Univariate and Multivariate Analysis

Getting into Relationships

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Univariate Analysis

1. Definitions and scope
2. Opening and defining the data
3. Variable classes
4. Univariate description

BREAK

1. Multivariate

Definition

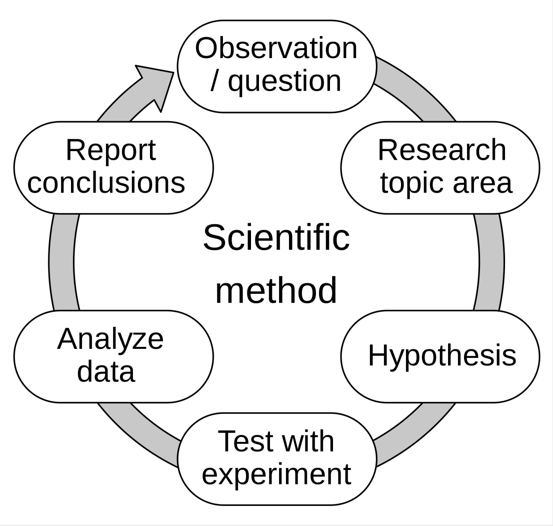
- Uni + variate
  - One + variable
  - Analysis of one variable

Scope

- How to analyze a single variable?
- How to think scientifically?
  - Typically, scientific theories concern more than one variable
  - I.e., education + wages; gender + voting
  - What might be a theory about education in isolation?
- Is there no point to univariate analysis?

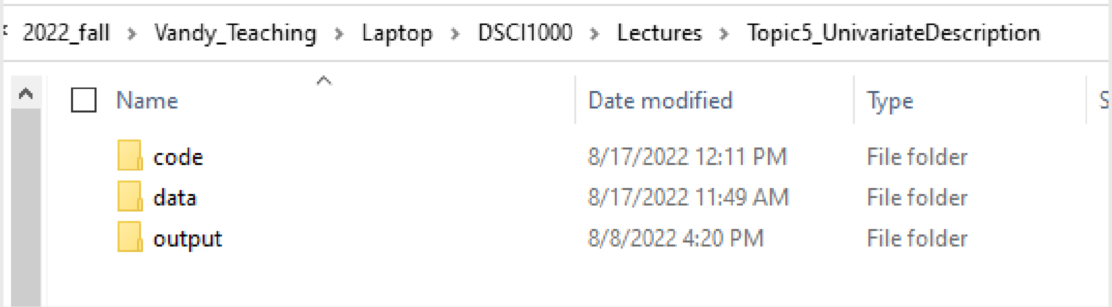
Univariate Analysis is **ESSENTIAL**

- Both from a practical data perspective...
  - Informs how we "wrangle" the data
- ...and from a scientific theory perspective
  - Generates hypotheses



Set-up and Load Data

- As always, create your topic folder first



- Open `R` via `RStudio` and `require(tidyverse)`

```
require(tidyverse)
```

- Load data from github

```
nba <-
read_rds('https://github.com/jbisbee1/ISP_Data_Science_2024/raw/main/da
```

Introducing the data

- Data on every NBA player active in the 2018-2019 season

Name	Definition
namePlayer	Player name
idPlayer	Unique player id
slugSeason	Season start and end
numberPlayerSeason	Which season for this player
isRookie	Rookie season, true or false
slugTeam	Team short name
idTeam	Unique team id
gp	Games Played
…	…

Thinking like a scientist

- What questions do we have? What hypotheses might we want answered?
- Overwhelming? Let's start simpler
- Total points (`pts`)
  - What does this measure?
  - What kind of variable is it?

```
glimpse(nba %>% select(pts))
```

```
## Rows: 530
## Columns: 1
## $ pts <dbl> 1727, 17, 1108, 165, 729, 37, 211, 32, 108, 7,…
```

Thinking like a scientist

- How can we analyze a single variable?
- Want to **summarize** it somehow
    - For example, look at the `mean()` and the `median()`

```
nba %>%
  summarise(mean_pts = mean(pts,na.rm=T),
            med_pts = median(pts,na.rm=T))
```

```
## # A tibble: 1 × 2
##   mean_pts med_pts
##      <dbl>   <dbl>
## 1     516.     419
```

Thinking like a scientist

- Or we could summarise the overall distribution with `summary()`

```
summary(nba$pts)
```

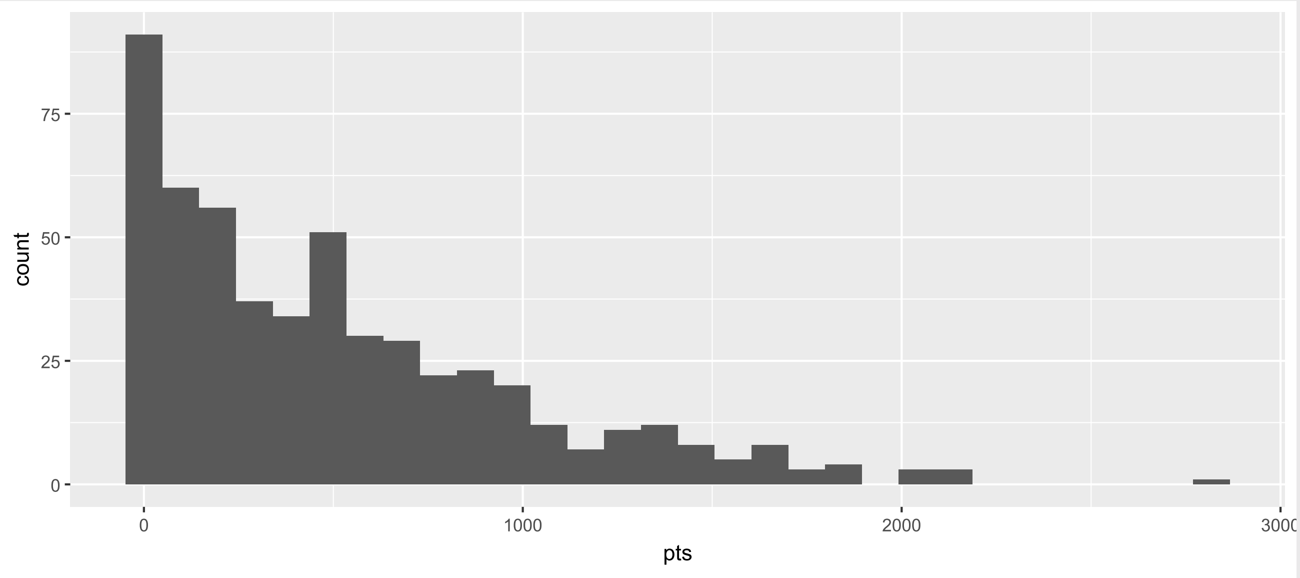
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##     0.0   115.0   419.0   516.2   759.5  2818.0
```

- In English:
    - There is at least one player who didn't score at all (`Min.`)
    - At least one player scored 2,818 points (`Max.`)
    - 25% of players scored less than 115 points (`1st Qu.`)
    - 25% of players scored more than ???
- What does a decimal mean here?

Visualization

- We could try and remember all these statements
- Or we could just visualize the data

