Multivariate Analysis

Part 1: Conditional Relationships

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Agenda

1. Mutivariate
2. What is "conditional"?
3. (Re-)Introducing the data
4. Visualization Principles

Definition

- Multi + variate
    - Many + variables
    - Analysis of multiple variables
- When we analyze **multiple** variables, we are in the world of "conditional analysis"

What is conditional?

- Put simply: "conditional" means "depending on"
  - I.e., How does a variable of interest vary *depending on* some other variable?
  - "Variable of interest": the **outcome** (or **dependent** variable Y)
  - "Some other variable": the **predictor** (or **independent** variable X)
  - "Vary depending on": the **relationship**
- Mapping concepts into data science
  - The relationship between the outcome and the predictor

What is conditional?

- "Depending on" suggests a **causal** interpretation
  - High wages "depend on" education → education **causes** high wages
  - In theory, this is reasonable: students acquire skills in school which are valued by the labor market.
  - But the positive correlation between education and wages might also be **"spurious"**
  - Higher education *AND* higher wages are outcomes of some **true cause** (i.e., upbringing, SES, etc.)

NOTE: The logic for why a relationship might be spurious is itself CAUSAL.

(Re-)Introducing the Data

- Using the Michigan exit poll data
- Download pre-wrangled data from GitHub and save to your `data` folder.
- `require(tidyverse)` and `readRDS()` the data to `mi_ep` object

```
require(tidyverse)

mi_ep <- read_rds('../data/MI2020_ExitPoll_small.Rds')
```

Some Light Data Science

- The "gender gap" in Trump support
- Theory: Trump has expressed sexist views against women. Therefore, women should be less likely to support him.
    - **NOTE** the causal assumptions in this theory!
- Analysis: compare support for Trump among men and women
- But first, some quick data wrangling

```
MI_final_small <- mi_ep %>%
  filter(preschoice=="Donald Trump, the Republican" |
preschoice=="Joe Biden, the Democrat") %>%
  mutate(BidenVoter=ifelse(preschoice=="Joe Biden, the
Democrat",1,0),
         TrumpVoter=ifelse(BidenVoter==1,0,1),
         AGE10=ifelse(AGE10==99,NA,AGE10))
```

Conditional Means

```
MI_final_small %>%
  count(preschoice,SEX) %>%
  mutate(PctSupport = n/sum(n),
         PctSupport = round(PctSupport, digits=2))
```

```
## # A tibble: 4 × 4
##   preschoice                          SEX     n PctSupport
##   <chr>                             <dbl> <int>      <dbl>
## 1 Donald Trump, the Republican          1   247       0.21
## 2 Donald Trump, the Republican          2   212       0.18
## 3 Joe Biden, the Democrat               1   304       0.26
## 4 Joe Biden, the Democrat               2   419       0.35
```

- Results are **consistent** with the theory
  - NB: results do not **prove** the theory

Conditional Means

- However, note that these proportions are out of *all* voters.
- This isn't directly addressing the theory
  - We want to know the proportion **of women** who supported Trump

```
MI_final_small %>%
  count(preschoice,SEX) %>%
  group_by(SEX) %>%
  mutate(totGender = sum(n)) %>%
  mutate(pctSupport = n / totGender)
```

```
## # A tibble: 4 × 5
## # Groups:   SEX [2]
##   preschoice                          SEX     n totGender pctSu…¹
##   <chr>                             <dbl> <int>     <int>   <dbl>
## 1 Donald Trump, the Republican          1   247       551   0.448
## 2 Donald Trump, the Republican          2   212       631   0.336
## 3 Joe Biden, the Democrat               1   304       551   0.552
## 4 Joe Biden, the Democrat               2   419       631   0.664
## # … with abbreviated variable name ¹pctSupport
```

Additional Theorizing

- The strength of the theorized relationship might vary by age
    - Younger women might be more offended by Trump's casual sexism
    - Older women might be more inured to Trump's casual sexism
- Theory: the "gender gap" will be larger among younger voters
    - (But also recognize that younger Americans are generally more progressive...meaning that **both** younger men and women are more offended by Trump's casual sexism!)

Two-Way Conditional Means

- We could just subset with `filter()`

```
MI_final_small %>%
  filter(AGE10==1) %>%
  group_by(SEX) %>%
  count(preschoice) %>%
  mutate(PctSupport = n/sum(n),
         PctSupport = round(PctSupport, digits=2))
```

```
## # A tibble: 4 × 4
## # Groups:   SEX [2]
##     SEX preschoice                          n PctSupport
##   <dbl> <chr>                           <int>      <dbl>
## 1     1 Donald Trump, the Republican        7       0.44
## 2     1 Joe Biden, the Democrat             9       0.56
## 3     2 Donald Trump, the Republican        1       0.06
## 4     2 Joe Biden, the Democrat            15       0.94
```

Two-Way Conditional Means

- Or we could add `AGE10` to the `group_by`

```
MI_final_small %>%
  group_by(SEX, AGE10) %>%
  summarize(PctTrump = mean(TrumpVoter),.groups = 'drop') %>%
  mutate(PctTrump = round(PctTrump, digits =2))
```

```
## # A tibble: 22 × 3
##      SEX AGE10 PctTrump
##    <dbl> <dbl>    <dbl>
##  1     1     1     0.44
##  2     1     2     0.42
##  3     1     3     0.42
##  4     1     4     0.24
##  5     1     5     0.42
##  6     1     6     0.58
##  7     1     7     0.54
##  8     1     8     0.44
##  9     1     9     0.39
## 10     1    10     0.43
## # … with 12 more rows
```

Two-Way Conditional Means

- A little hard to make comparisons

```
MI_final_small %>%
  group_by(SEX, AGE10) %>%
  summarize(PctTrump = mean(TrumpVoter),.groups = 'drop') %>%
  spread(SEX,PctTrump) %>% rename(Male = `1`,Female = `2`)
```

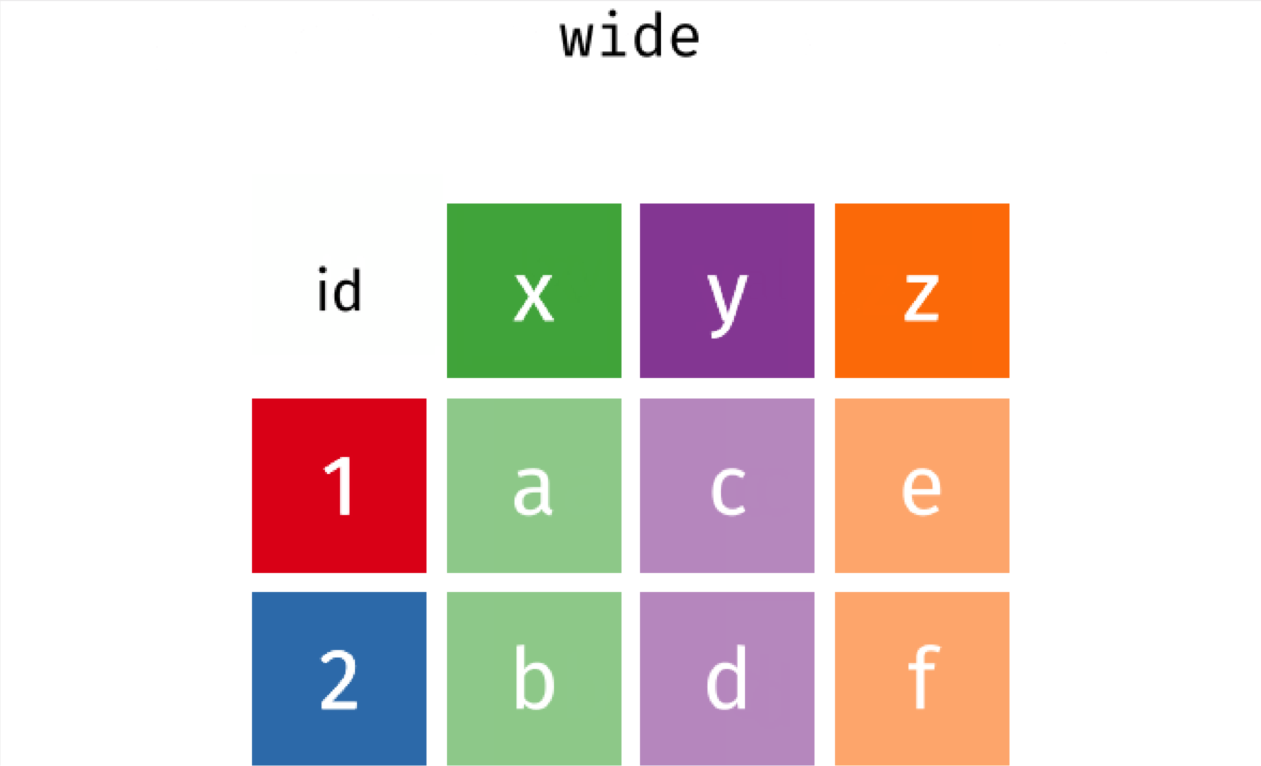
```
## # A tibble: 11 × 3
##    AGE10  Male Female
##    <dbl> <dbl>  <dbl>
##  1     1 0.438 0.0625
##  2     2 0.417 0.0714
##  3     3 0.423 0.308
##  4     4 0.241 0.294
##  5     5 0.419 0.484
##  6     6 0.583 0.4
##  7     7 0.537 0.367
##  8     8 0.443 0.263
##  9     9 0.395 0.311
## 10    10 0.425 0.387
## 11    NA 0.667 0.571
```

Introducing `spread()` & `gather()`

- Data in `R` is either "long" or "wide"
- **Long**: One column for a categorical label and multiple rows
  - I.e., For each age group, we have one **row** for men and one **row** for women
- **Wide**: Multiple columns for each categorical label and a single row
  - I.e., For each age group, we have one **column** for men and one **column** for women
- In `R`, we can switch between **wide** and **long** with two functions:
  1. `spread()` (or `pivot_wider()`): converts from long to wide
  2. `gather()` (or `pivot_longer()`): converts from wide to long

