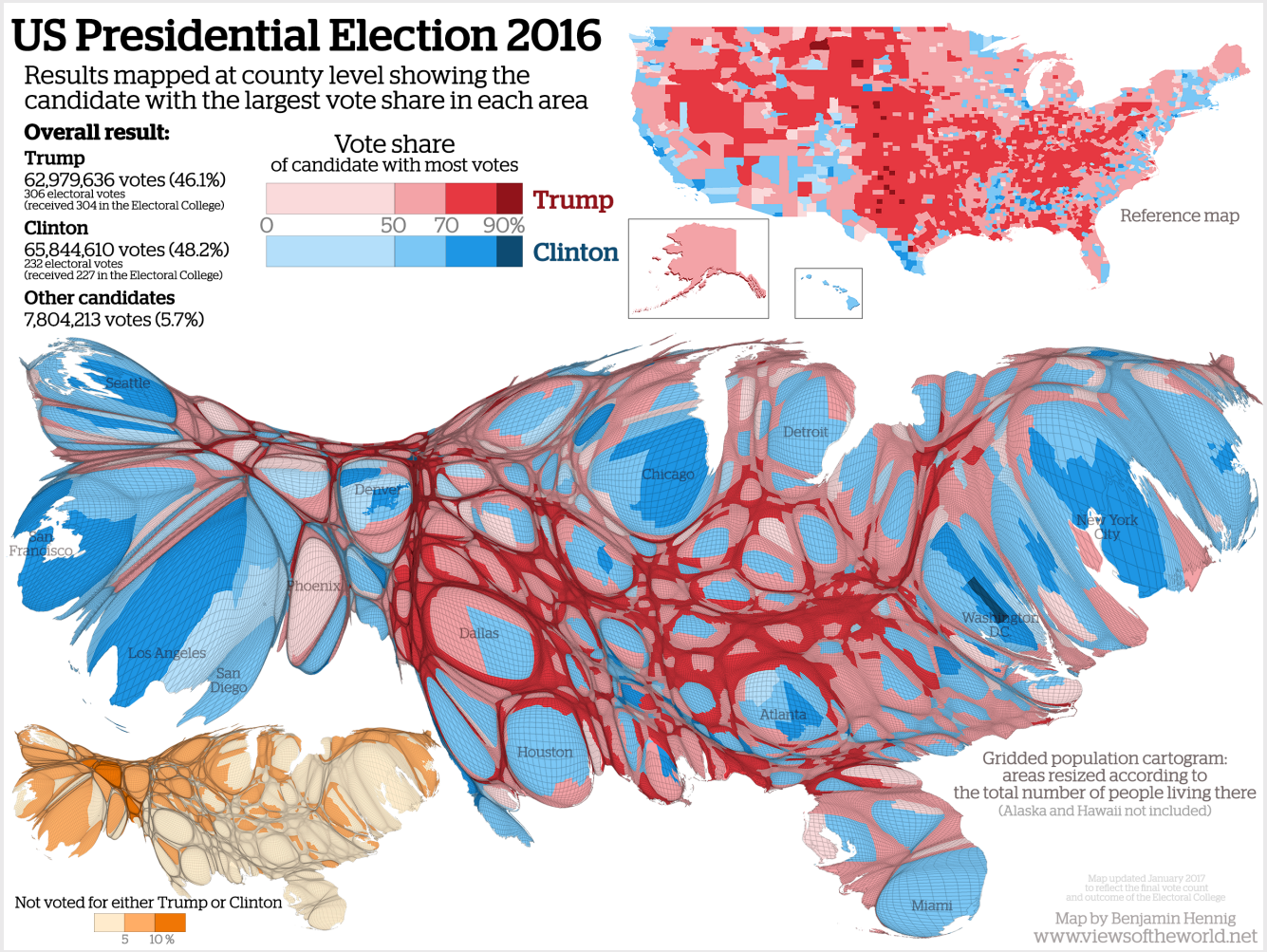
Correcting Maps

- Fundamental challenge due to distribution of population across land



Correcting Maps

- Fundamental challenge due to distribution of population across land



Introducing Data

- We will attempt to use state polls to predict 2020 winner
- National polls are great at predicting popular vote share...
- ...but presidents aren't elected based on popular vote
- With a few exceptions, states have a "winner take all" system
    - Winner of state's popular vote gets **all** of the state's EC votes
- Thus we need good state-level polls
- Load `Pres2020_StatePolls.Rds` to `statePoll` object

```
require(tidyverse)
statePoll <- readRDS('../data/Pres2020_StatePolls.Rds')
```