```
nba %>%
  ggplot(aes(x = pts)) +
  geom_histogram()
```

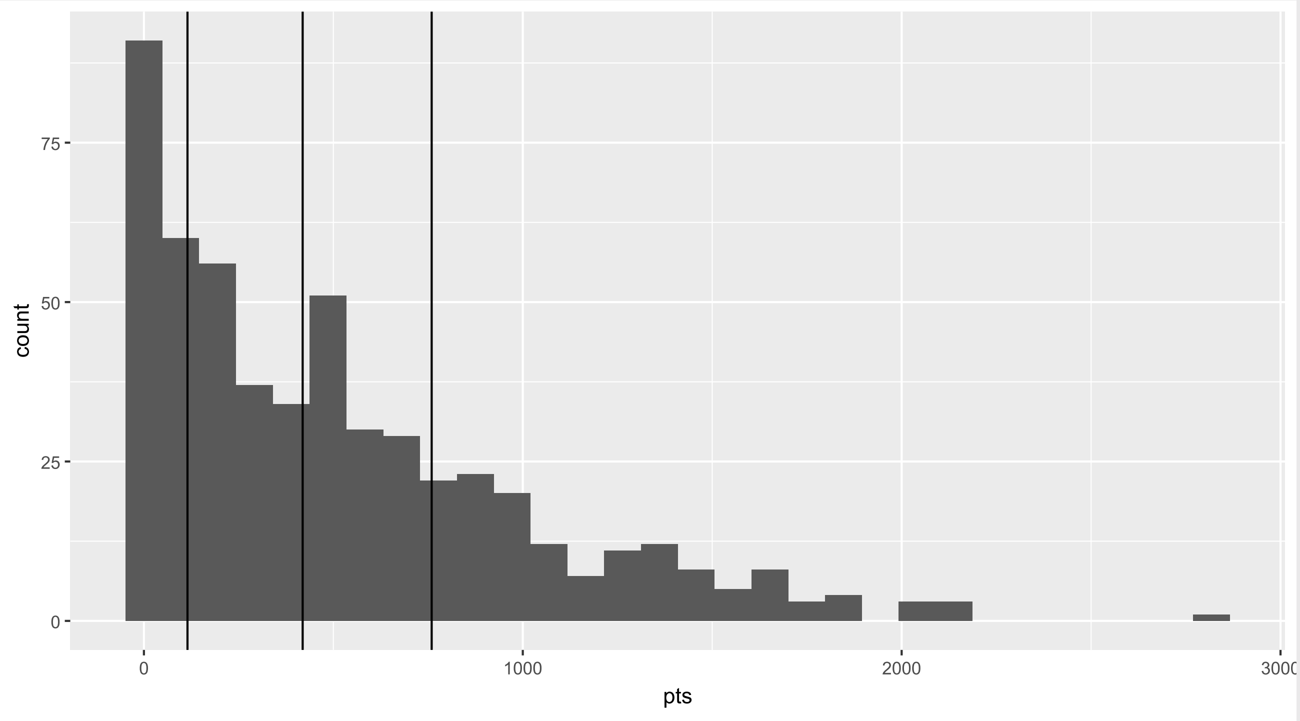


Visualization

- Plotting the histogram reveals some things!
  - There are **MANY** players who didn't score any points
  - There are **VERY FEW** who scored many
- We can combine the substantive interpretation with the visualization by plotting vertical lines for the quartiles
  - A "quartile" is 25% increments
  - A "decile" is 10% increments, a "quantile" is 20% increments
  - A "percentile" is 1% increments

Visualization

```
nba %>%
  ggplot(aes(x = pts)) +
  geom_histogram() +
  geom_vline(xintercept = quantile(nba$pts,c(.25,.5,.75)))
```



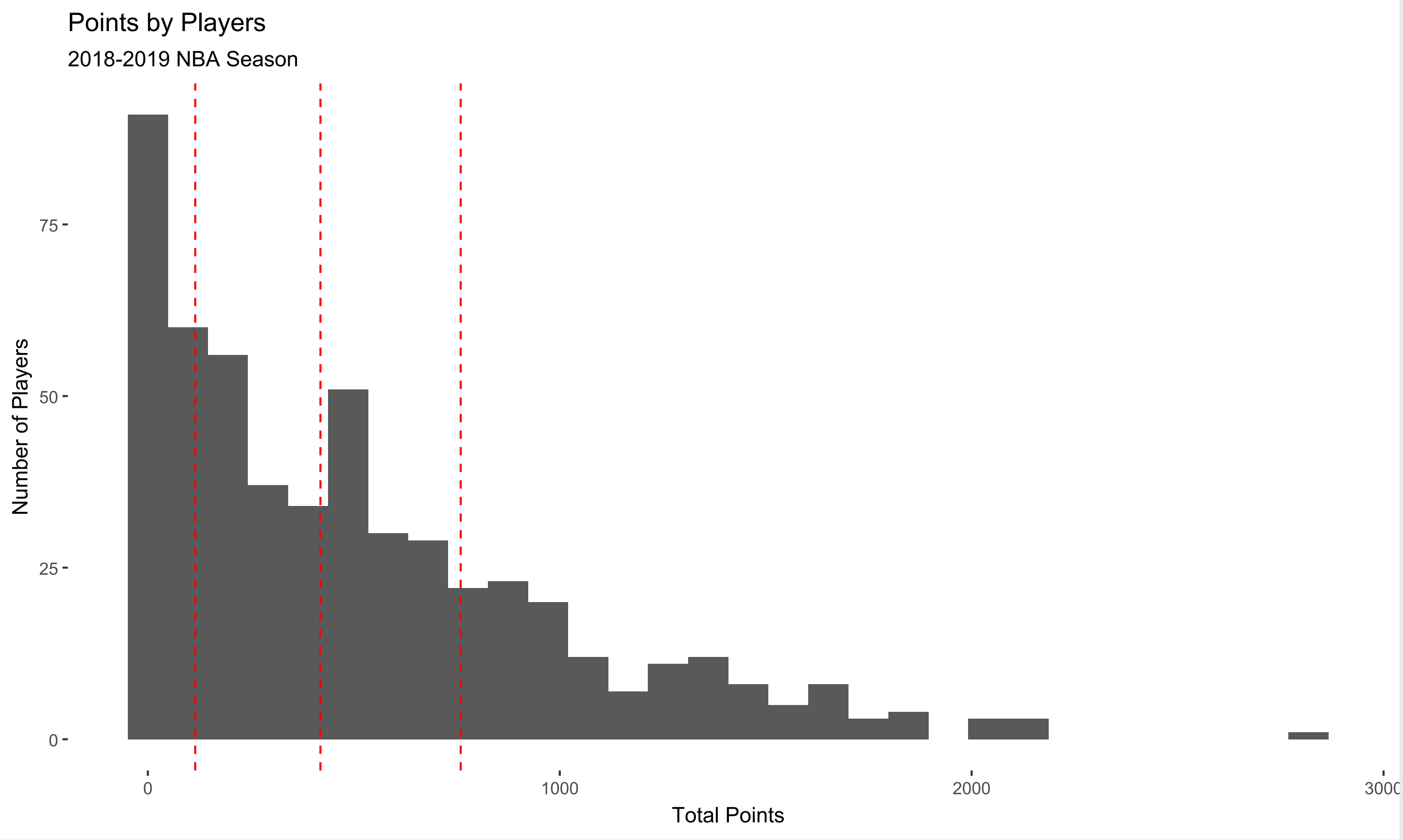
Visualization

- We can save and update plots using the object assignment operator `<-`

```
p <- nba %>%
  ggplot(aes(x = pts)) +
  geom_histogram()

p <- p + geom_vline(xintercept =
quantile(nba$pts,c(.25,.5,.75)),linetype = 'dashed',color = 'red')

p <- p + xlab('Total Points') + ylab('Number of Players')

p <- p + theme(panel.background = element_rect(fill = 'white'))

p <- p + labs(title = 'Points by Players',subtitle = '2018-2019 NBA
Season')
```

Visualization