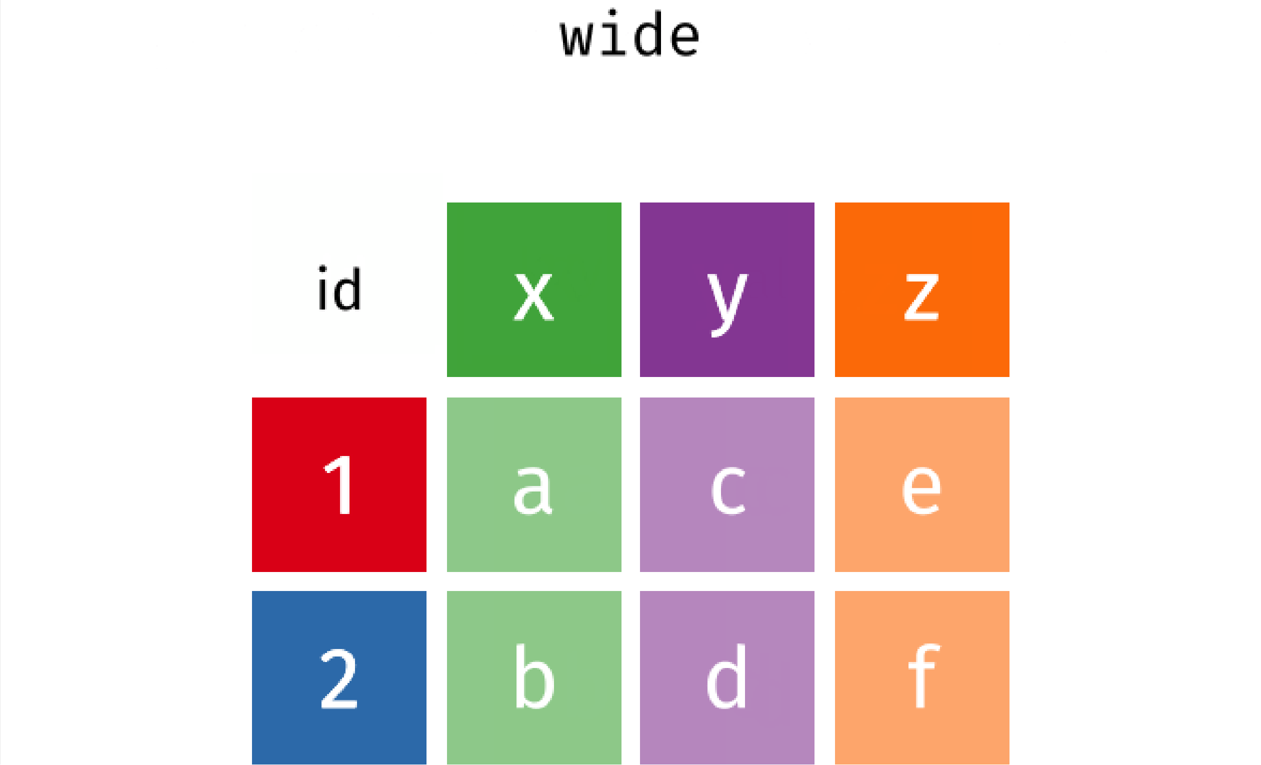
`spread()` and `gather()`

- `spread([key],[value])`
  - `key`: variable containing categories to make into columns labels
  - `value`: variable containing values put into these new columns



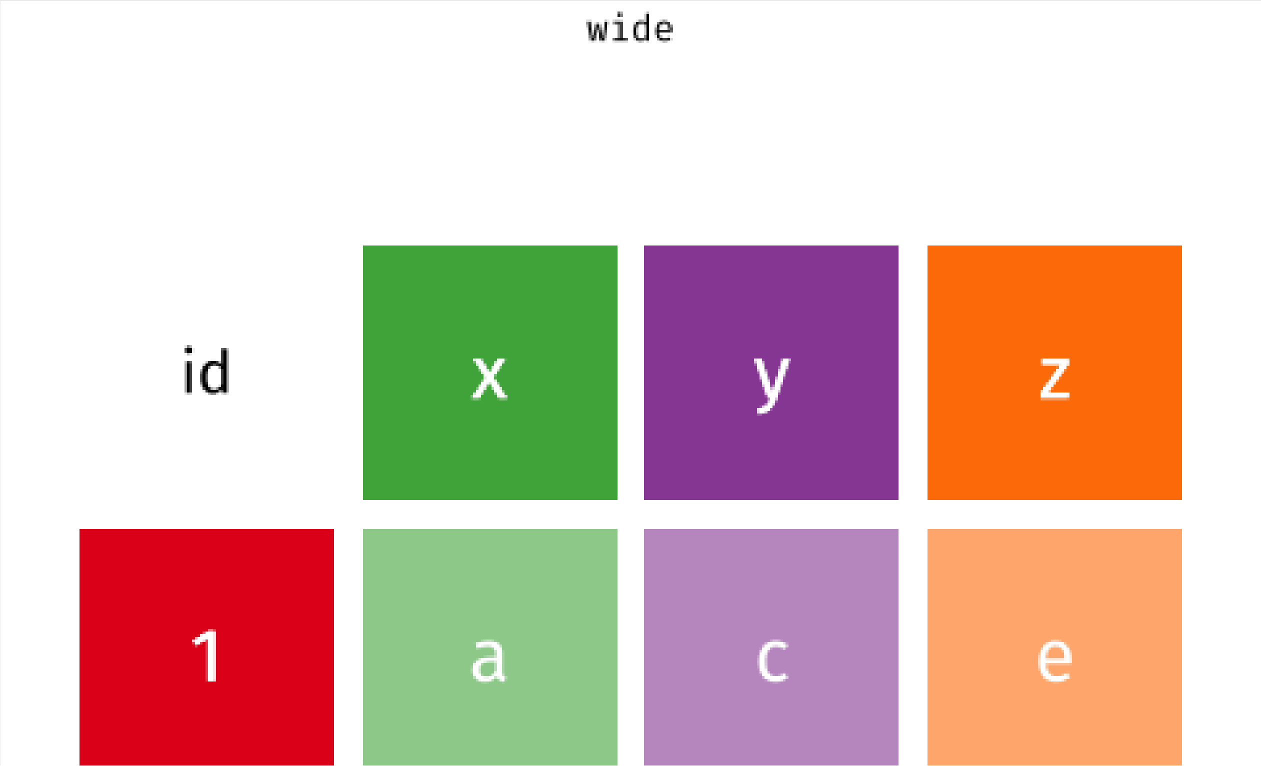
`spread()` and `gather()`

- `gather([key],[value],[columns])`
    - `key`: name of **new column** that contains categories
    - `value`: values you want to put into this new column



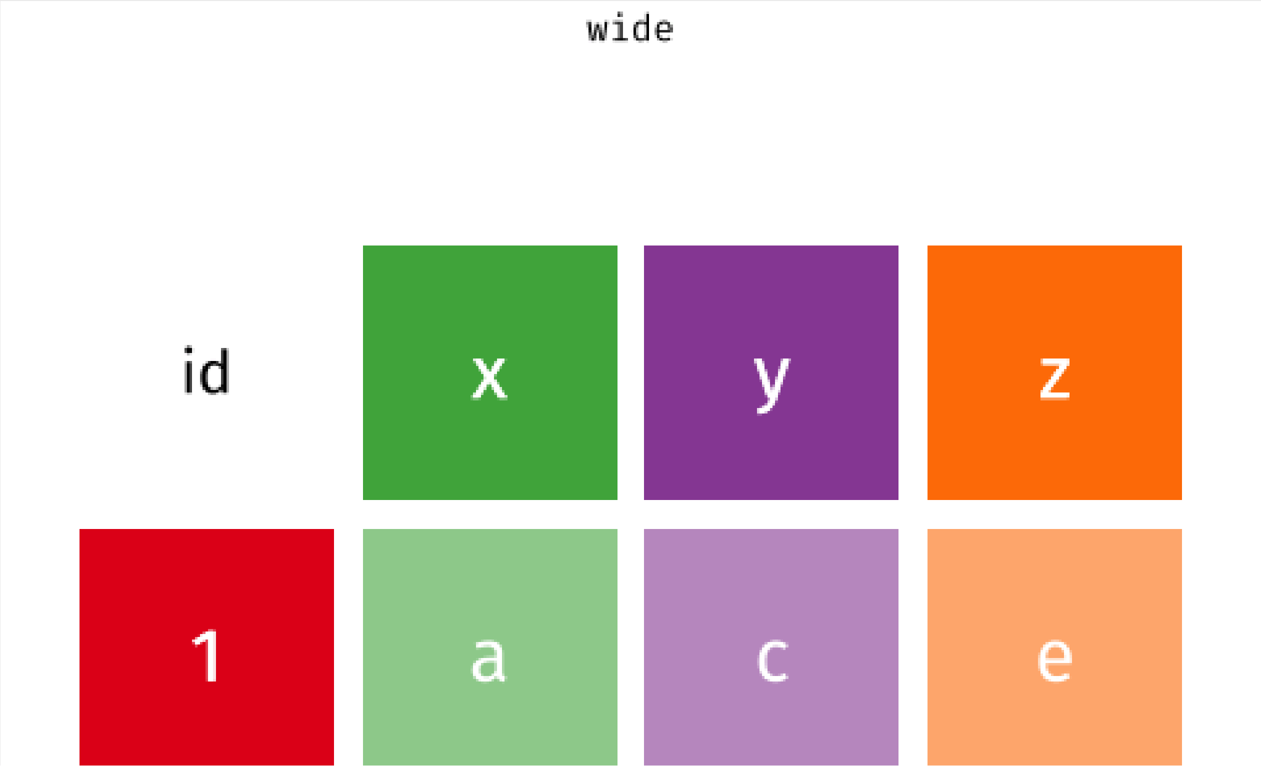
pivot_wider()

- `pivot_wider([names_from],[values_from])`
  - `names_from`: variable containing categories to make into column labels
  - `values_from`: variable containing values put into these new columns



