

# 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

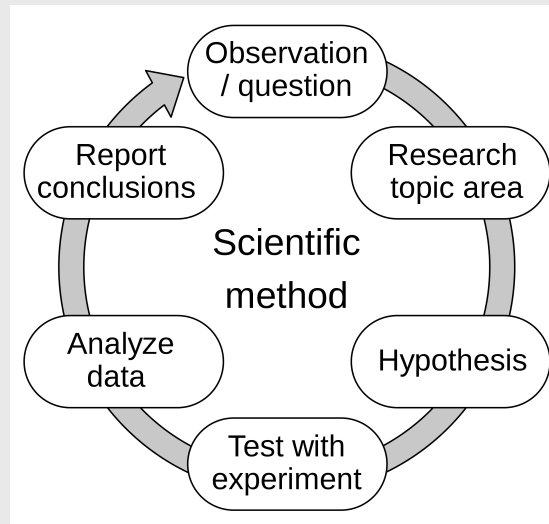
- Uni + variate
  - One + variable
  - Analysis of one variable

# 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?

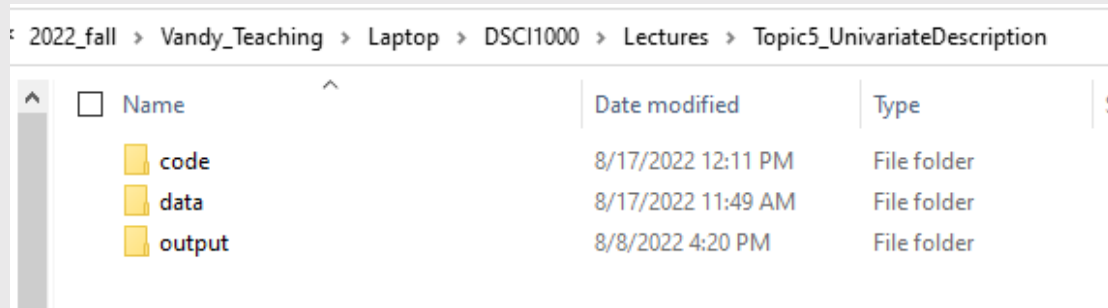
# Univariate Analysis is **ESSENTIAL**




- 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



2022_fall > Vandy_Teaching > Laptop > DSCI1000 > Lectures > Topic5_UnivariateDescription			
<input type="checkbox"/> Name	Date modified	Type	S
 code	8/17/2022 12:11 PM	File folder	
 data	8/17/2022 11:49 AM	File folder	
 output	8/8/2022 4:20 PM	File folder	

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

```
require(tidyverse)
```

- Load data from [github](https://github.com/jbisbee1/ISP_Data_Science_2024)

```
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)
```

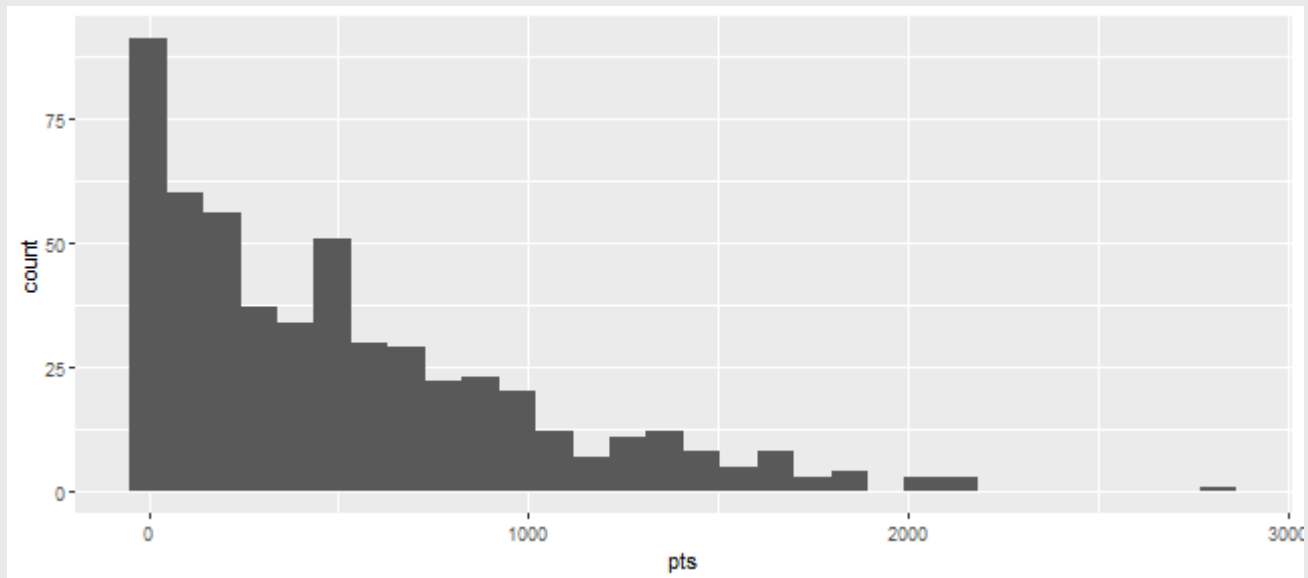
##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	0.0	115.0	419.0	516.2	759.5	2818.0