```
p
```



Visualization informs science

- Looking at the data can help generate research questions, theories, and hypotheses
  - **Question:** Why do some players not score any points?
  - **Theory:** Players need minutes to score points.
  - **Hypothesis:** The number of points a player scores should be positively correlated with their minutes.

Univariate Description

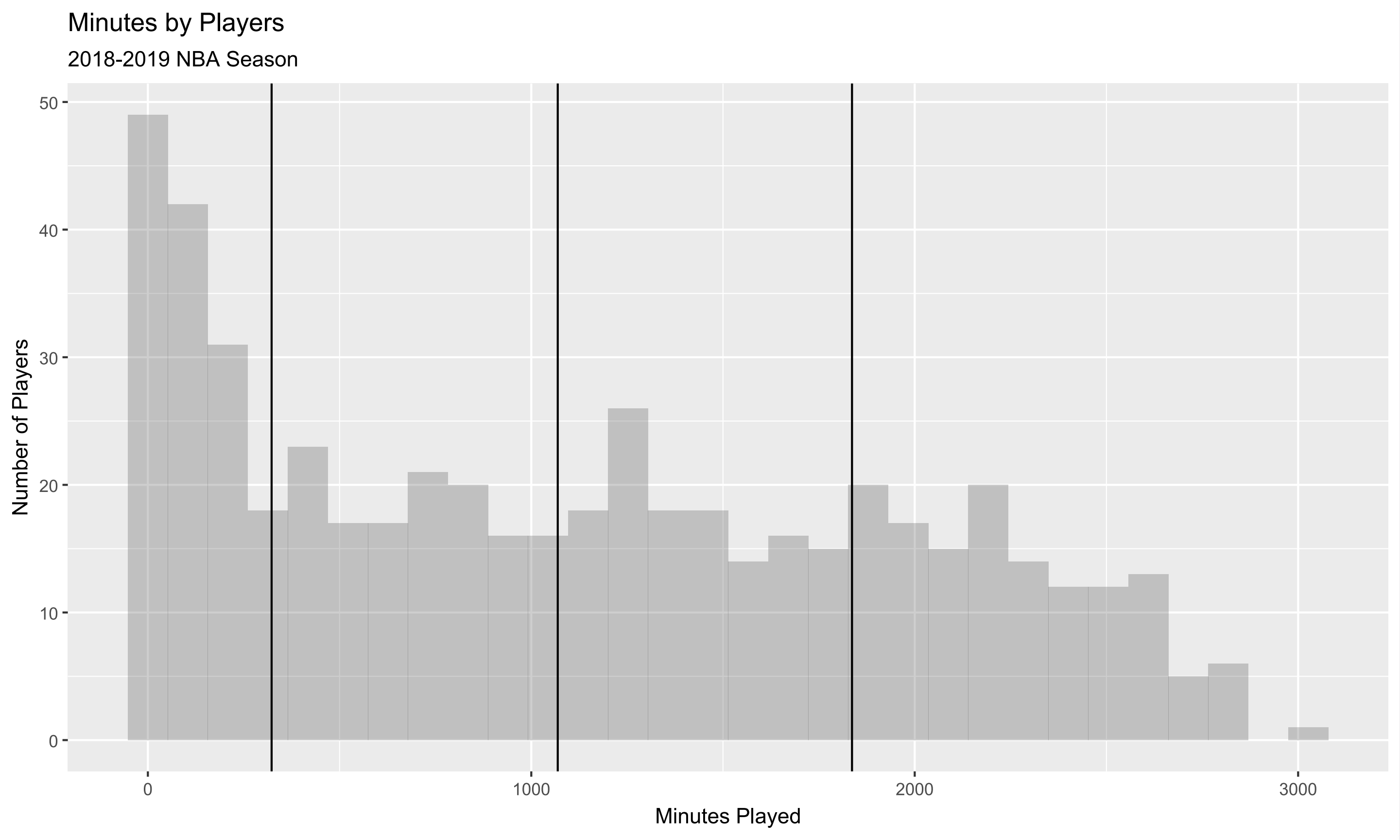
- Testing this hypothesis comes later
- For now, let's also describe the minutes variable

```
summary(nba$minutes)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##     1.0   322.8  1069.0  1121.6  1836.5  3028.0
```

- At minimum, every player played at least 1 minute
- Does the distribution of this variable look similar to the points?

```
nba %>%
  ggplot(aes(x = minutes)) +
  geom_histogram(alpha = .3) +
  geom_vline(xintercept = quantile(nba$minutes,c(.25,.5,.75))) +
  labs(title = 'Minutes by Players',subtitle = '2018-2019 NBA
Season',x = 'Minutes Played',y = 'Number of Players')
```



Other Variables

- Thus far, `pts` and `minutes` are both `dbl`

```
glimpse(nba %>% select(pts,minutes))
```

```
## Rows: 530
## Columns: 2
## $ pts     <dbl> 1727, 17, 1108, 165, 729, 37, 211, 32, 108…
## $ minutes <dbl> 2687, 123, 2669, 588, 1913, 120, 416, 194,…
```

- What about other variable types?

Other Variabes

```
glimpse(nba)
```

```
## Rows: 530
## Columns: 37
## $ namePlayer          <chr> "LaMarcus Aldridge", "Quincy Ac…
## $ idPlayer            <dbl> 200746, 203112, 203500, 203518,…
## $ slugSeason          <chr> "2018-19", "2018-19", "2018-19"…
## $ numberPlayerSeason  <dbl> 12, 6, 5, 2, 1, 0, 0, 0, 0, 0, …
## $ isRookie            <lgl> FALSE, FALSE, FALSE, FALSE, FAL…
## $ slugTeam            <chr> "SAS", "PHX", "OKC", "OKC", "MI…
## $ idTeam              <dbl> 1610612759, 1610612756, 1610612…
## $ gp                  <dbl> 81, 10, 80, 31, 82, 10, 38, 19,…
## $ gs                  <dbl> 81, 0, 80, 2, 28, 1, 2, 3, 1, 0…
## $ fgm                 <dbl> 684, 4, 481, 56, 280, 13, 67, 1…
## $ fga                 <dbl> 1319, 18, 809, 157, 486, 39, 17…
## $ pctFG               <dbl> 0.519, 0.222, 0.595, 0.357, 0.5…
## $ fg3m                <dbl> 10, 2, 0, 41, 3, 3, 32, 6, 25, …
## $ fg3a                <dbl> 42, 15, 2, 127, 15, 12, 99, 23,…
## $ pctFG3              <dbl> 0.2380952, 0.1333333, 0.0000000…
## $ pctFT               <dbl> 0.847, 0.700, 0.500, 0.923, 0.7…
## $ fg2m                <dbl> 674, 2, 481, 15, 277, 10, 35, 5…
## $ fg2a                <dbl> 1277, 3, 807, 30, 471, 27, 79, …
```

Categorical Variables

- Already introduced you to `dbl`, `fct`, `chr` and `int`
- Taking a step back: Outside `R`, data science uses "categorical" variables
  1. Mutually exclusive: observations can only be in one category
  2. Exhaustive: every observation is assigned to a category
- For example, `isRookie`
  1. Mutually exclusive: Players are either in their rookie season in 2018-2019, or are not
  2. Exhaustive: these categories define every player in the data

Categorical Variables

- Categorical variables can be divided into the following sub-types
- **Ordered:** There is a sensible order (i.e., education)
    - Should be arranged intuitively (i.e., LTHS, HS Degree, Some coll, etc.)
    - To summarize, calculate the proportions for each category.
    - If there are too many categories, use the "mode"

Categorical Variables

- Categorical variables can be divided into the following sub-types
- **Ordered, Binary:** An ordered categorical variable with just two levels
    - Should be arranged in intuitive order (i.e., is not a rookie / is a rookie)
    - To summarize, just convert to a [0,1] number and take the mean

Categorical Variables

- Categorical variables can be divided into the following sub-types
- **Unordered**: No sensible order of categories (i.e., major degree)
  - Order by most commonly occurring categories
  - As before, use the mode for too many categories

Categorical Variables

- Categorical variables can be divided into the following sub-types
- **Unordered, Binary**: No sensible order and only two levels (i.e., edible)

Categorical Variables

- Categorical variables are meaningfully different from continuous variables
    - Continuous variables are ordered and can theoretically be divided into arbitrarily small measures
    - Technically can be defined as either **interval** or **ratio** variables
    - In practice, we rarely worry about this distinction, but we **DO** care about continuous versus categorical variables

Categorical Variables

- `fct` is a class that is unique to `R`
  - Meant for ordered categorical variables
  - `fct` stores the order and assigns a numeric value + a definition
  - Most of the time, better to store as a `chr` (but not always)

Variables

- `R` may store categorical variables as `chr`, `fct`, `lgl`, `int`, or even `dbl`
- Continuous variables typically stored as `int` or `dbl`
- Up to the data scientist to look at the data and determine
- Simple **process**

  1. Look at a few observations and make a guess about the variable type
  2. Create a plot or table based on that guess
  3. If the result is sensible, proceed. OTW go back to #1.

In Practice

- Let's look at field goals (`fgm`)
- What type of variable should this be?
  - *Technically* not continuous, since it can't be divided into fractions (i.e., what is 35.5 field goals?)
  - But we typically don't care about this distinction
  - We just want to make sure it is not a categorical variable (i.e., less than 20 FGs, 20-40 FGs...etc. would be categorical)
- To check, follow the process!

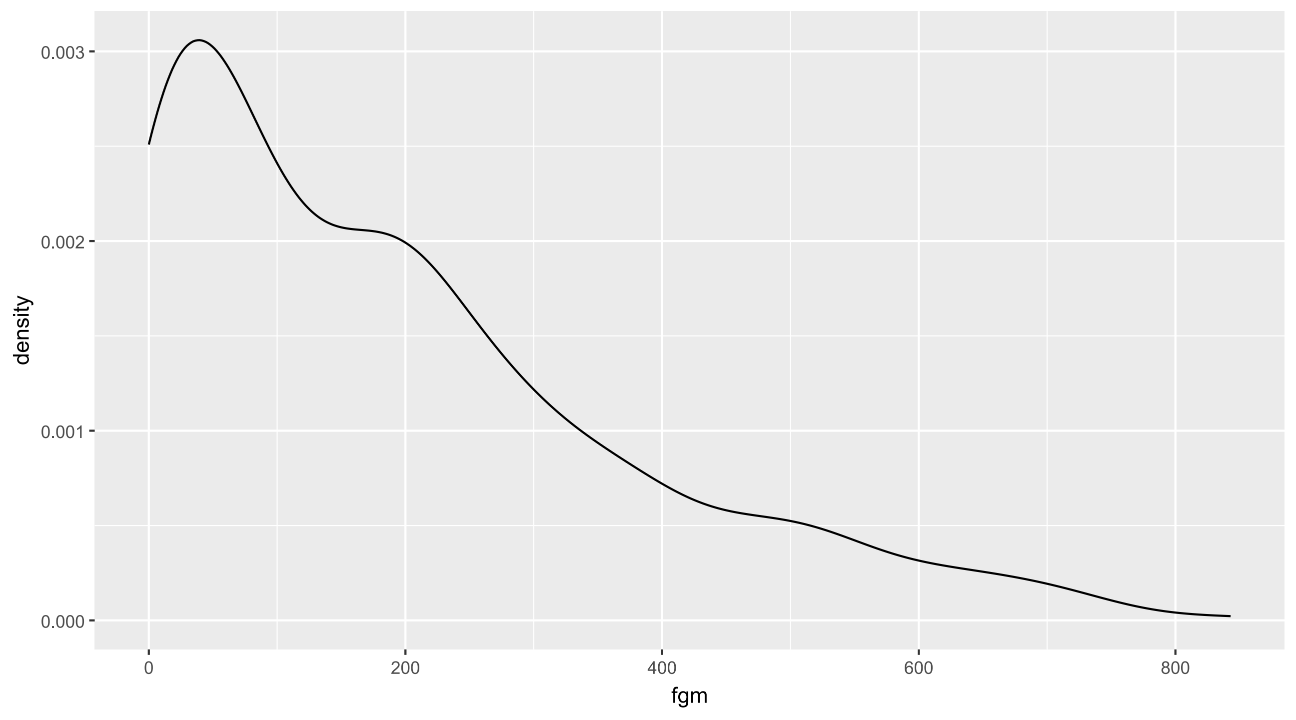
The Process: #1 Look