OR pivot_longer()

- `pivot_longer([names_from],[values_from])`
  - `names_from`: variable containing categories to make into column labels
  - `values_from`: variable containing values put into these new columns



spread()

```
MI_final_small %>%
  group_by(SEX, AGE10) %>%
  summarize(PctTrump = mean(TrumpVoter),.groups = 'drop') %>%
  spread(key = SEX,value = PctTrump,fill = NA) %>%
  rename(Male = `1`,Female = `2`)
```

```
## # A tibble: 11 × 3
##    AGE10  Male Female
##    <dbl> <dbl>  <dbl>
##  1     1 0.438 0.0625
##  2     2 0.417 0.0714
##  3     3 0.423 0.308
##  4     4 0.241 0.294
##  5     5 0.419 0.484
##  6     6 0.583 0.4
##  7     7 0.537 0.367
##  8     8 0.443 0.263
##  9     9 0.395 0.311
## 10    10 0.425 0.387
## 11    NA 0.667 0.571
```

gather()

```
MI_final_small %>%
  group_by(SEX, AGE10) %>%
  summarize(PctTrump = mean(TrumpVoter),.groups = 'drop') %>%
  spread(key = SEX,value = PctTrump,fill = NA) %>%
  rename(Male = `1`,Female = `2`) %>%
  gather(SEX,PctTrump,-AGE10)
```

```
## # A tibble: 22 × 3
##    AGE10 SEX   PctTrump
##    <dbl> <chr>    <dbl>
##  1     1 Male     0.438
##  2     2 Male     0.417
##  3     3 Male     0.423
##  4     4 Male     0.241
##  5     5 Male     0.419
##  6     6 Male     0.583
##  7     7 Male     0.537
##  8     8 Male     0.443
##  9     9 Male     0.395
## 10    10 Male     0.425
## # … with 12 more rows
```

Save Summary for Later Use

```
SexAge <- MI_final_small %>%
  group_by(SEX, AGE10) %>%
  summarize(PctTrump = mean(TrumpVoter),.groups = 'drop')

SexAge %>% filter(SEX == 2)
```

```
## # A tibble: 11 × 3
##       SEX AGE10 PctTrump
##     <dbl> <dbl>    <dbl>
##  1      2     1   0.0625
##  2      2     2   0.0714
##  3      2     3   0.308
##  4      2     4   0.294
##  5      2     5   0.484
##  6      2     6   0.4
##  7      2     7   0.367
##  8      2     8   0.263
##  9      2     9   0.311
## 10      2    10   0.387
## 11      2    NA   0.571
```

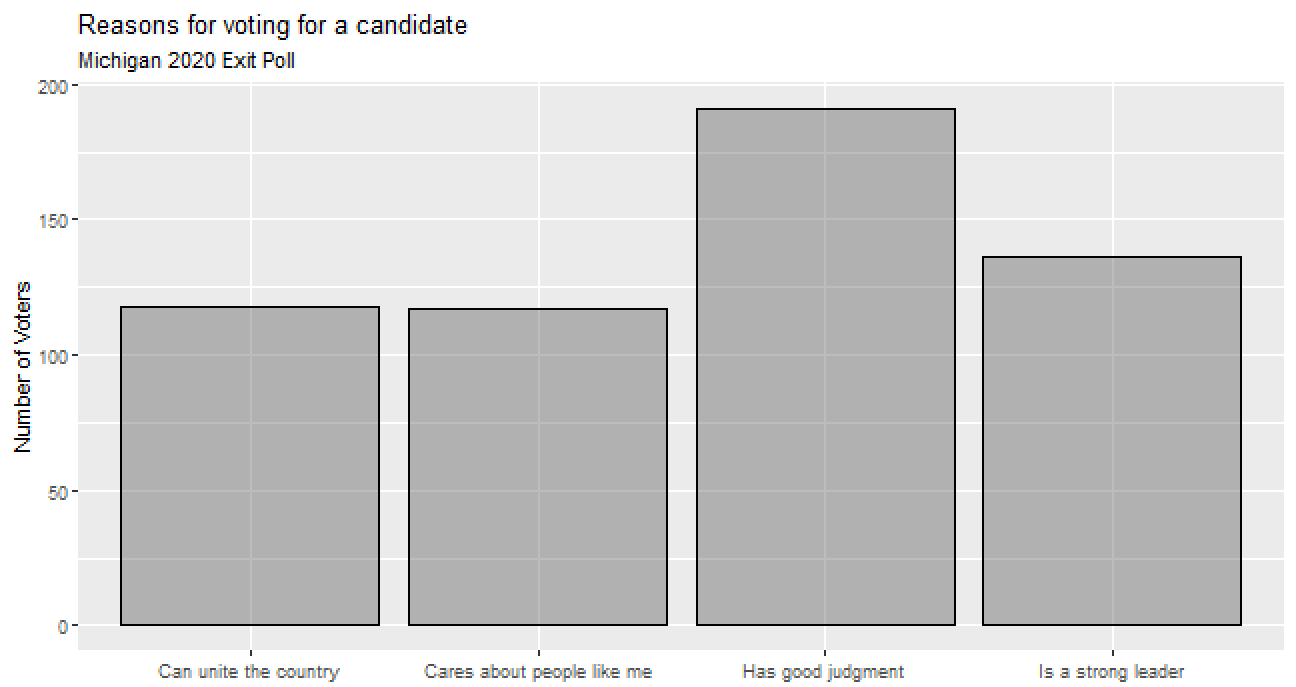
Conditional Categorical Analysis

- Want to know **reason** for voting for candidate by **vote choice**
  - `Quality`: 4 category unordered
  - `preschoice`: 2 category unordered
- Some light data wrangling

```
toplot <- mi_ep %>%
    select(Quality,preschoice,SEX) %>%
    filter(grepl('Biden|Trump',preschoice)) %>%
    drop_na() %>%
    filter(Quality != "[DON'T READ] Don’t know/refused")
```

Conditional Categorical Analysis

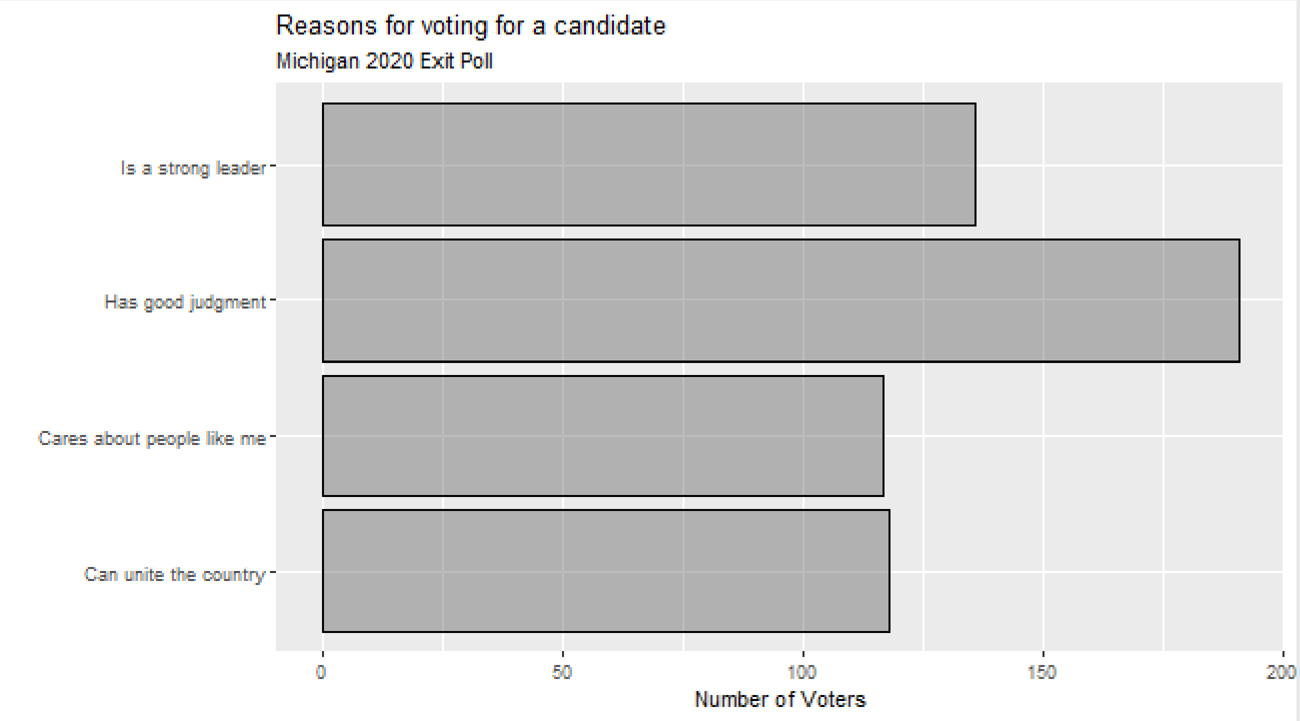
```
(pReasonOverall <- toplot %>%
  ggplot(aes(x = Quality)) +
  labs(y = "Number of Voters",x = "",
         title = "Reasons for voting for a candidate",
       subtitle = "Michigan 2020 Exit Poll") +
    geom_bar(color="black",alpha = .4))
```