Look at the data

```
glimpse(statePoll)
```

```
## Rows: 1,545
## Columns: 19
## $ StartDate      <date> 2020-03-21, 2020-03-24, 2020-03-24…
## $ EndDate        <date> 2020-03-30, 2020-04-03, 2020-03-29…
## $ DaysinField    <dbl> 10, 11, 6, 2, 3, 5, 2, 2, 7, 3, 3, …
## $ MoE            <dbl> 2.8, 3.0, 4.2, NA, 4.0, 1.7, 3.0, 3…
## $ Mode           <chr> "Phone/Online", "Phone/Online", "Li…
## $ SampleSize     <dbl> 1331, 1000, 813, 962, 602, 3244, 10…
## $ Biden          <dbl> 41, 47, 48, 67, 46, 46, 46, 48, 52,…
## $ Trump          <dbl> 46, 34, 45, 29, 46, 40, 48, 45, 39,…
## $ Winner         <chr> "Rep", "Dem", "Dem", "Dem", "Dem", …
## $ poll.predicted <dbl> 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1,…
## $ Funded         <chr> "UtahPolicy.com & KUTV 2News", "Sac…
## $ Conducted      <chr> "Y2 Analytics", "GreatBlue Research…
## $ margin         <dbl> -5, 13, 3, 38, 0, 6, -2, 3, 13, -7,…
## $ DaysToED       <drtn> 218 days, 214 days, 219 days, 219 …
## $ StateName      <chr> "Utah", "Connecticut", "Wisconsin",…
## $ EV             <int> 6, 7, 10, 55, 16, 29, 16, 16, 12, 1…
## $ State          <chr> "UT", "CT", "WI", "CA", "MI", "FL",…
## $ BidenCertVote  <dbl> 38, 59, 49, 64, 51, 48, 50, 51, 58,…
## $ TrumpCertVote  <dbl> 58, 39, 49, 34, 48, 51, 49, 48, 39,…
```

Scientific Goal: Predict Winner

- Need to calculate predicted probability of Biden victory
  1. Fraction of polls with Biden in the lead
  2. Fraction of respondents supporting Biden
  3. Fraction of twoway respondents supporting Biden
- Wrangling time!

```
statePoll <- statePoll %>%
  mutate(Biden2W = Biden / (Biden+Trump),
         Biden = Biden / 100,
         Trump = Trump/100)

stateProbs <- statePoll %>%
  group_by(StateName,State) %>%
  summarise(BidenProb1 = mean(Biden > Trump),
            BidenProb2 = mean(Biden),
            BidenProb3 = mean(Biden2W),
            EV = mean(EV),.groups = 'drop') # This is just the value of EV
```

Looking at data

```
stateProbs
```

```
## # A tibble: 50 × 6
##    StateName   State BidenProb1 BidenProb2 BidenProb3    EV
##    <chr>       <chr>      <dbl>      <dbl>      <dbl> <dbl>
##  1 Alabama     AL         0          0.389      0.407     9
##  2 Alaska      AK         0          0.442      0.466     3
##  3 Arizona     AZ         0.840      0.484      0.519    11
##  4 Arkansas    AR         0          0.381      0.395     6
##  5 California  CA         1          0.618      0.661    55
##  6 Colorado    CO         1          0.534      0.571     9
##  7 Connecticut CT         1          0.584      0.631     7
##  8 Delaware    DE         1          0.603      0.627     3
##  9 Florida     FL         0.798      0.486      0.517    29
## 10 Georgia     GA         0.548      0.474      0.504    16
## # … with 40 more rows
```