```
nba %>%
  select(namePlayer,slugTeam,fgm) %>%
  arrange(-fgm)
```

```
## # A tibble: 530 × 3
##    namePlayer              slugTeam   fgm
##    <chr>                   <chr>    <dbl>
##  1 James Harden            HOU        843
##  2 Bradley Beal            WAS        764
##  3 Kemba Walker            CHA        731
##  4 Giannis Antetokounmpo MIL        721
##  5 Kevin Durant            GSW        721
##  6 Paul George             OKC        707
##  7 Nikola Vucevic          ORL        701
##  8 LaMarcus Aldridge       SAS        684
##  9 Damian Lillard          POR        681
## 10 Karl-Anthony Towns      MIN        681
## # ℹ 520 more rows
```

The Process: #2 Create

```
nba %>%
  ggplot(aes(x = fgm)) +
  geom_density()
```



The Process: #3 Evaluate

- Looks like a continuous variable to me!
- Summarize it!

```
nba %>%
  summarise(mean_fg = mean(fgm,na.rm=T),
            med_fg = median(fgm,na.rm=T))
```

```
## # A tibble: 1 × 2
##   mean_fg med_fg
##     <dbl>  <dbl>
## 1    191.    157
```

- `mean()` is more easily understood, but more sensitive to outliers
- `median()` is harder to explain to a general audience, but more sensible when there are outliers

Other Variables: Use the process!

- What kind of variable is field goal percentage?
- Follow the process!

```
# INSERT CODE HERE
```

Another example

- Player age
- What kind of variable do we think this might be?
    - Continuous? It is ordered and divisible to arbitrary fractions! (Just ask any 6 and three quarters year old)
    - But is it also useful to think of it as a categorical? In the context of NBA players, there aren't many categories!
- Time for the **process**!

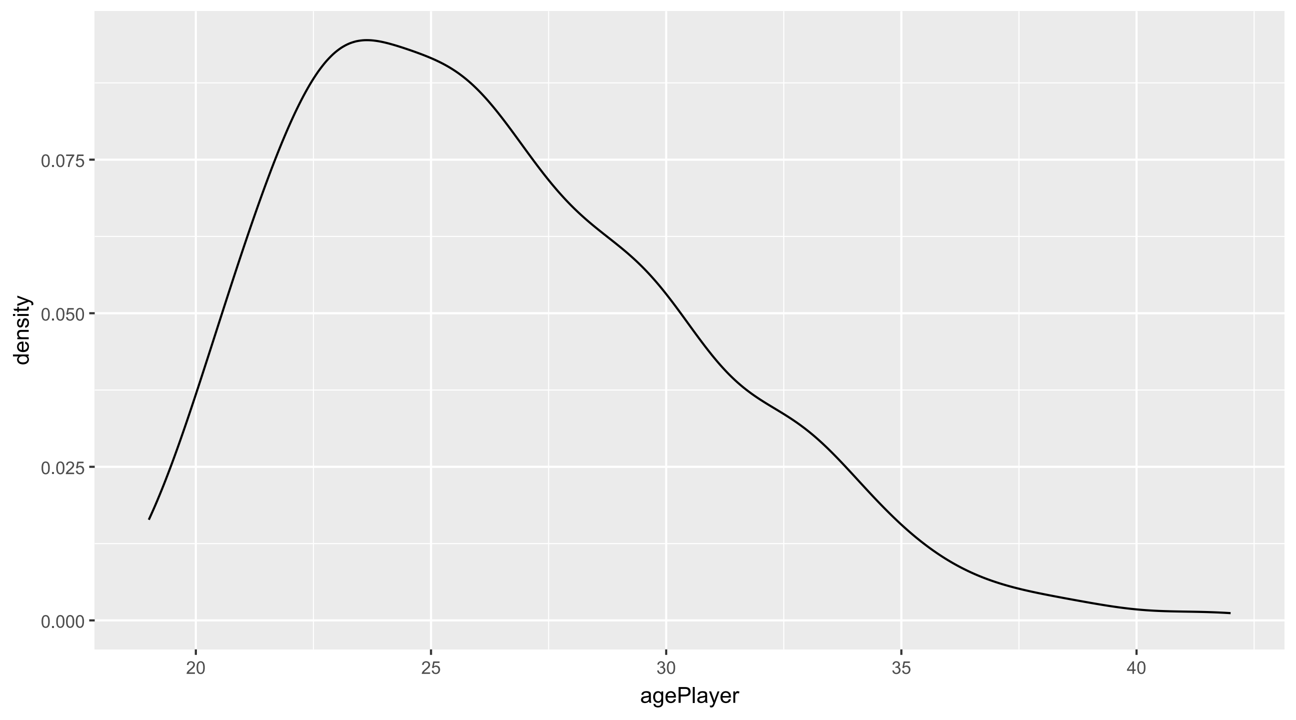
The Process: #1 Look