Conditional Categorical Analysis

- Can swap axes with `coord_flip()`

```
pReasonOverall + coord_flip()
```



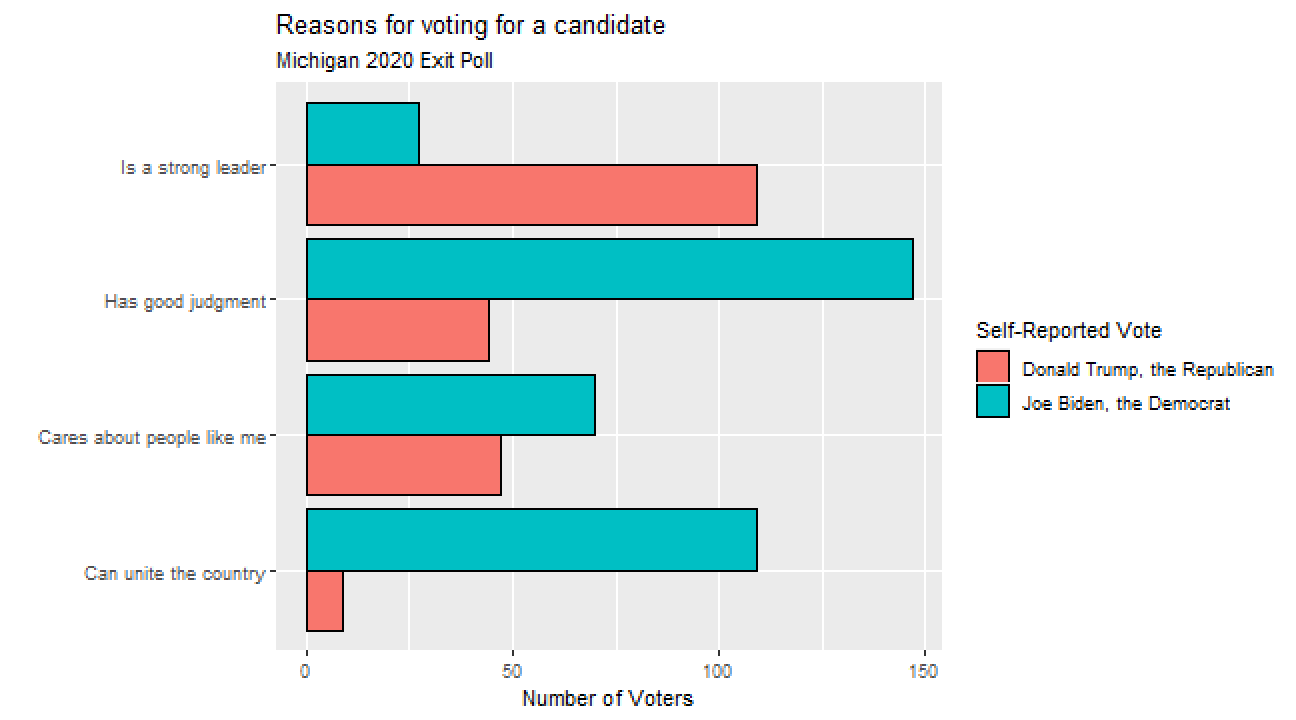
Conditional Categorical Analysis

- `fill` and `position = "dodge"` for **conditional** analysis

```
pReasonChoice <- toplot %>%
  ggplot(aes(x = Quality,fill = preschoice)) +
  labs(y = "Number of Voters",x = "",
         title = "Reasons for voting for a candidate",
       subtitle = "Michigan 2020 Exit Poll",
       fill = 'Self-Reported Vote') +
    geom_bar(color="black",position = "dodge") +
   coord_flip()
```

Conditional Categorical Analysis

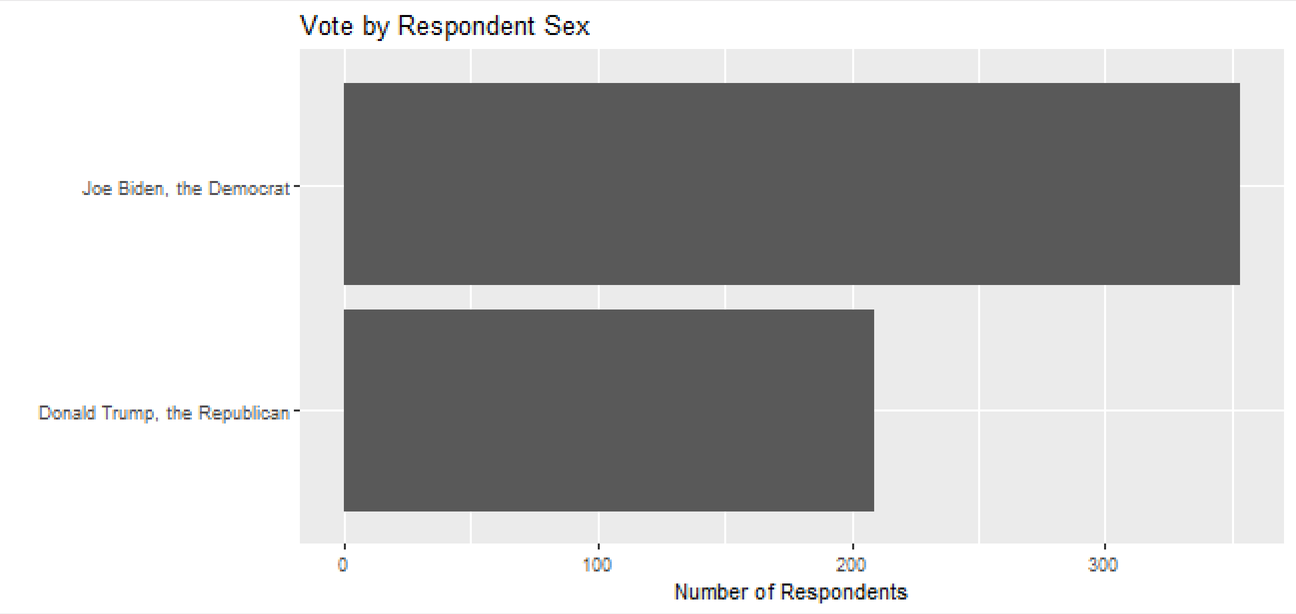
```
pReasonChoice
```



Conditional Categorical Analysis

- What about if we do this by `SEX`?

```
toplot %>%
    ggplot(aes(x= preschoice, fill = SEX)) +
    labs(y = "Number of Respondents",x = "",
         title = "Vote by Respondent Sex",fill = "Sex") +
    geom_bar(position="dodge") + coord_flip()
```



Be Attentive to `class()`

- How is `SEX` stored in the data?

```
class(mi_ep$SEX)
```

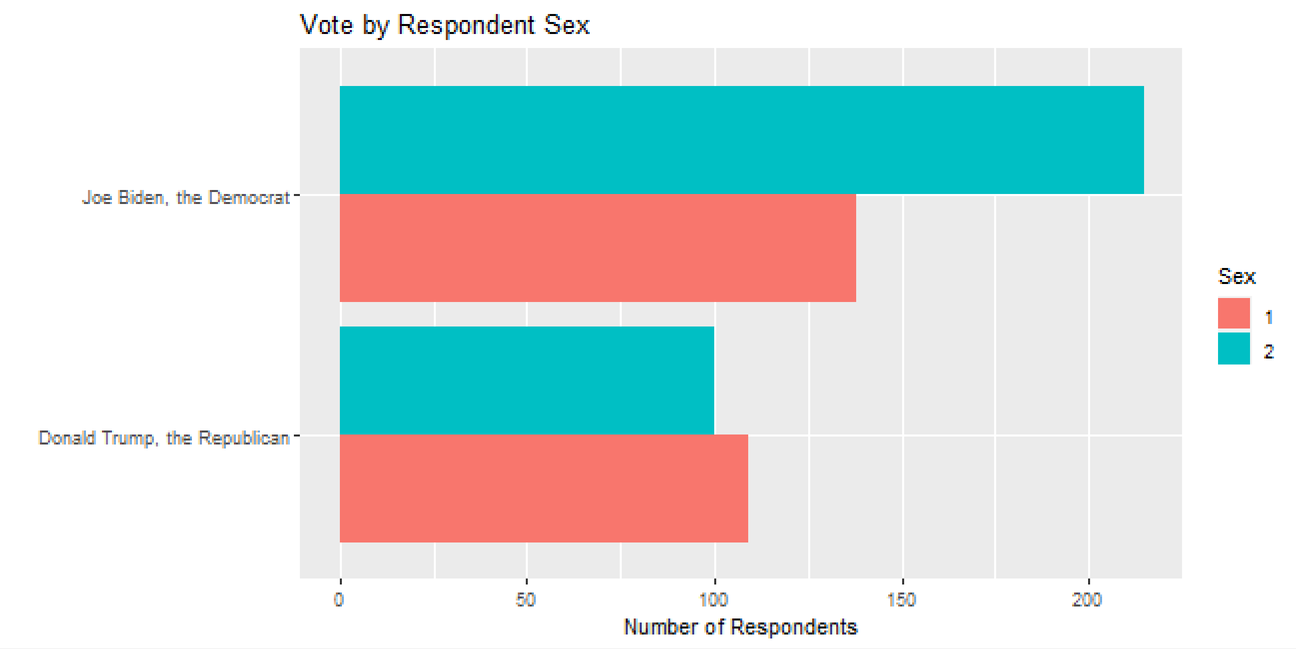
```
## [1] "numeric"
```

- Need to convert it to a `character` or `factor`

```
pVoteSex <- toplot %>%
    ggplot(aes(x= preschoice, fill = factor(SEX))) +
    labs(y = "Number of Respondents",x = "",
         title = "Vote by Respondent Sex",fill = "Sex") +
    geom_bar(position="dodge") + coord_flip()
```

Be Attentive to `class()`

```
pVoteSex
```



- Why is this a bad visualization? **Poorly labeled legend!**

Continuous by Categorical

- Let's introduce a different dataset!
    - Download and open `Pres2020_PV.Rds`
    - Wrangle to get the popular vote margin, expressed in decimals