- 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()
```

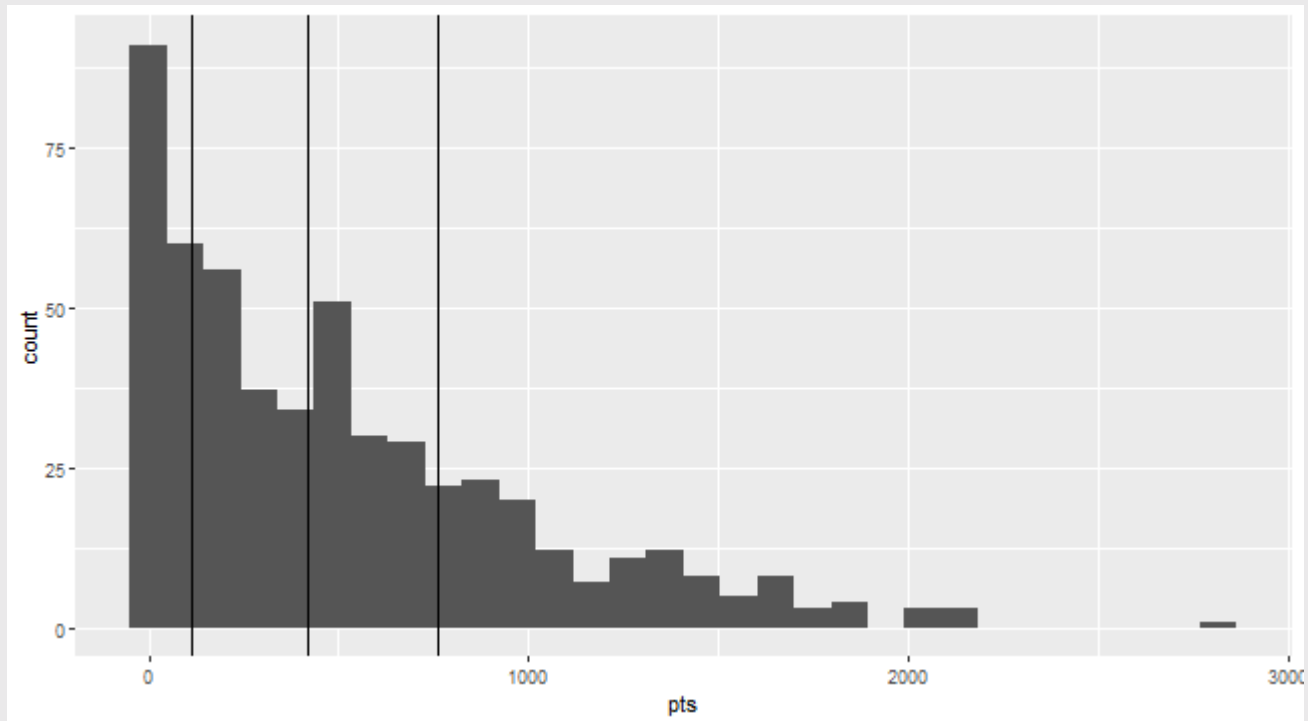


# Visualization

- 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)))
```