```
nba %>%
  select(namePlayer,agePlayer) %>%
  arrange(-agePlayer)
```

```
## # A tibble: 530 × 2
##    namePlayer     agePlayer
##    <chr>              <dbl>
##  1 Vince Carter          42
##  2 Dirk Nowitzki         41
##  3 Jamal Crawford        39
##  4 Udonis Haslem         39
##  5 Pau Gasol             38
##  6 Kyle Korver           38
##  7 Jose Calderon         37
##  8 Tony Parker           37
##  9 Dwyane Wade           37
## 10 Channing Frye         36
## # ℹ 520 more rows
```

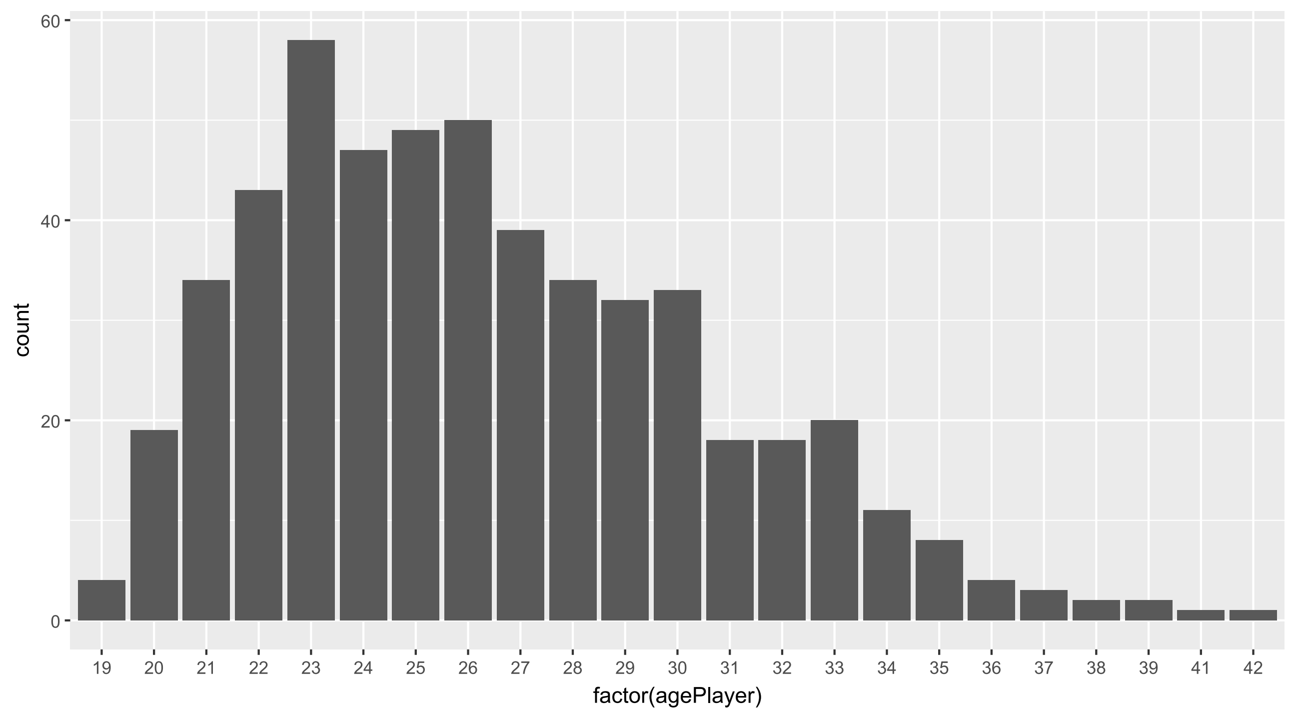
The Process: #2 Create

```
nba %>%
  ggplot(aes(x = agePlayer)) +
  geom_density()
```



The Process: #2 Create

```
nba %>%
  ggplot(aes(x = factor(agePlayer))) +
  geom_bar(stat = 'count')
```



The Process: #2 Create

The Process: #3 Evaluate

```
quantile(nba$agePlayer,c(.1,.25,.5,.75,.9,.95))
```

```
## 10% 25% 50% 75% 90% 95%
##  21  23  26  29  32  34
```

Some more examples!

- Which of these variables is an unordered categorical variable?
- Follow the process and calculate which category in this variable is the most commonly occurring

```
# INSERT CODE HERE
```

Career Prior to NBA (org)

- If you chose this as your unordered categorical variable, you probably saw something like the following in step #1 of the process

```
nba %>%
  count(org) %>%
  arrange(-n)
```

```
## # A tibble: 68 × 2
##    org                          n
##    <fct>                    <int>
##  1 <NA>                       157
##  2 Other                       85
##  3 Kentucky                    25
##  4 Duke                        17
##  5 California-Los Angeles      15
##  6 Kansas                      11
##  7 Arizona                     10
##  8 Texas                       10
##  9 North Carolina               9
## 10 Michigan                     8
## # ℹ 58 more rows
```

Career Prior to NBA (org)

- The most commonly occurring categories are NA and Other!
- Wrangle some data and re-calculate

```
nba %>%
  filter(!is.na(org)) %>%
  filter(org != 'Other') %>%
  count(org) %>%
  arrange(-n)
```

```
## # A tibble: 66 × 2
##    org                         n
##    <fct>                   <int>
##  1 Kentucky                   25
##  2 Duke                       17
##  3 California-Los Angeles     15
##  4 Kansas                     11
##  5 Arizona                    10
##  6 Texas                      10
##  7 North Carolina              9
##  8 Michigan                    8
##  9 Villanova                   7
```

Categorical: Unordered, Binary

- Which variable is an unordered binary categorical?
- Follow the process and summarize it

```
# INSERT CODE HERE
```

Categorical: Unordered, Binary (`idConference`)

- Example of the default variable class (`dbl`) not corresponding to the type of variable (unordered binary)
- Should wrangle into something better

```
nba <- nba %>%
  mutate(west_conference = ifelse(idConference == 1,1,0))

nba %>%
  summarise(propWest = mean(west_conference))
```

```
## # A tibble: 1 × 1
##   propWest
##      <dbl>
## 1    0.508
```

A Preview of Multivariate Analysis

- Let's take a "conditional mean"
    - I.e., conditional on players going to Kentucky, how many points did NBA players score in the 2018-2019 season?
    - (Simpler is just to say "how many points did NBA players who went to Kentucky score?")
- Recall the `group_by()` command

A Preview of Multivariate Analysis

```r
nba %>%
  filter(!is.na(org)) %>%
  filter(org != 'Other') %>%
  group_by(org) %>%
  summarise(tot_pts = sum(pts,na.rm=T))
```

```
## # A tibble: 66 × 2
##    org                         tot_pts
##    <fct>                         <dbl>
##  1 Anadolu Efes S.K.              1270
##  2 Arizona                        5467
##  3 Baylor                          861
##  4 Boston College                 1659
##  5 Butler                         1255
##  6 California                     1942
##  7 California-Los Angeles         9061
##  8 Cincinnati                      531
##  9 Colorado                       2367
## 10 Connecticut                    3634
## # ℹ 56 more rows
```

A Preview of Multivariate Analysis

- Some non-college organizations snuck in there
  - `Anadolu Efes S.K.` is a professional Turkish basketball team

A Preview of Multivariate Analysis

```
nba %>%
  filter(!is.na(org)) %>%
  filter(org != 'Other') %>%
  filter(!str_detect(org,"CB|KK|rytas|FC|B.C.|S.K.|Madrid")) %>%
  group_by(org) %>%
  summarise(tot_pts = sum(pts,na.rm=T))
```

```
## # A tibble: 57 × 2
##    org                       tot_pts
##    <fct>                       <dbl>
##  1 Arizona                      5467
##  2 Baylor                        861
##  3 Boston College               1659
##  4 Butler                       1255
##  5 California                   1942
##  6 California-Los Angeles       9061
##  7 Cincinnati                    531
##  8 Colorado                     2367
##  9 Connecticut                  3634
## 10 Creighton                    1230
## # ℹ 47 more rows
```

Another Preview

- Do the same but for free throw percentage (`pctFT`)
- **NB**: should you summarise with `sum()` or `mean()`? Why?

```
# INSERT CODE HERE
```

BREAK

Agenda

1. Mutivariate
2. What is "conditional"?
3. Understanding Trump support

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('https://github.com/jbisbee1/ISP_Data_Science_2024/raw/main/da
```

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 pctSupport
##   <chr>                     <dbl> <int>     <int>      <dbl>
## 1 Donald Trump, the Republ…     1   247       551      0.448
## 2 Donald Trump, the Republ…     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
```

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
## # ℹ 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`)
```