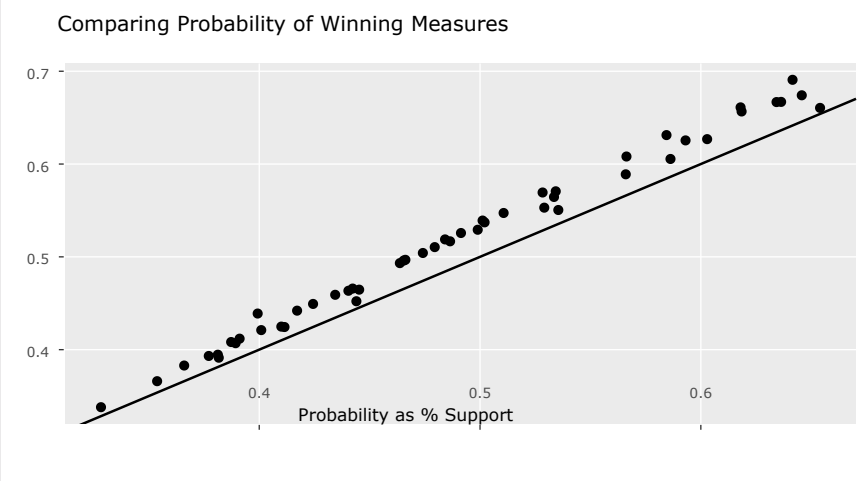
Visualizing Data

- `R` has fancy packages that allow for interactive plots (`plotly`)

```
# install.packages('plotly')
require(plotly)

gg <- stateProbs %>%
  ggplot(aes(x=BidenProb2, y=BidenProb3,text=paste(StateName))) +
  geom_point() +
  geom_abline(intercept=0,slope=1) +
  labs(x= "Probability as % Support",
       y = "Probability as Two-Party % Support",
       title = "Comparing Probability of Winning Measures")
```

Visualizing Data

```
ggplotly(gg,tooltip = 'text')
```



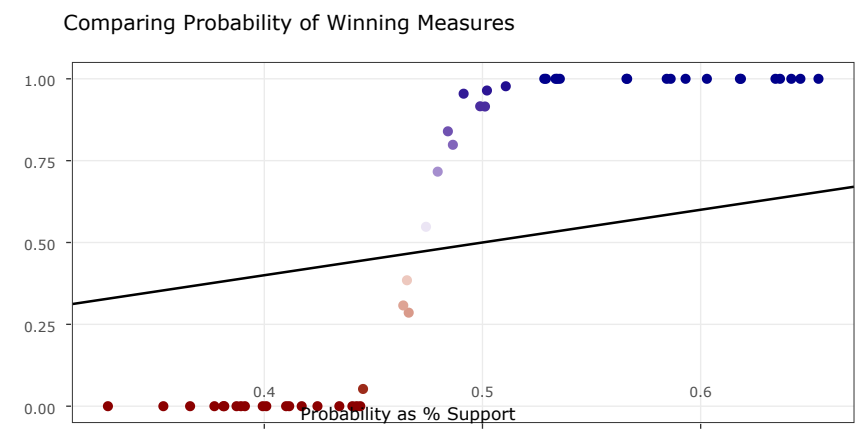
Visualizing Data

- What about the % of polls that predict a Biden victory?
    - I.e., we know Trump won't win California or Biden won't win Tennessee

```
gg <- stateProbs %>%
  ggplot(aes(x=BidenProb2, y=BidenProb1,text=paste(StateName),color = BidenProb1)) +
  geom_point() +
  geom_abline(intercept=0,slope=1) +
  labs(x= "Probability as % Support",
       y = "Probability as % Polls Winning",
       title = "Comparing Probability of Winning Measures") +
  scale_color_gradient2(guide = 'none',low = "darkred",mid = "white",high = "darkblue",midpoint = .5) +
  theme_bw()
```