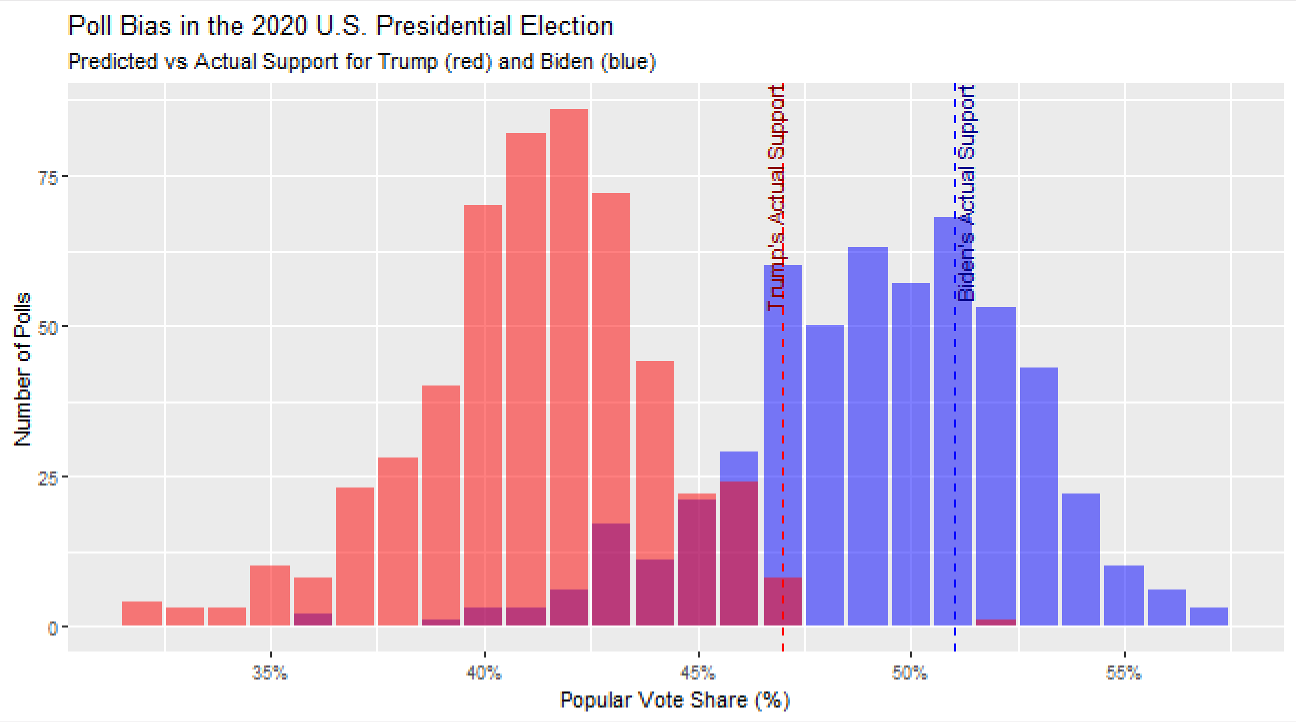
```
poll <- read_rds('../data/Pres2020_PV.Rds')

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

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

```r
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
```

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

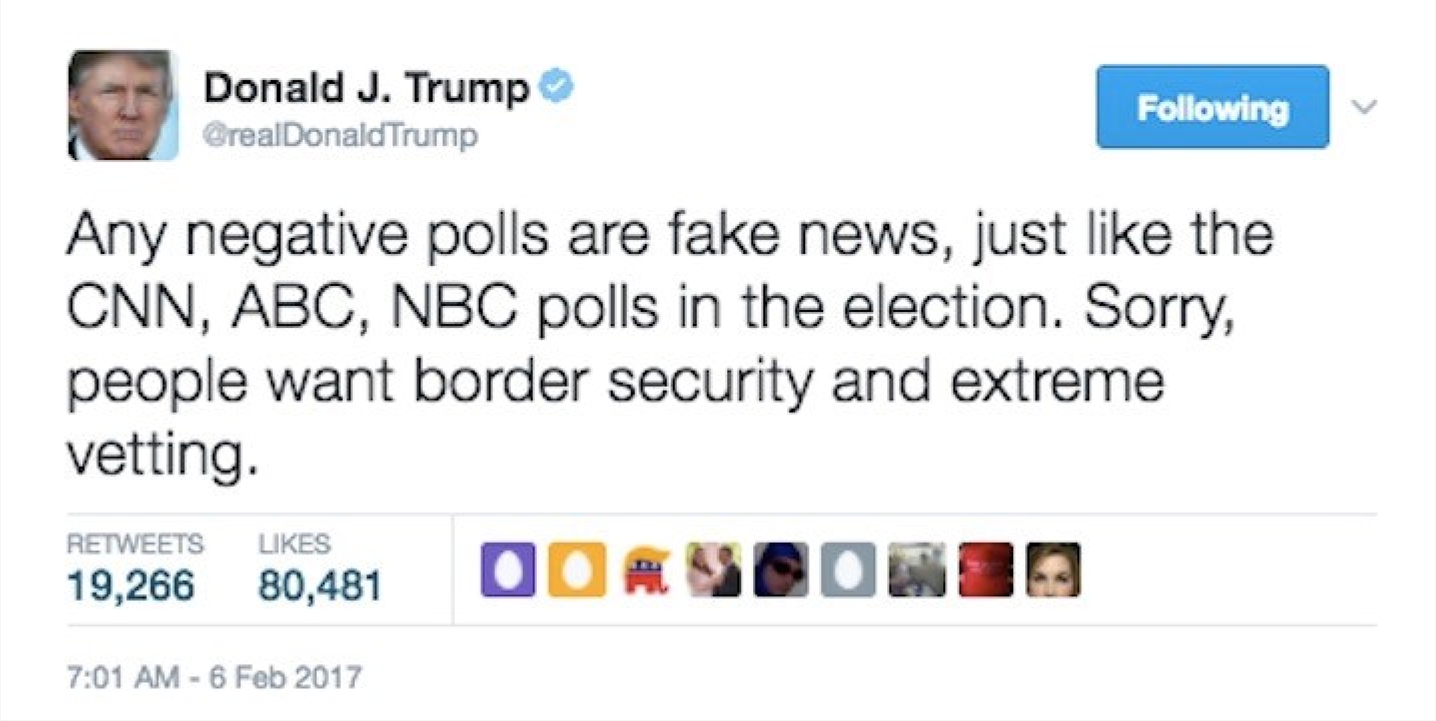
```
## # A tibble: 1 × 2
##   avgBidenErr avgTrumpErr
##         <dbl>       <dbl>
## 1      0.0175      0.0577
```

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

- However...

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!

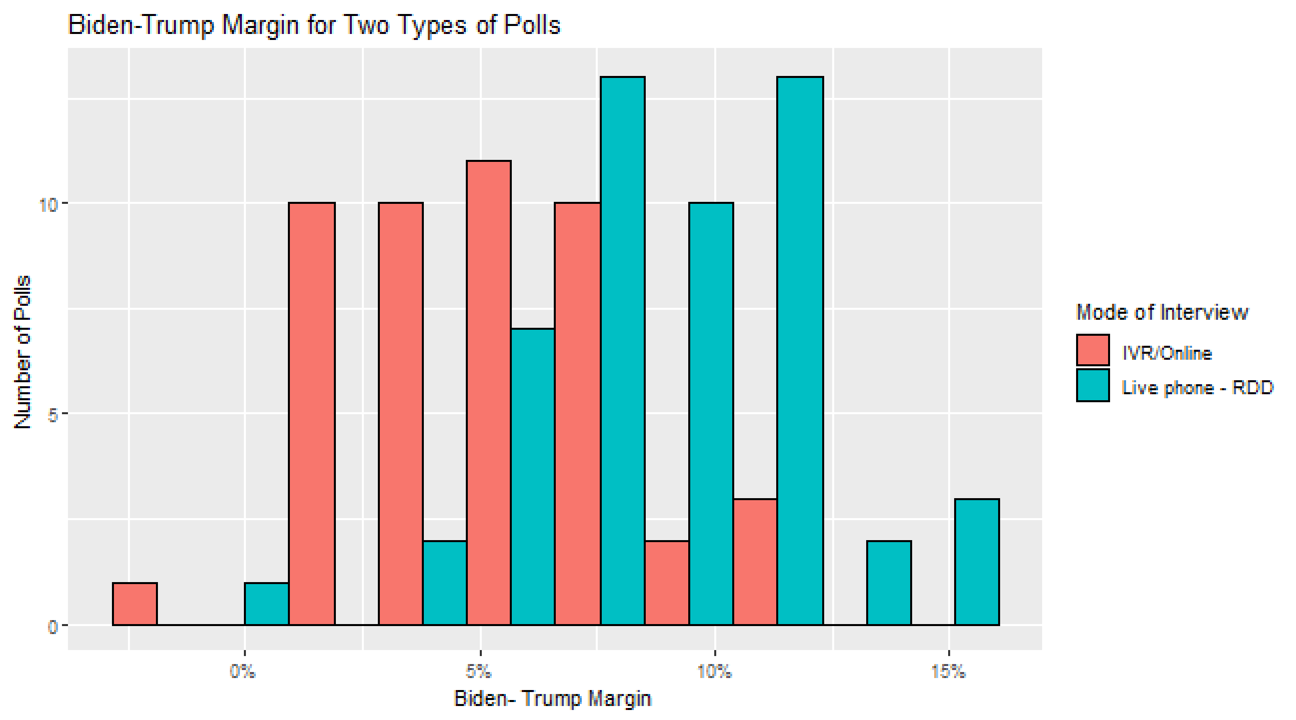
Analyzing

- 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

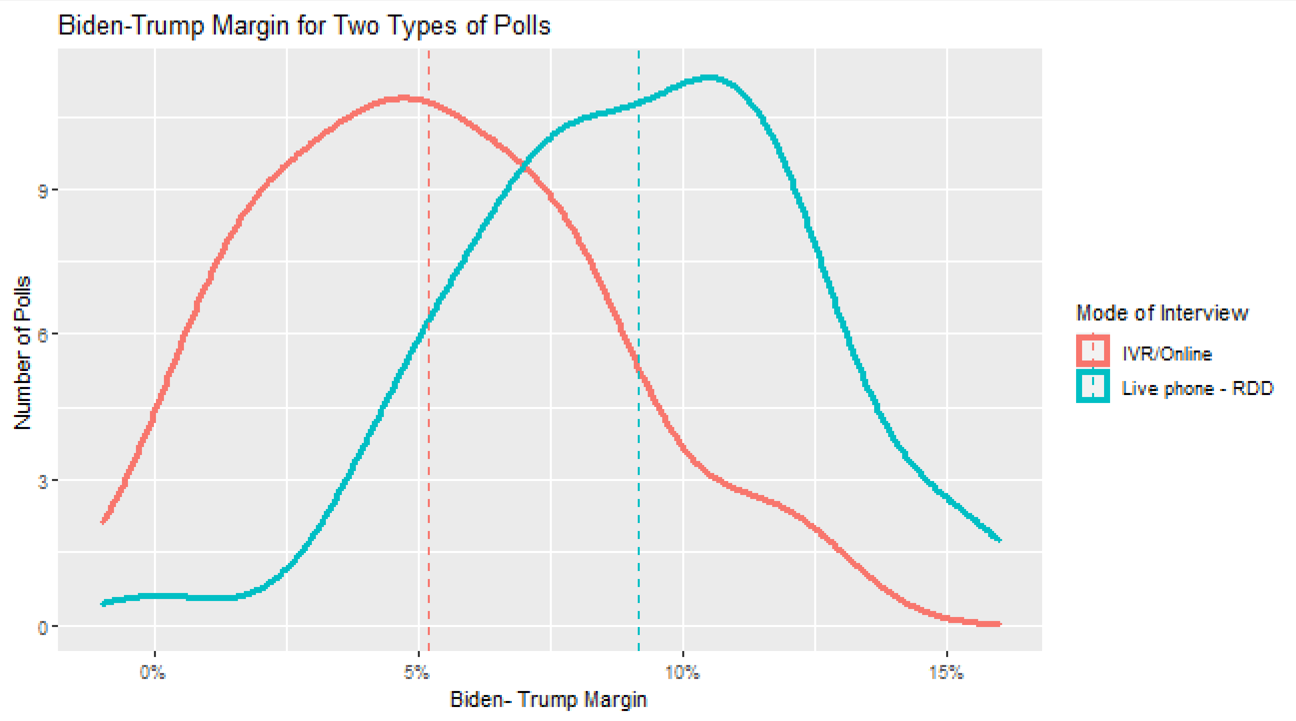
- How can we improve this? Perhaps `geom_density()` and `geom_vline()`?