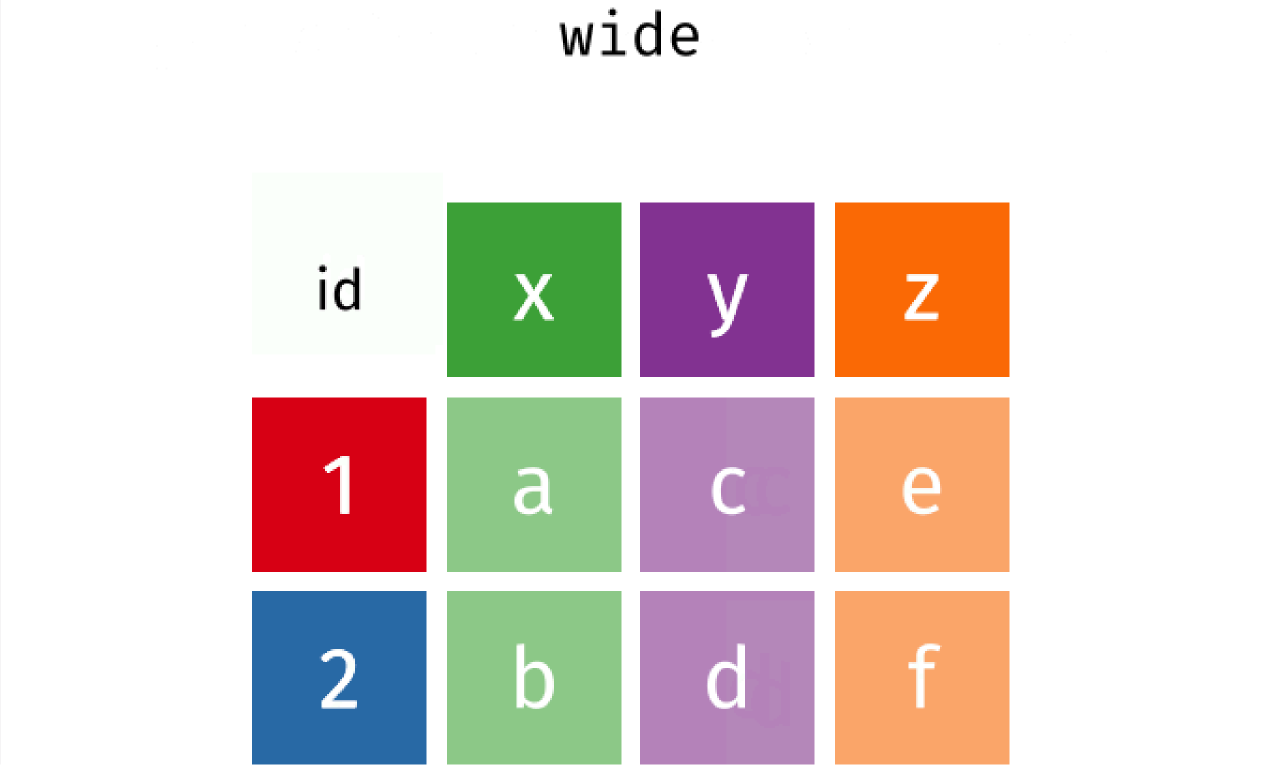
```
## # A tibble: 11 × 3
##    AGE10  Male Female
##    <dbl> <dbl>  <dbl>
##  1     1 0.438 0.0625
##  2     2 0.417 0.0714
##  3     3 0.423 0.308
##  4     4 0.241 0.294
##  5     5 0.419 0.484
##  6     6 0.583 0.4
##  7     7 0.537 0.367
##  8     8 0.443 0.263
##  9     9 0.395 0.311
## 10   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

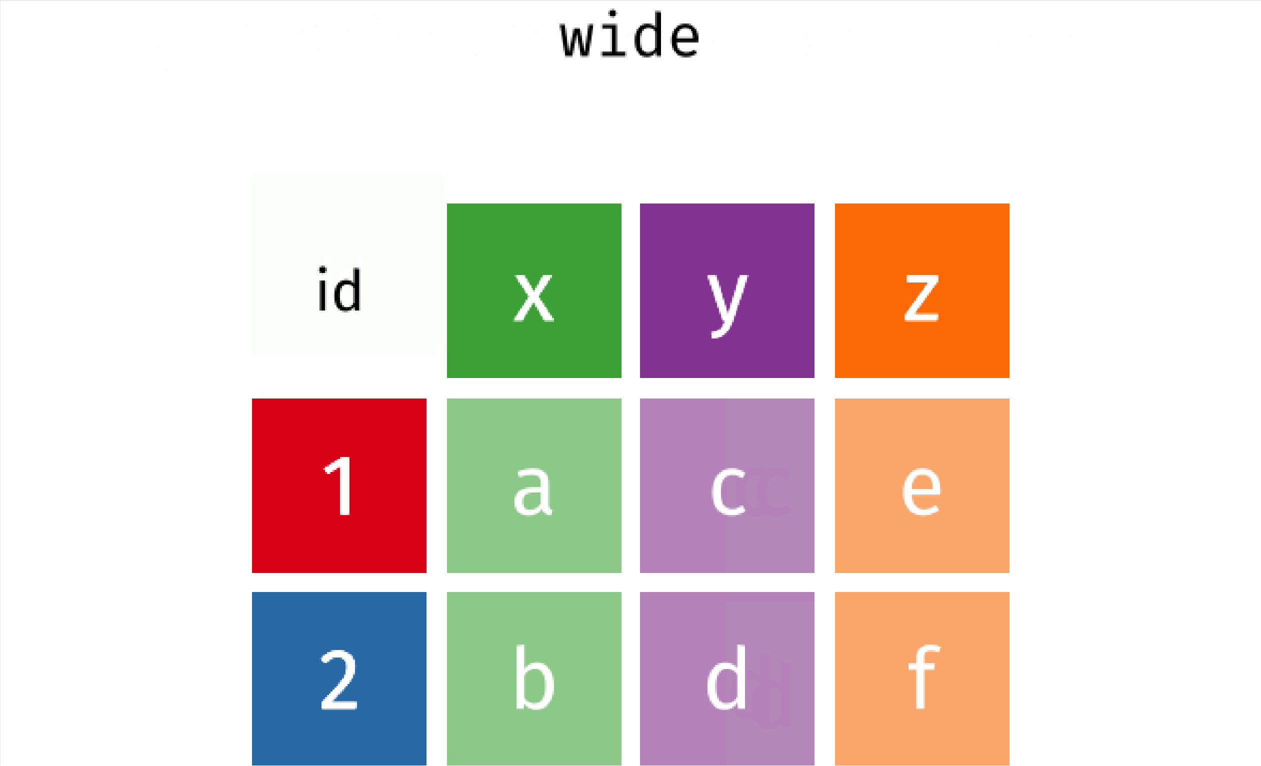
`spread()` and `gather()`

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



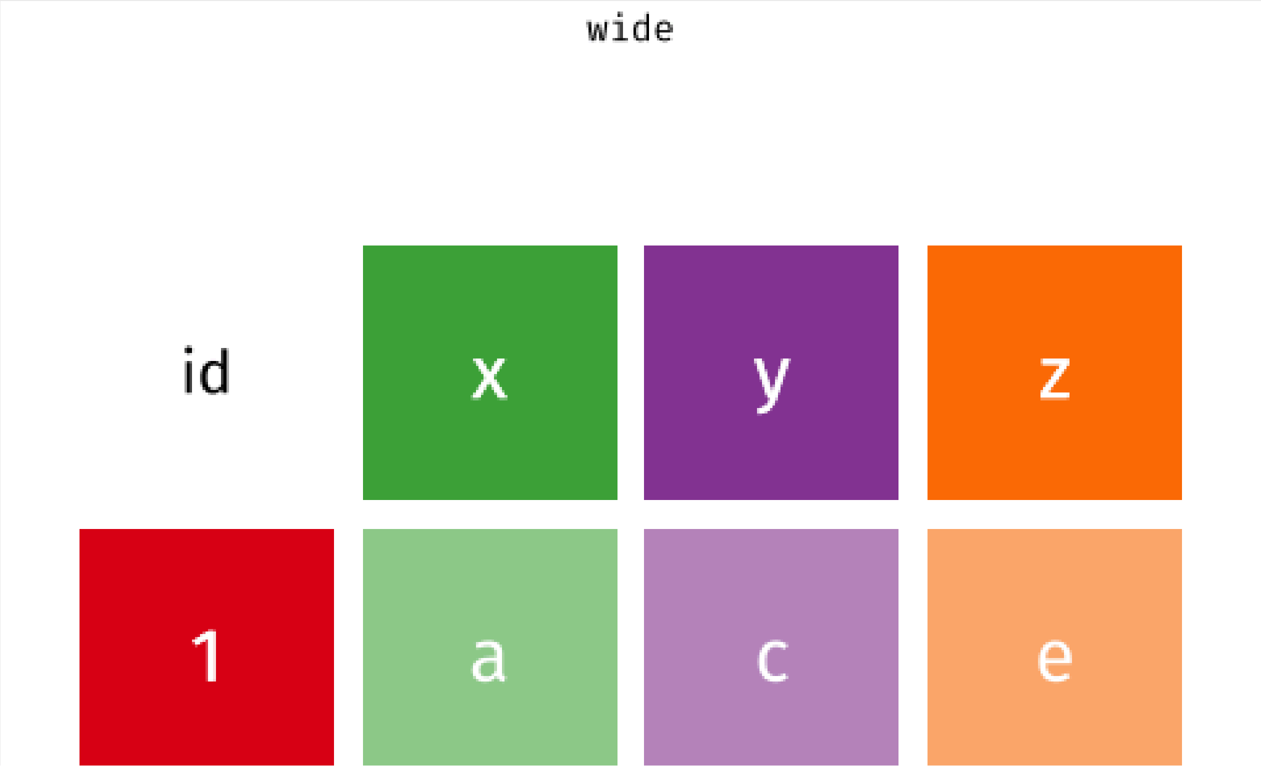
`spread()` and `gather()`

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



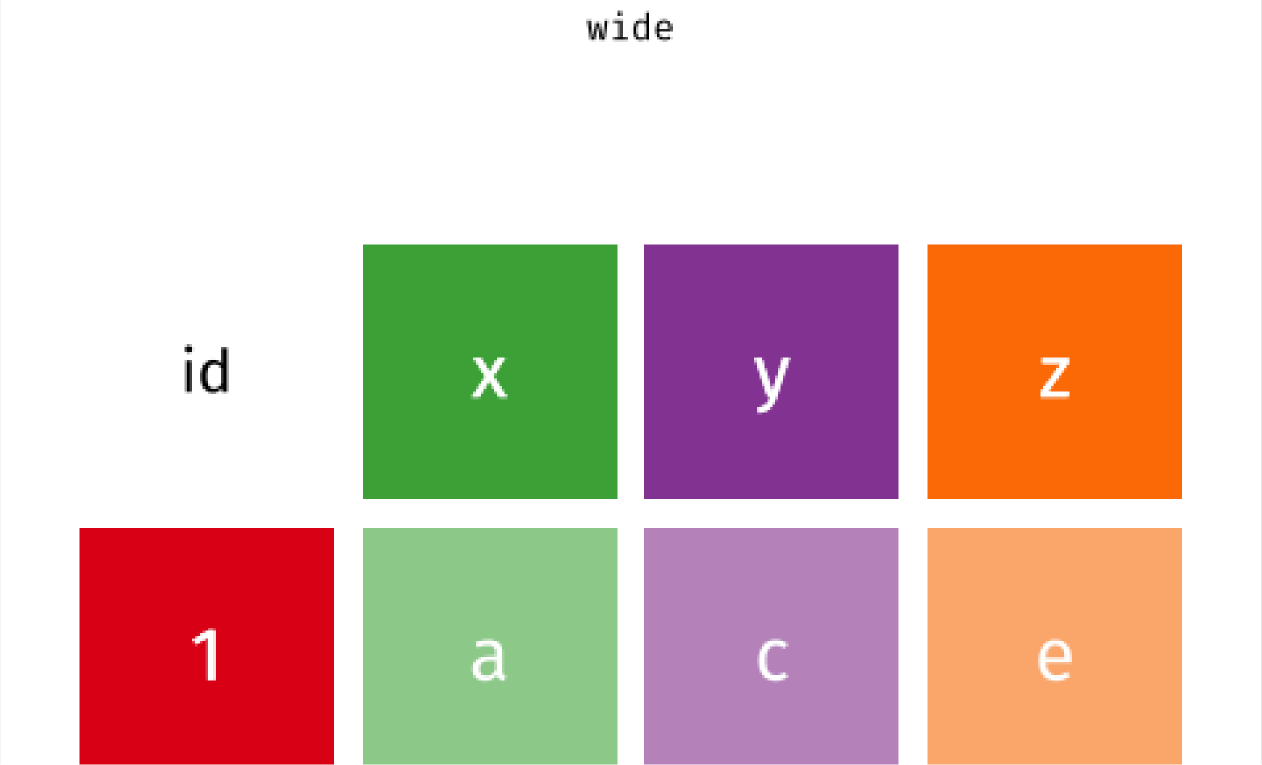
`pivot_wider()`

- `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
## # ℹ 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
```