Visualizing Data

```
ggplotly(gg,tooltip = 'text')
```



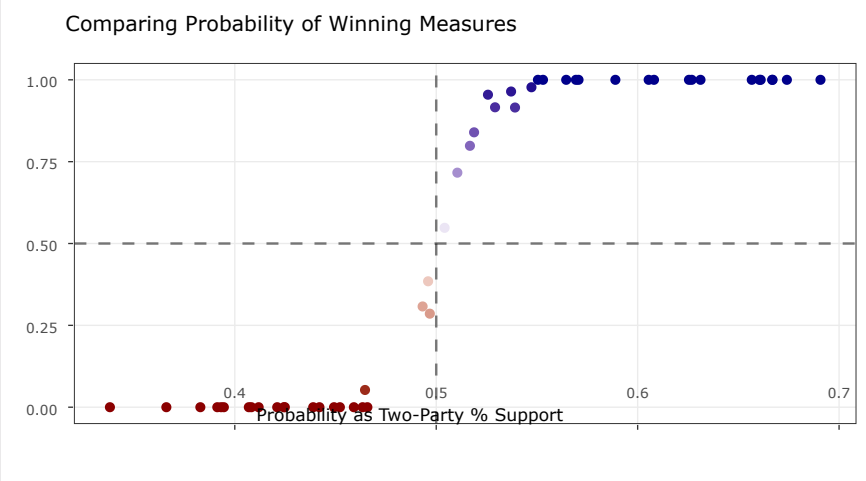
Visualizing Data

- Comparing to two-way

```
gg <- stateProbs %>%
  ggplot(aes(x=BidenProb3, y=BidenProb1,text=paste(StateName),color = BidenProb1)) +
  geom_point() +
  labs(x= "Probability as Two-Party % Support",
       y = "Probability as % Polls Winning",
       title = "Comparing Probability of Winning Measures") +
  scale_color_gradient2(guide = 'none',low = "darkred",mid = "white",high = "darkblue",midpoint = .5) +
  theme_bw() +
  geom_hline(yintercept = .5,linetype = 'dashed',alpha = .5) +
  geom_vline(xintercept = .5,linetype = 'dashed',alpha = .5)
```

Visualizing Data

```
ggplotly(gg,tooltip = 'text')
```



Translate to EC Votes

- Start with a single state to get the idea
- **Expected Value** (EV...could also be Expected Votes): Probability * Value

```
stateProbs %>%
  filter(State == 'PA') %>%
  mutate(BEV1 = BidenProb1 * EV,
         BEV2 = BidenProb2 * EV,
         BEV3 = BidenProb3 * EV) %>%
  select(EV,matches('^B.*\\d'))
```

```
## # A tibble: 1 × 7
##      EV BidenProb1 BidenProb2 BidenProb3  BEV1  BEV2  BEV3
##   <dbl>      <dbl>      <dbl>      <dbl> <dbl> <dbl> <dbl>
## 1    20      0.916      0.499      0.529  18.3  9.98  10.6
```

- Probability matters! Biden could get between 18.3 and 9.98 votes in PA!

Translate to EC Votes

- Do this for every state

```
stateProbs %>%
  mutate(BidenEV1 = BidenProb1 * EV,
         BidenEV2 = BidenProb2 * EV,
         BidenEV3 = BidenProb3 * EV,
         TrumpEV1 = EV - BidenEV1,
         TrumpEV2 = EV - BidenEV2,
         TrumpEV3 = EV - BidenEV3) %>%
  summarise_at(vars(matches('EV\\d')),sum) # Fancy shortcut!
```

```
## # A tibble: 1 × 6
##   BidenEV1 BidenEV2 BidenEV3 TrumpEV1 TrumpEV2 TrumpEV3
##      <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
## 1     345.     272.     289.     190.     263.     246.
```