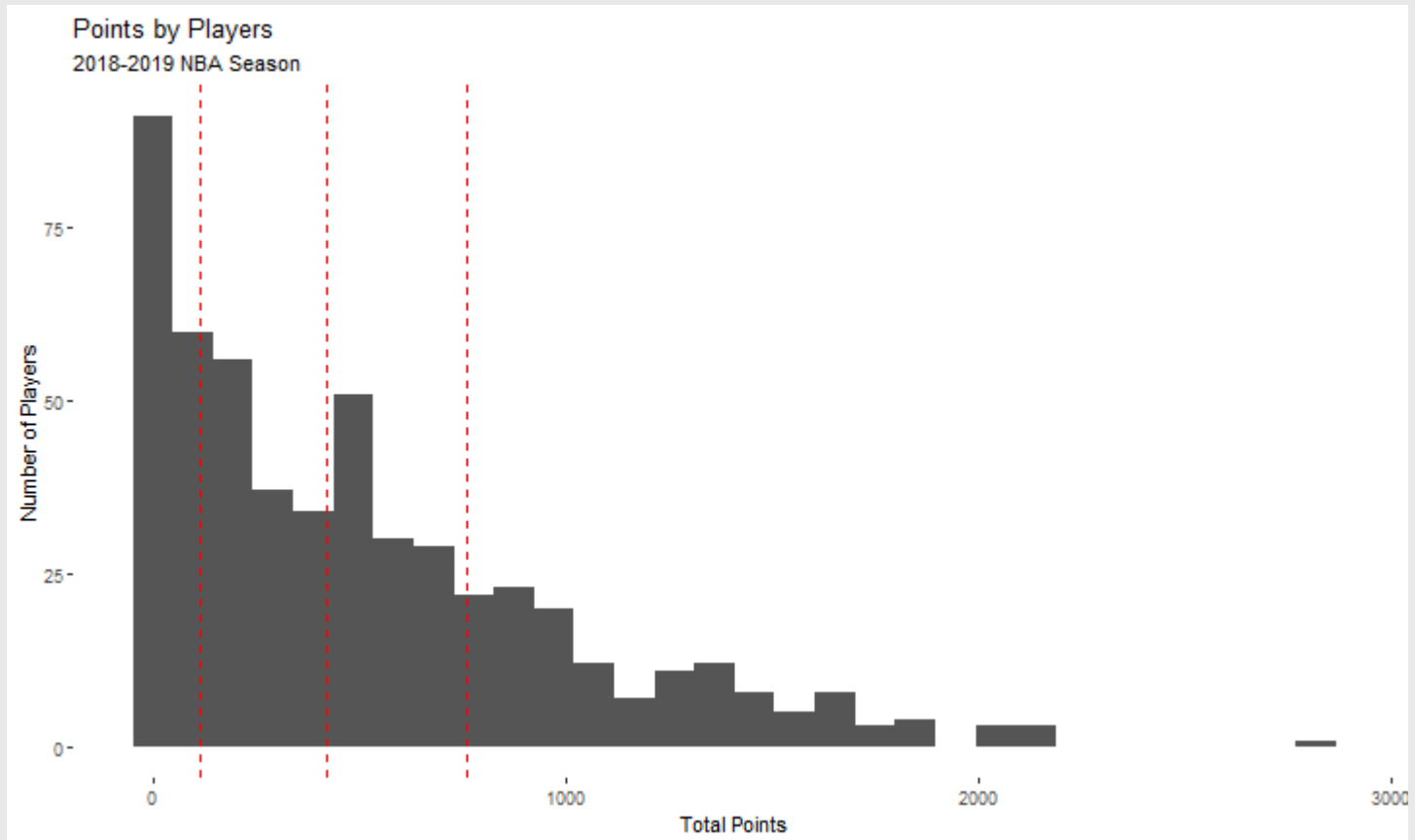
# Visualization

- 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

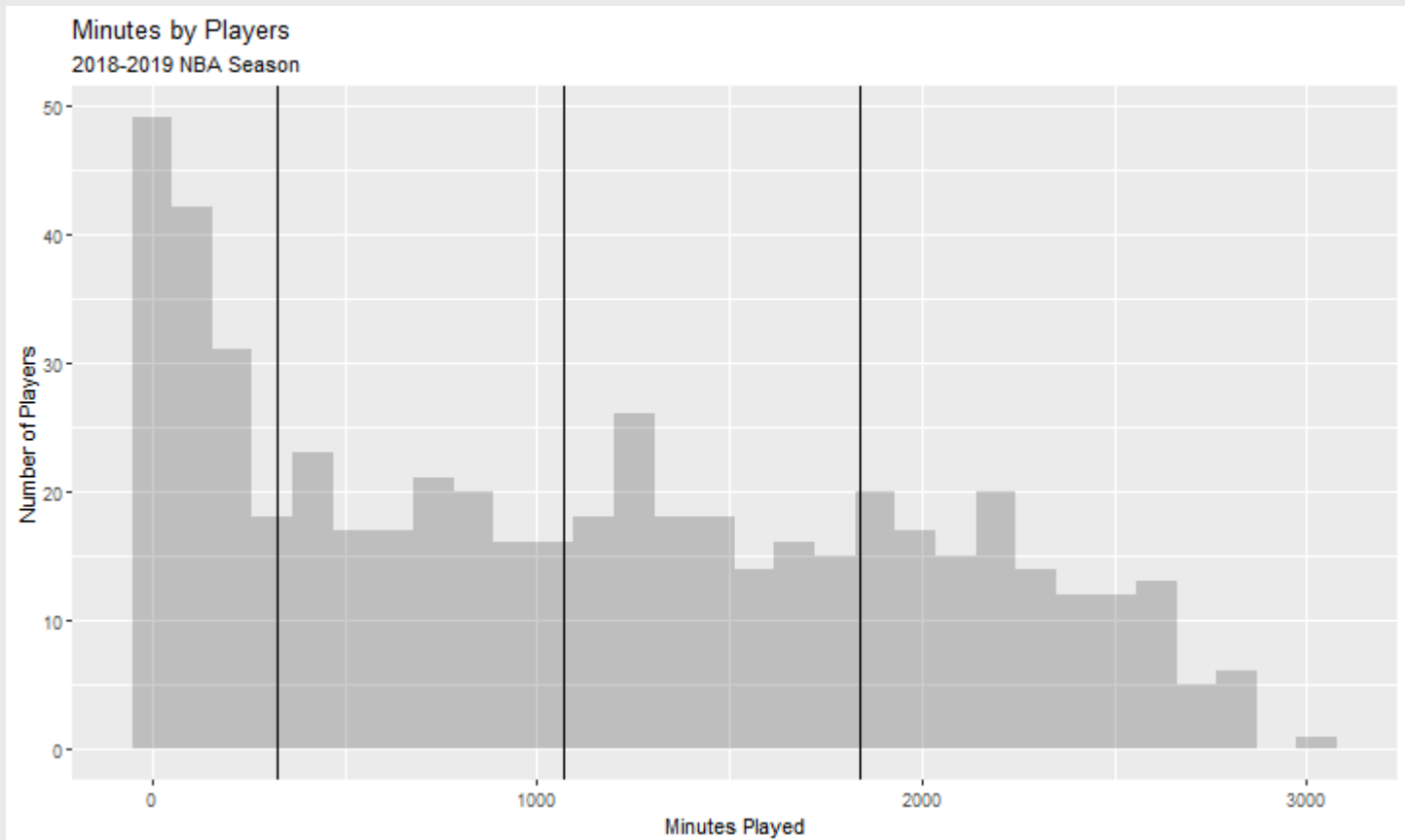
- Testing this hypothesis comes later
- For now, let's also describe the minutes variable

```
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 Variables