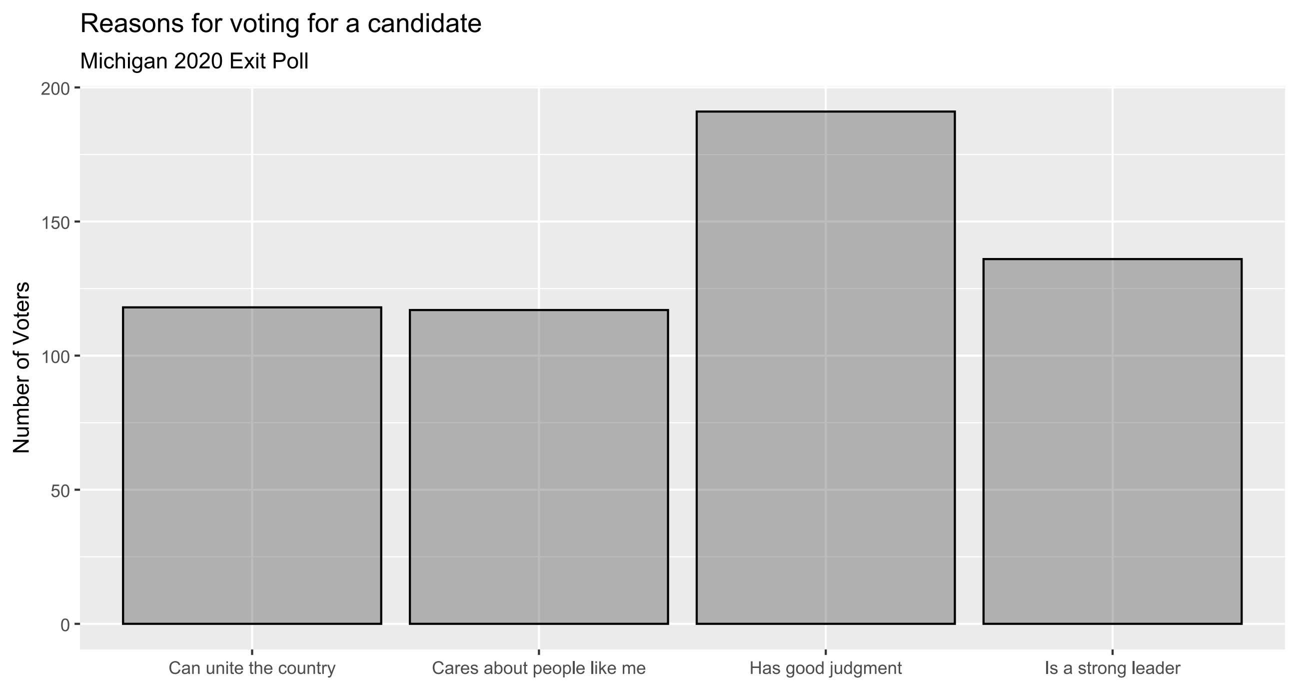
Conditional Categorical Analysis

- 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

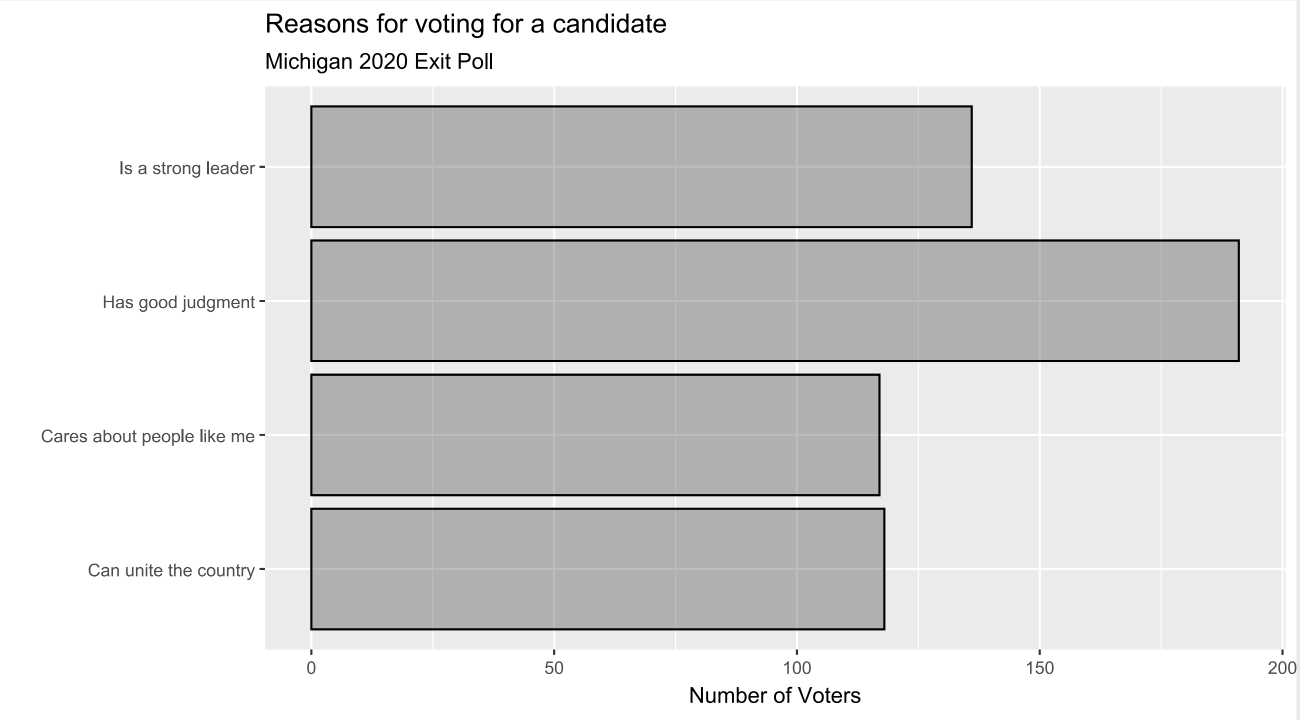
```
(pReasonOverall <- toplot %>%
  ggplot(aes(x = Quality)) +
  labs(y = "Number of Voters",x = "",
         title = "Reasons for voting for a candidate",
       subtitle = "Michigan 2020 Exit Poll") +
    geom_bar(color="black",alpha = .4))
```