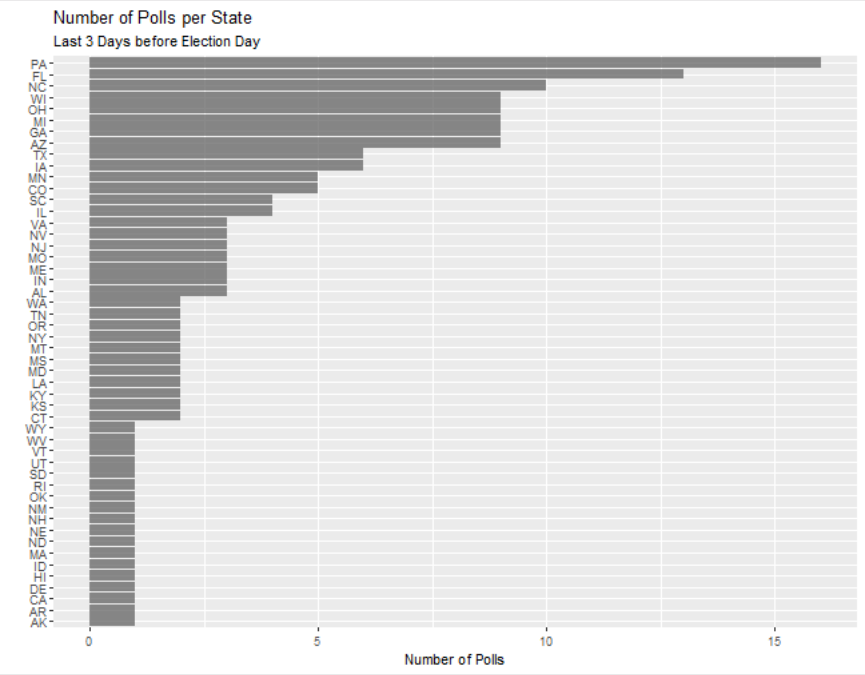
- Overall EC votes *always* favored Biden (always above 270)
- But none of our estimates are close to the true outcome of 306 to 232

Science Questions

- We know that **national** polls changed closer to election
- Can we do better if we look only at **state** polls close to election day?
- Data limitations!

```
pollsPerState <- statePoll %>%
  filter(DaysToED <= 3) %>%
  count(State) %>%
  ggplot(aes(x = n,y = reorder(State,n))) +
  geom_bar(stat = 'identity',alpha = .7) +
  labs(title = 'Number of Polls per State',
       subtitle = 'Last 3 Days before Election Day',
       x = 'Number of Polls',
       y = '')
```

Data Limitations



Do better with recent polls?

```
statePoll %>%
  filter(DaysToED <= 3) %>%
  group_by(StateName,State) %>%
  summarise(BidenProb1 = mean(Biden > Trump),
            BidenProb2 = mean(Biden),
            BidenProb3 = mean(Biden2W),
            EV = mean(EV),.groups = 'drop') %>%
  mutate(BidenEV1 = BidenProb1 * EV,
         BidenEV2 = BidenProb2 * EV,
         BidenEV3 = BidenProb3 * EV,
         TrumpEV1 = EV - BidenEV1,
         TrumpEV2 = EV - BidenEV2,
         TrumpEV3 = EV - BidenEV3) %>%
  summarise_at(vars(matches('EV\\d')),sum)
```

```
## # A tibble: 1 × 6
##   BidenEV1 BidenEV2 BidenEV3 TrumpEV1 TrumpEV2 TrumpEV3
##      <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
## 1     334.     277.     285.     201.     258.     250.
```

Conclusion

- Still not nailing the true votes!
  - Not even within the distributions of the bootstrapped estimates!
- Why?
  1. Polls have their own uncertainty (could weight by total respondents?)
  2. Polls might not be representative of voters
  3. Polls might not be independent of each other

Quiz & Homework

- Go to Brightspace and take the **8th** quiz
  - The password to take the quiz is ####
- **Homework:**
  1. Work through Multivariate_Analysis_part3_hw.Rmd
  2. Start on Problem Set 4 (Brightspace)