```
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, ...
## $ 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`, `lg1`, `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!

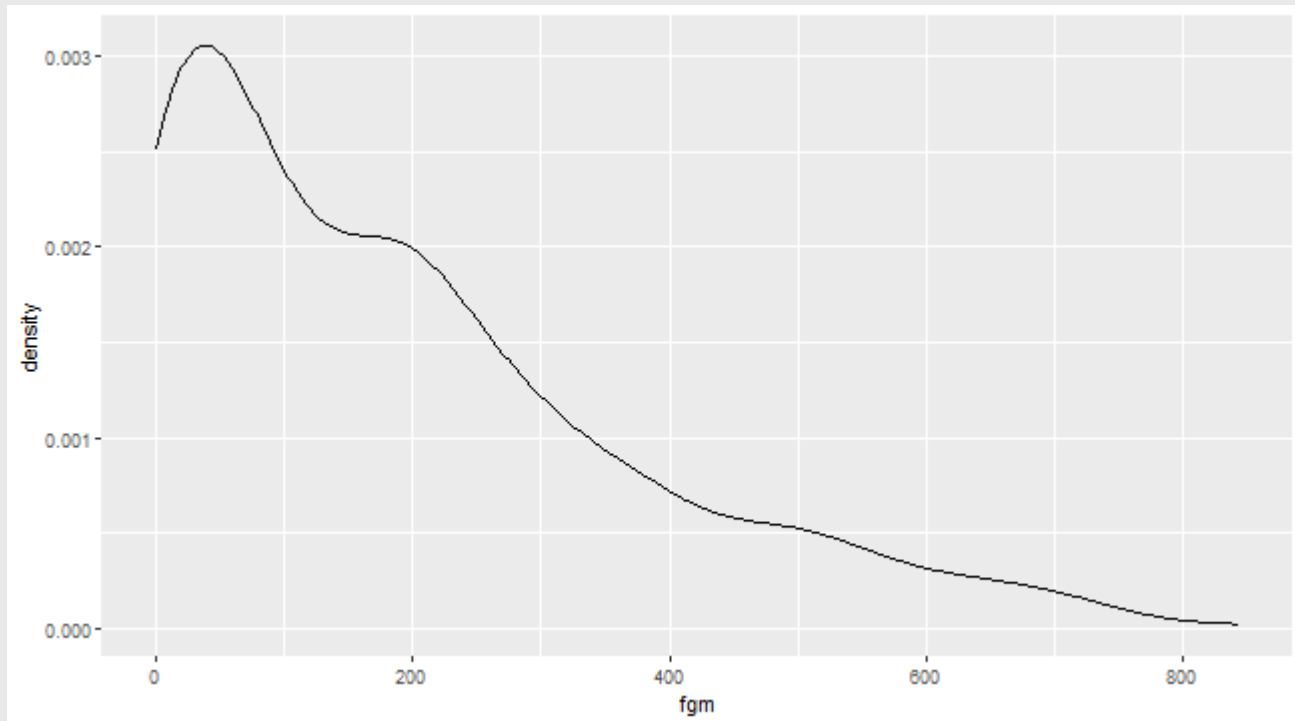
# The Process: #1 Look

```
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**!

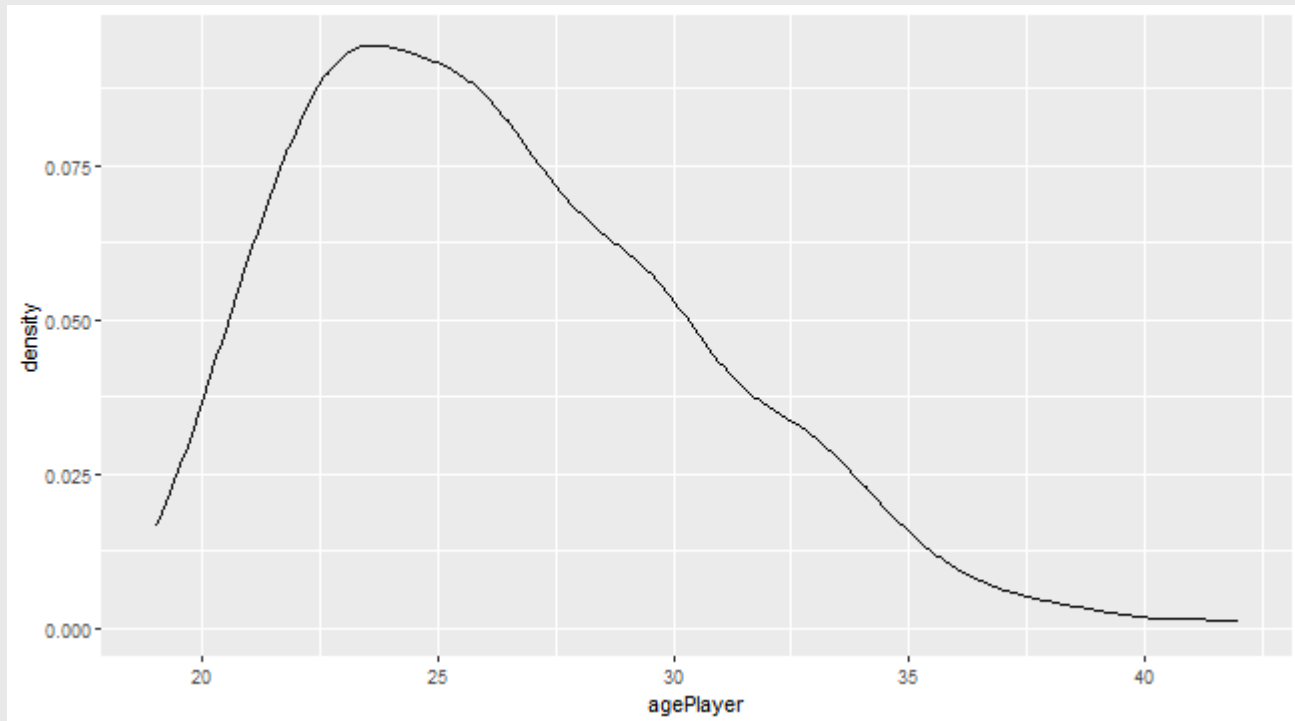
# The Process: #1 Look