```
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')
```

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

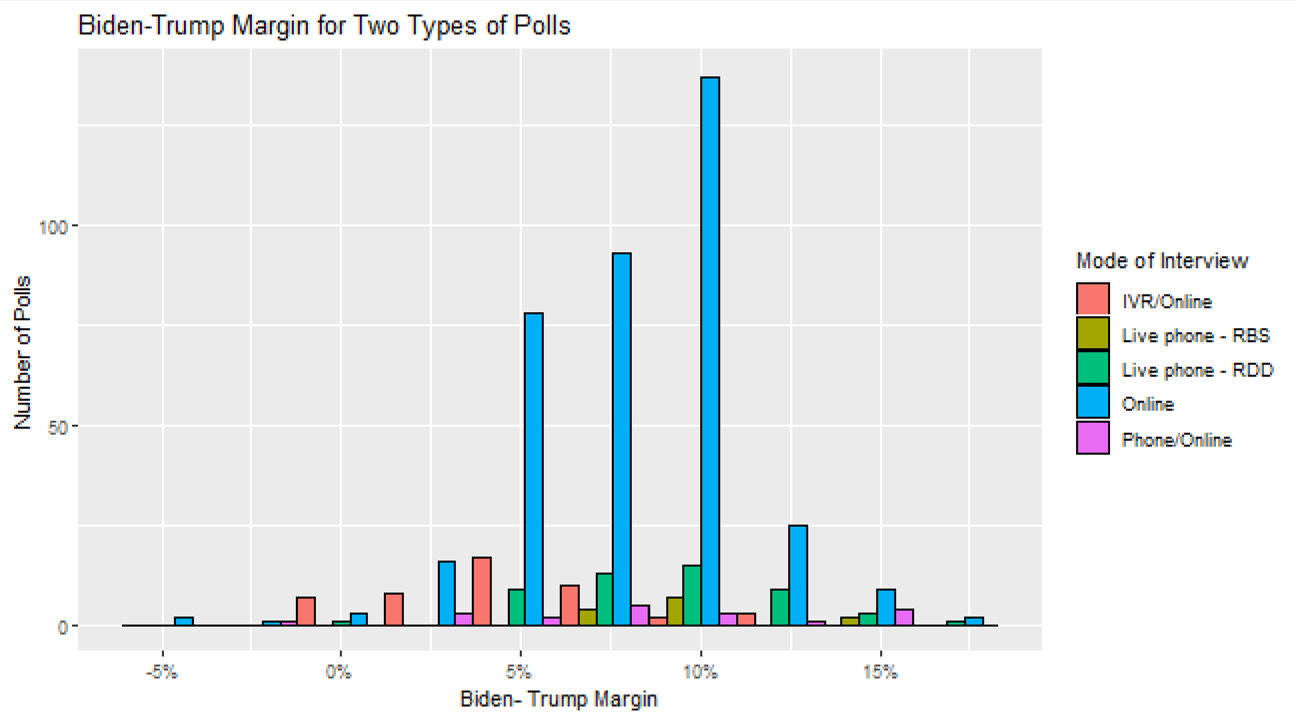
- How hard is `geom_histogram()` with more categories?

```
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

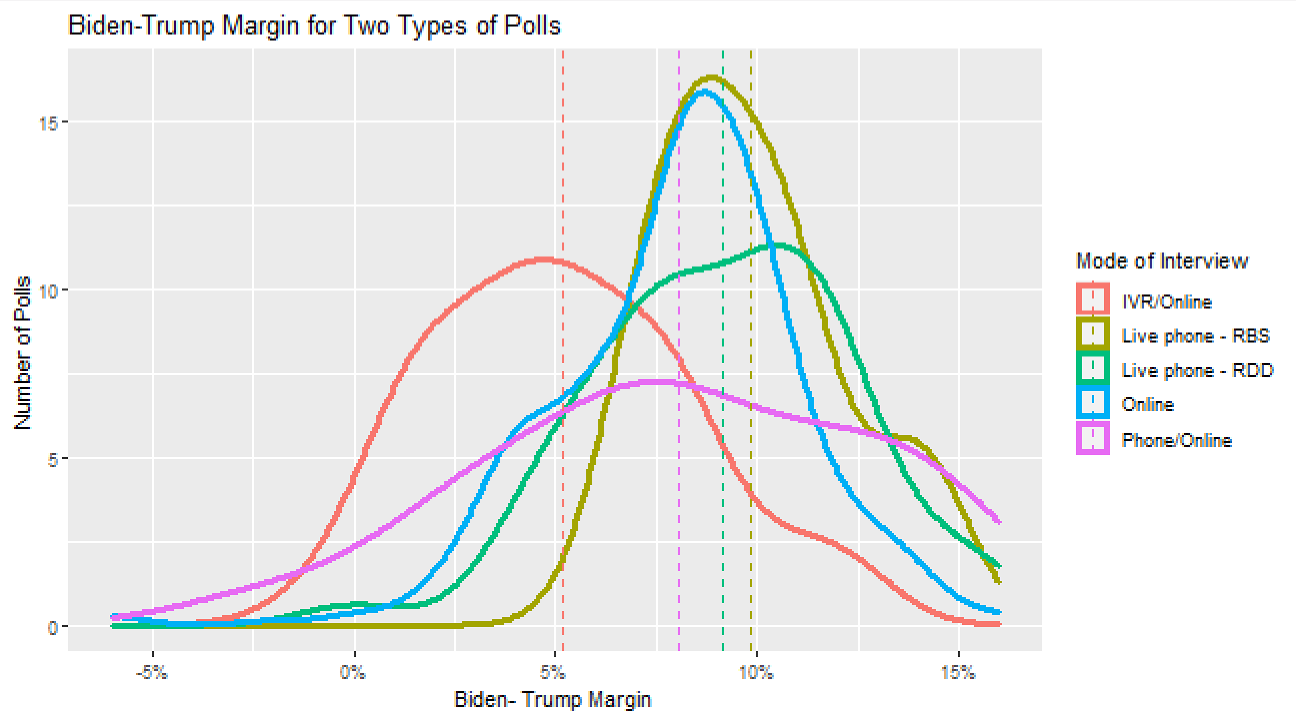
- How hard is `geom_density()` with more categories?

```
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()

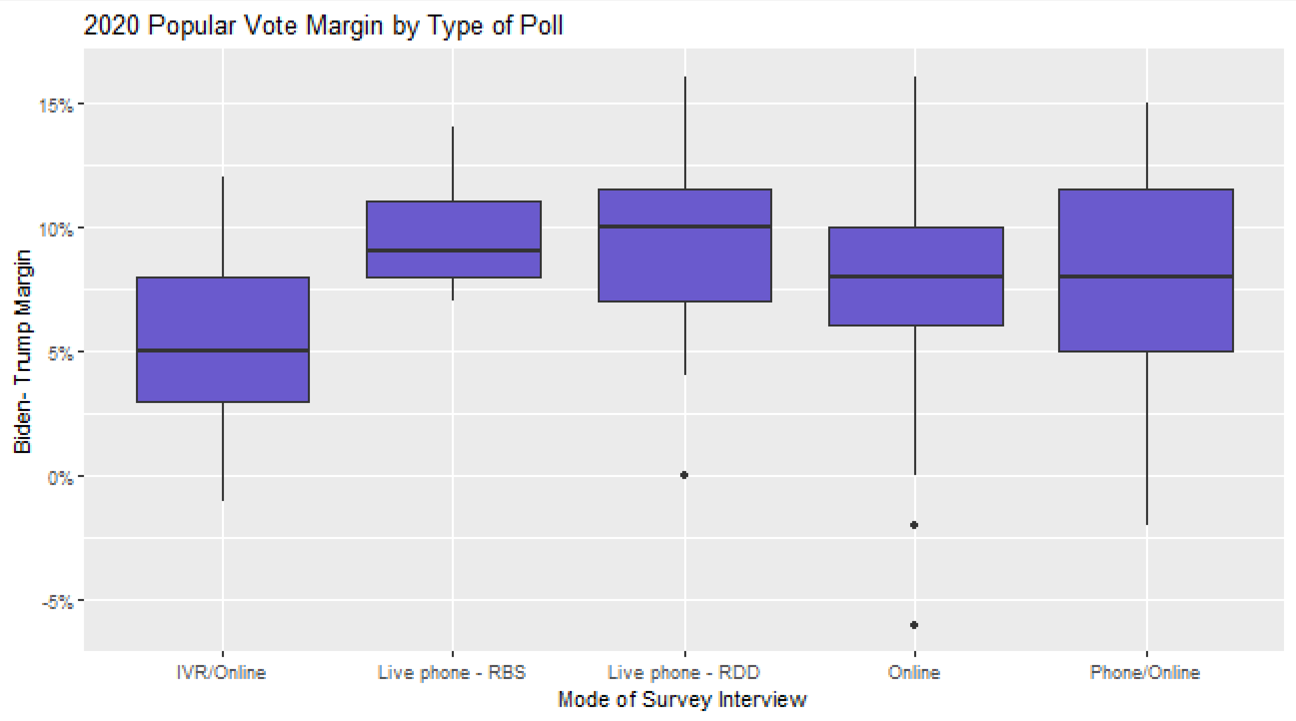
- More categories requires more compact ways of visualizing distributions