Conditional Categorical Analysis

- Can swap axes with `coord_flip()`

```
pReasonOverall + coord_flip()
```



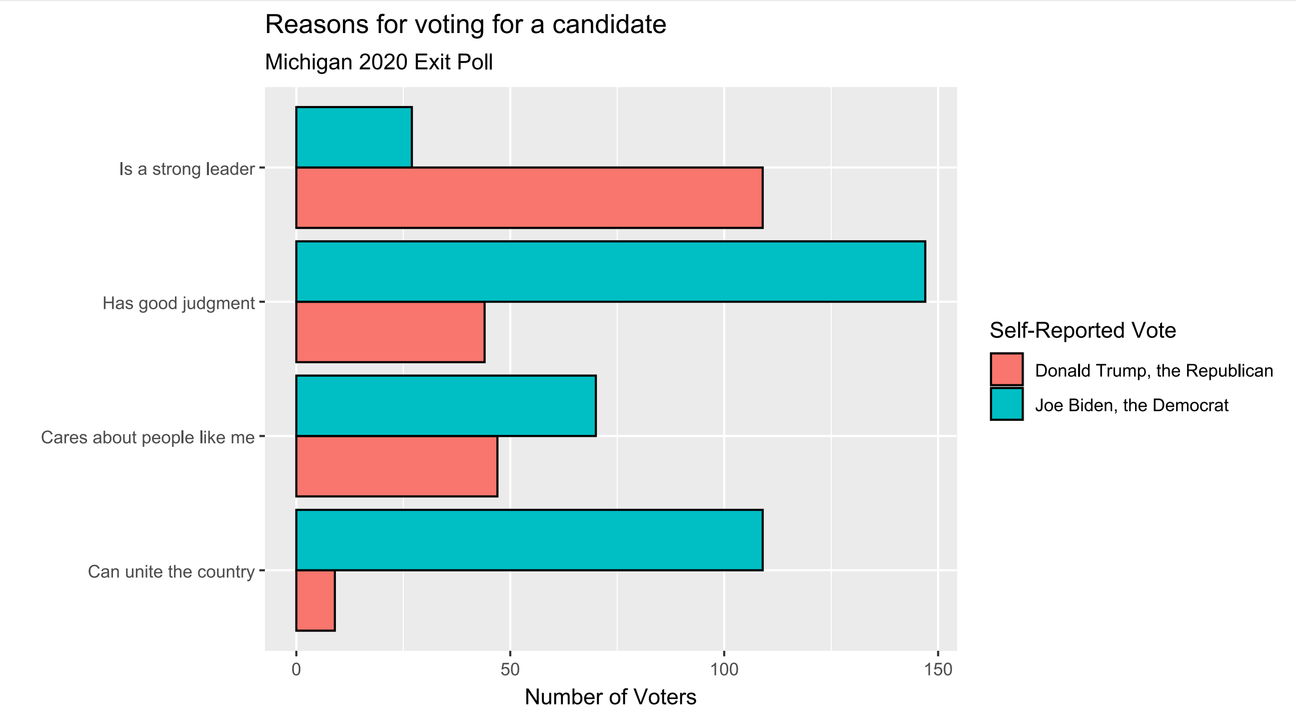
Conditional Categorical Analysis

- `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
```

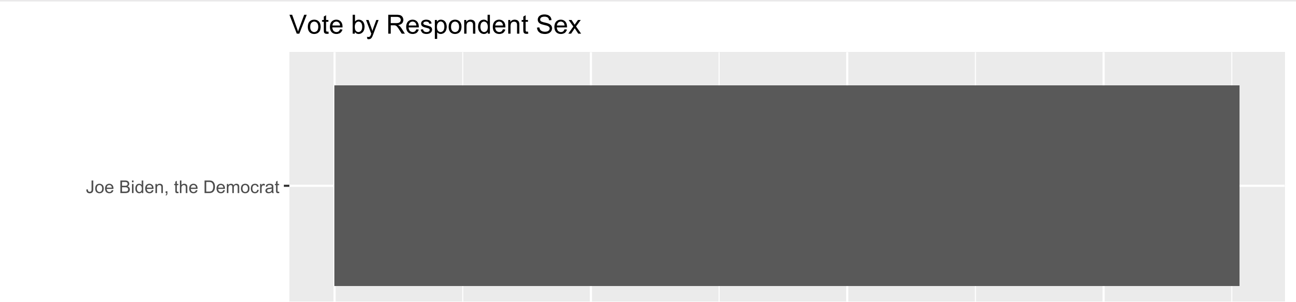


Conditional Categorical Analysis

- 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()
```

```
## Warning: The following aesthetics were dropped during statistical
## transformation: fill.
## ℹ This can happen when ggplot fails to infer the correct
##   grouping structure in the data.
## ℹ Did you forget to specify a `group` aesthetic or to
##   convert a numerical variable into a factor?
```



Be Attentive to `class()`

- How is `SEX` stored in the data?

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

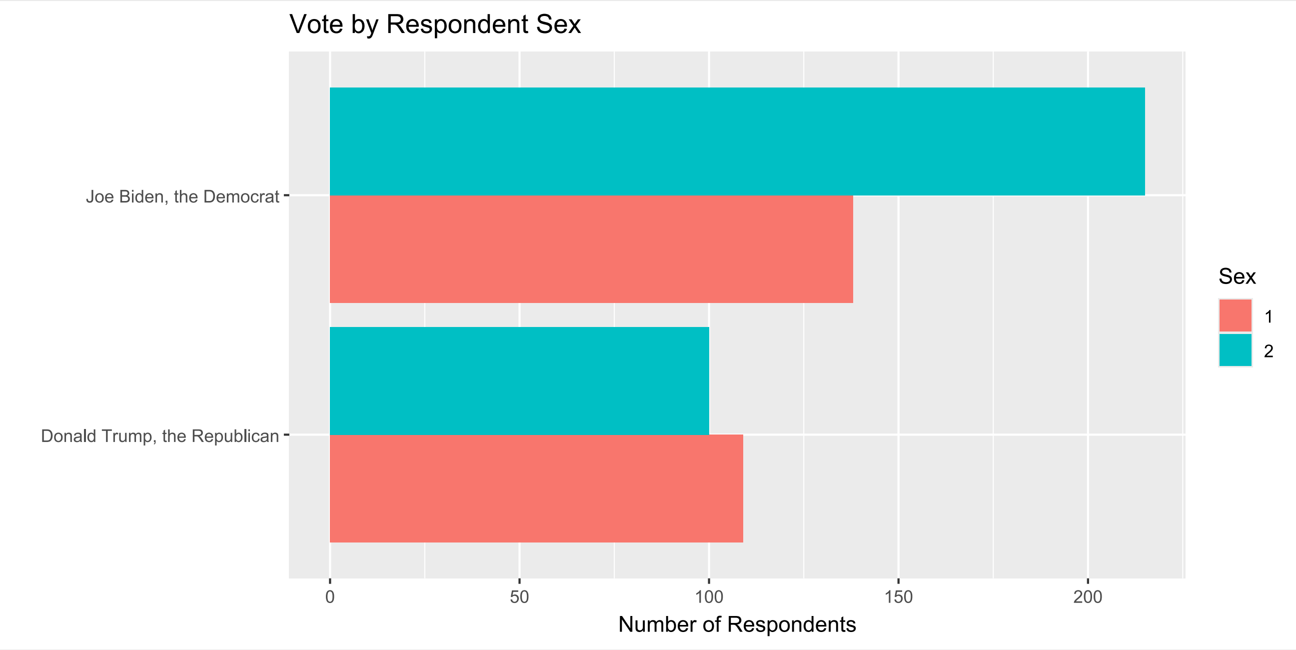
```
## [1] "numeric"
```

- 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!**