```
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
```

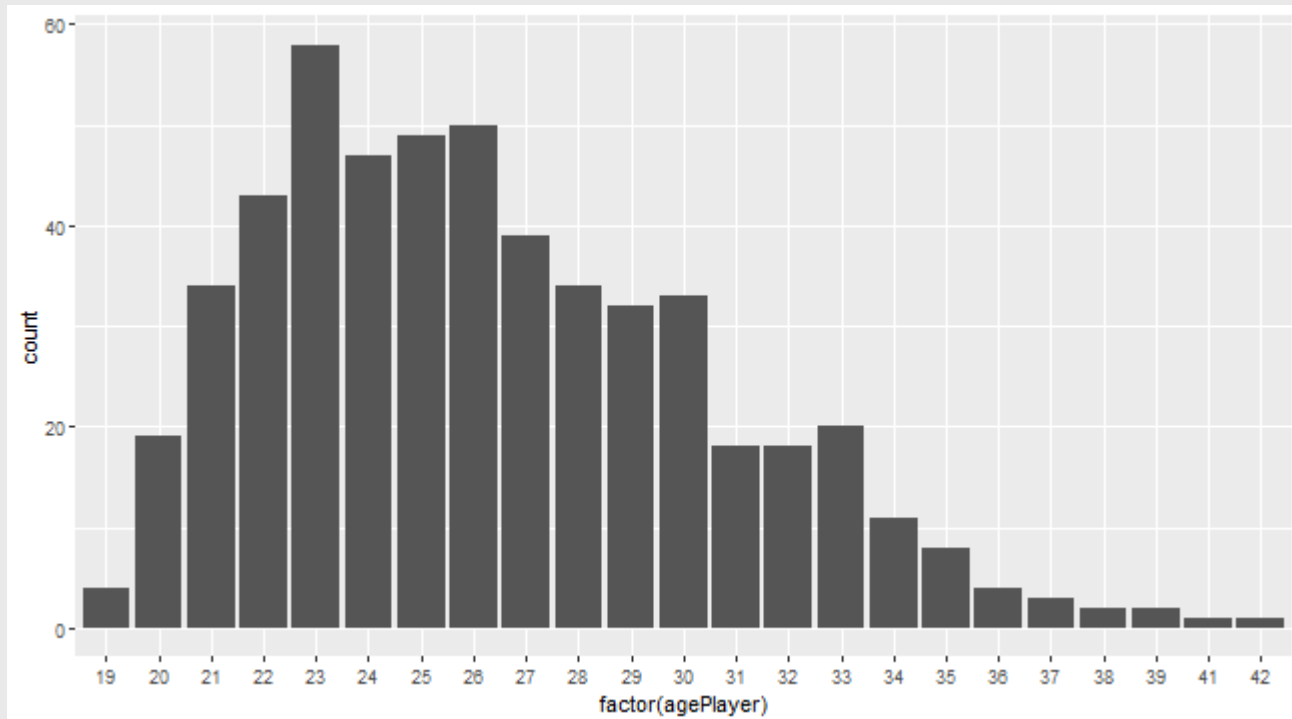
# The Process: #2 Create