```
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

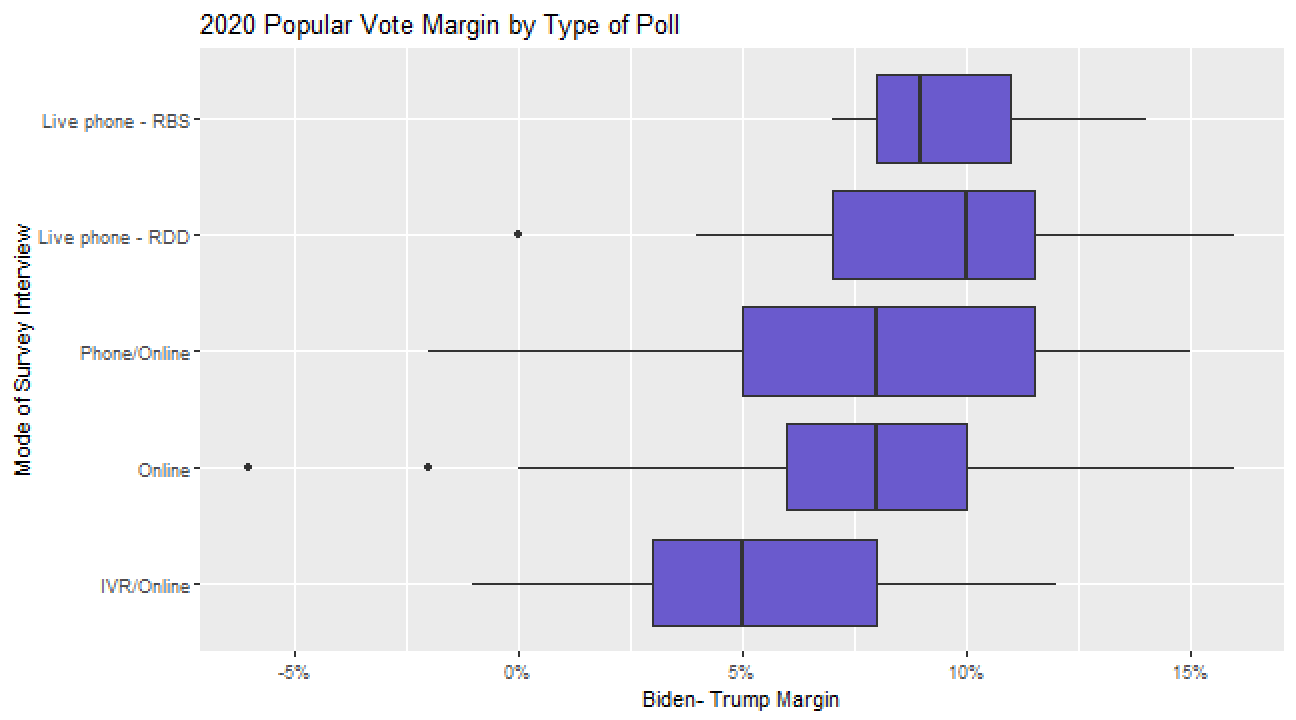
- We can use `reorder()` to arrange categories by the data

```
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()
```



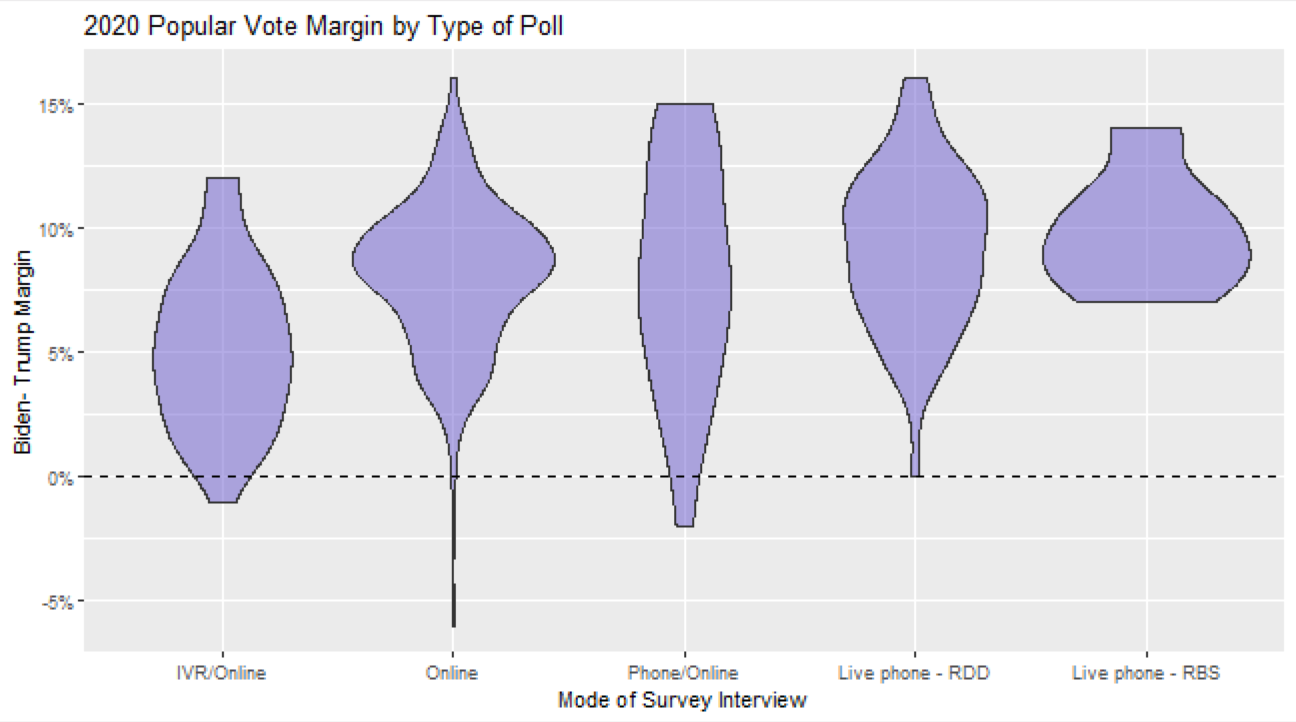
geom_violin()

- 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

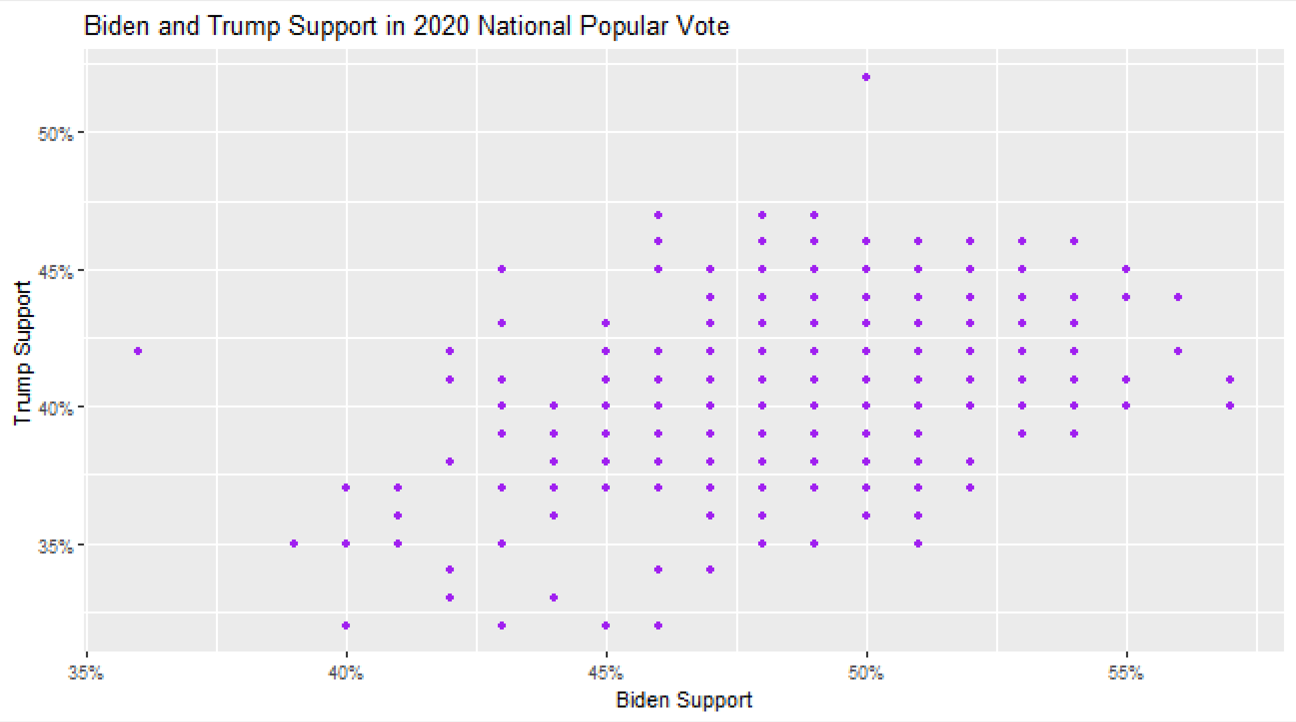
Analysis

- 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?