```
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

```
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. Multivariate
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/d
```



# 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

wide		long	
id	x	y	z
1	a	c	e
2	b	d	f

# 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

wide

id	x	y	z
1	a	c	e
2	b	d	f

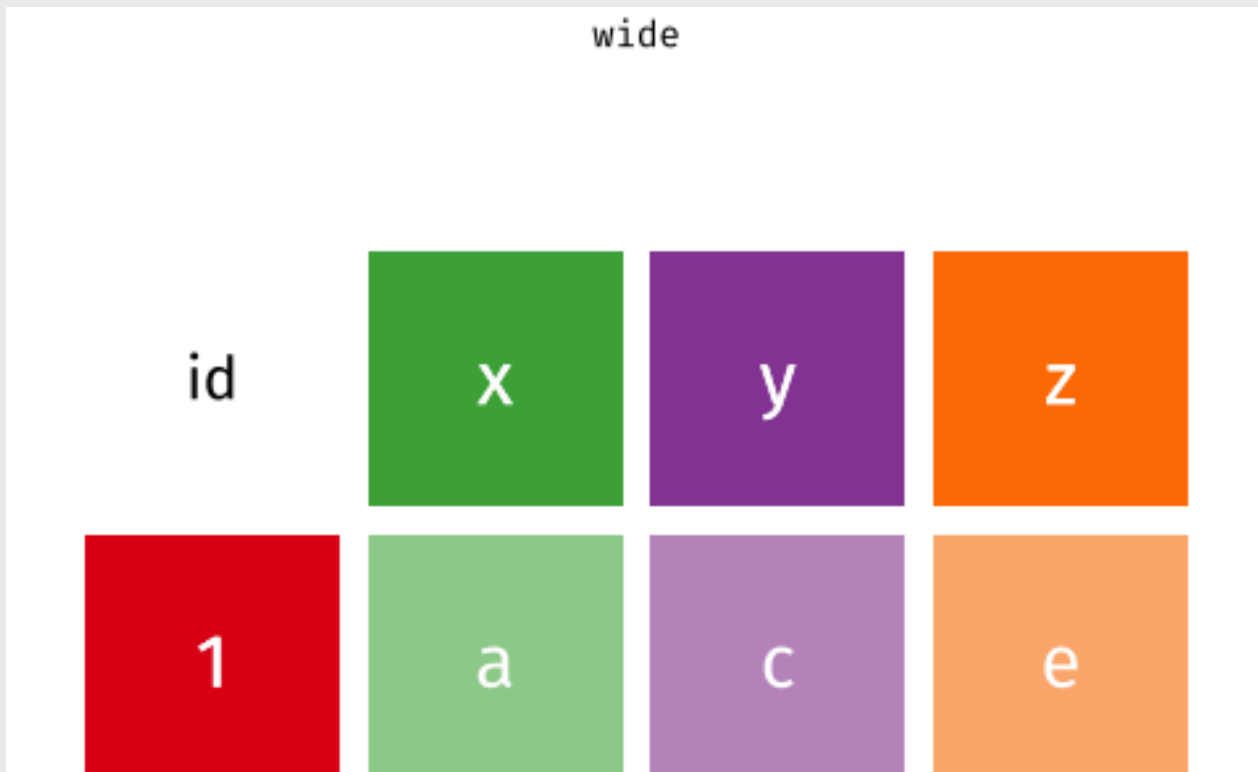
# pivot\_wider()

- `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

wide			
id	x	y	z
1	a	c	e

# 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  1 Male    0.438  
## 2     2  2 Male    0.417  
## 3     3  3 Male    0.423  
## 4     4  4 Male    0.241  
## 5     5  5 Male    0.419  
## 6     6  6 Male    0.583  
## 7     7  7 Male    0.537  
## 8     8  8 Male    0.443  
## 9     9  9 Male    0.395  
## 10    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

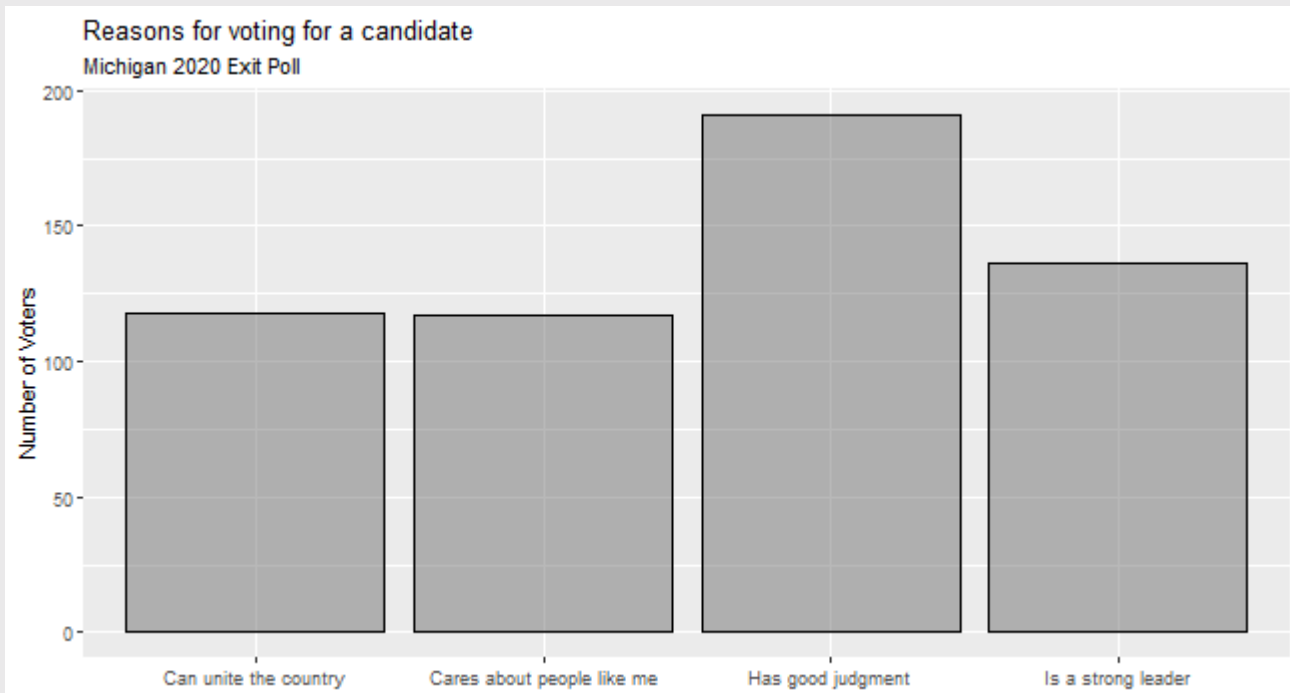
- Want to know **reason** for voting for candidate by **vote choice**
  - **Quality**: 4 category unordered
  - **preschoice**: 2 category unordered
- Some light data wrangling

```
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

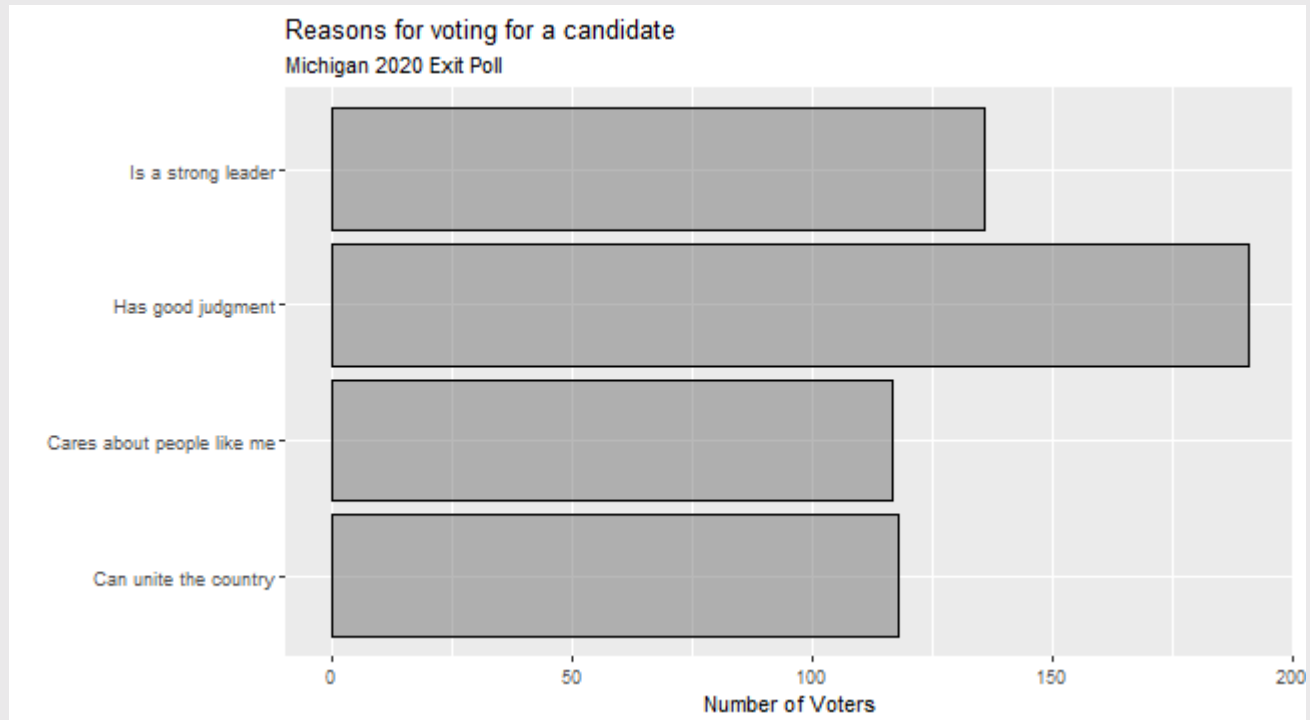
```
(pReasonOverall <- toplot %>%  
  ggplot(aes(x = Quality)) +  
  labs(y = "Number of Voters", x = "",  
        title = "Reasons for voting for a candidate",  
        subtitle = "Michigan 2020 Exit Poll") +  
  geom_bar(color="black", alpha = .4))
```



# Conditional Categorical Analysis

- Can swap axes with `coord_flip()`