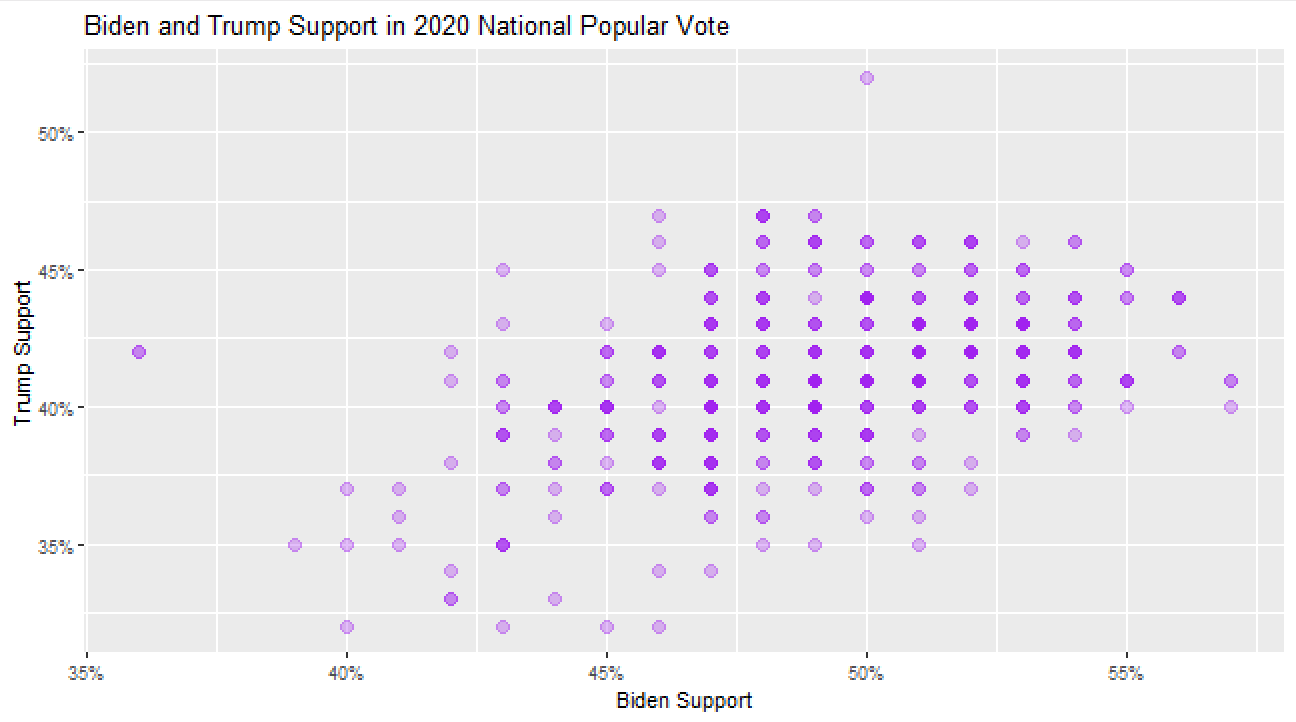
Tweaking `alpha`

- 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
```



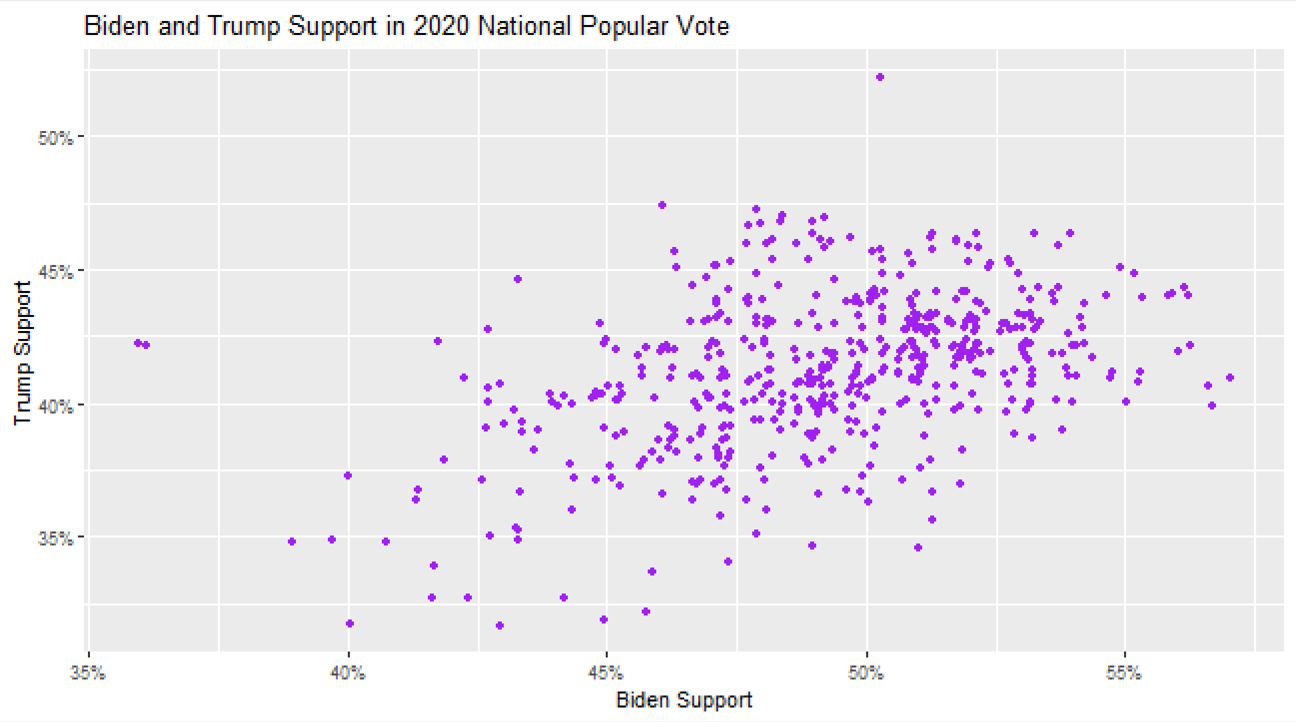
geom_jitter()

- 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

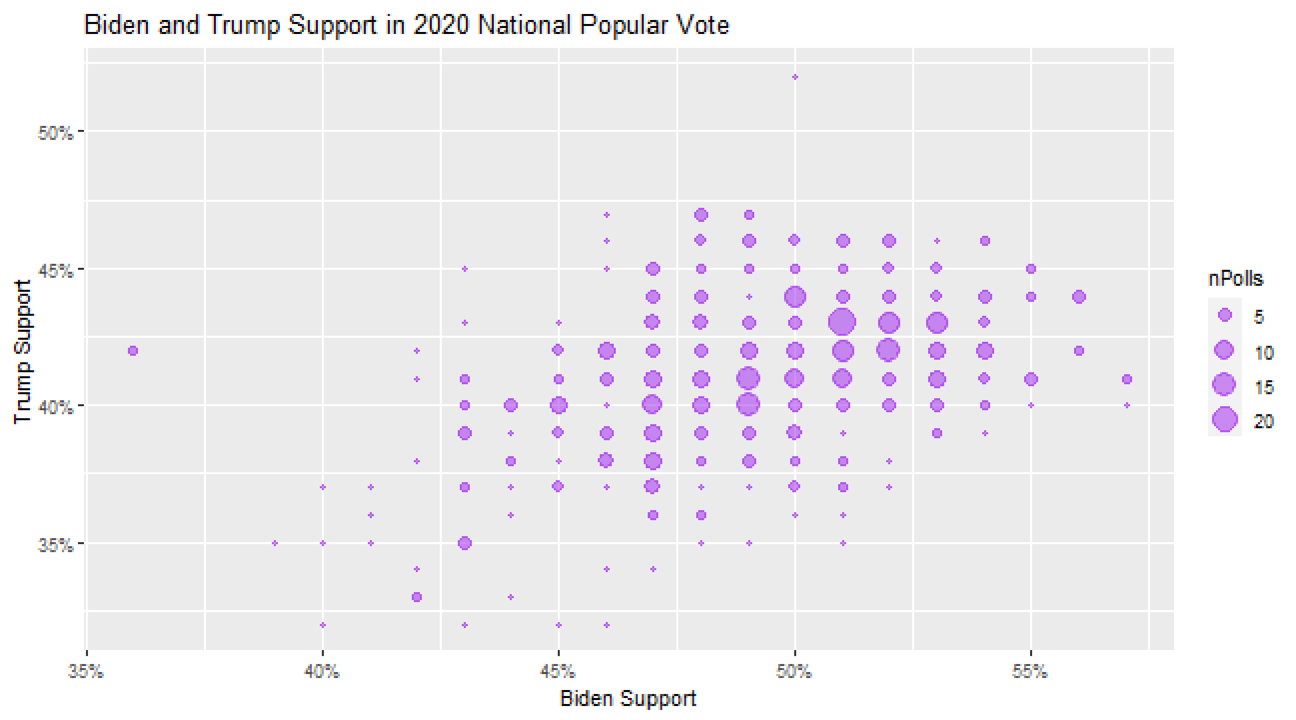
- Finally, we could simply count the number of polls at each x,y coordinate
  - Then size the points by the number of polls

```
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

Quiz & Homework

- Go to Brightspace and take the **7th** quiz
  - The password to take the quiz is ####
- **Homework:**
  1. Work through Multivariate_Analysis_part1_hw.Rmd
  2. Problem Set 3 (on Brightspace)