```
pReasonOverall + coord_flip()
```



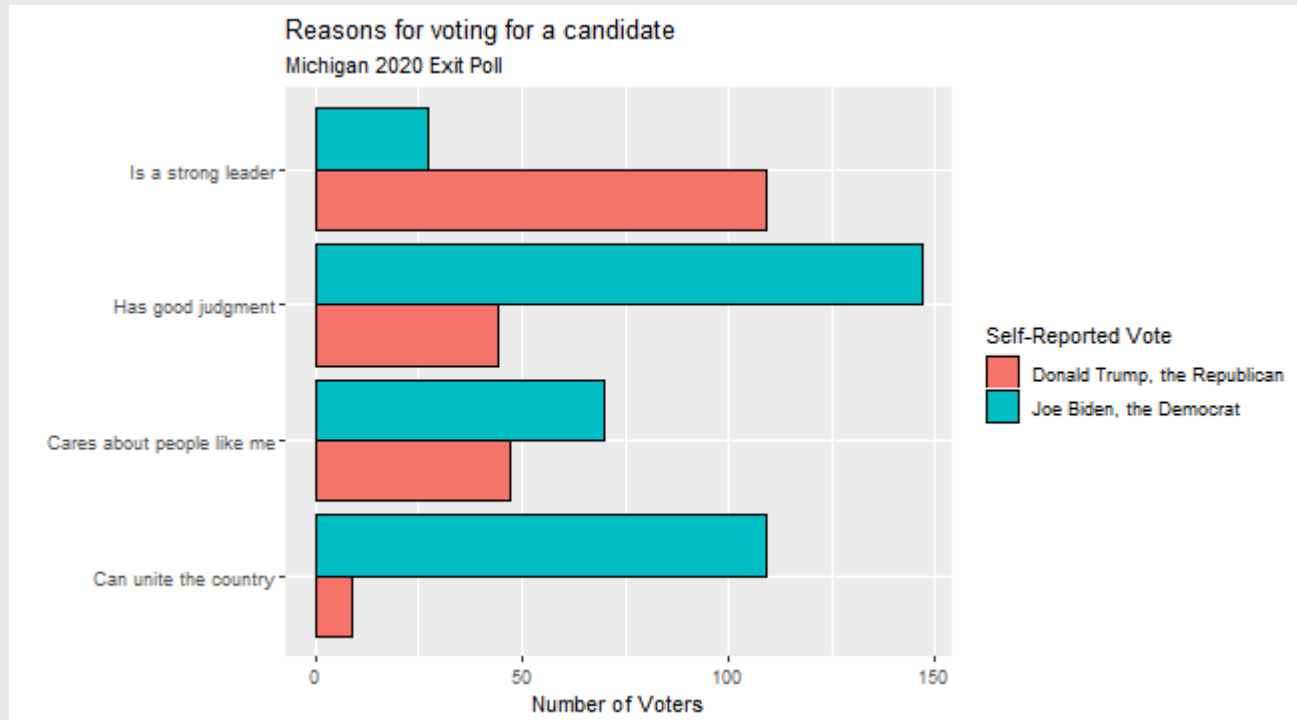
# Conditional Categorical Analysis

- `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

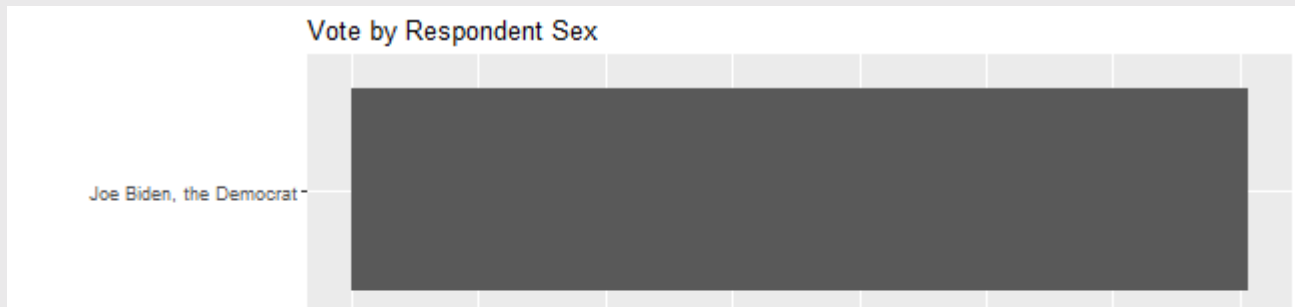


# Conditional Categorical Analysis

- 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)
```

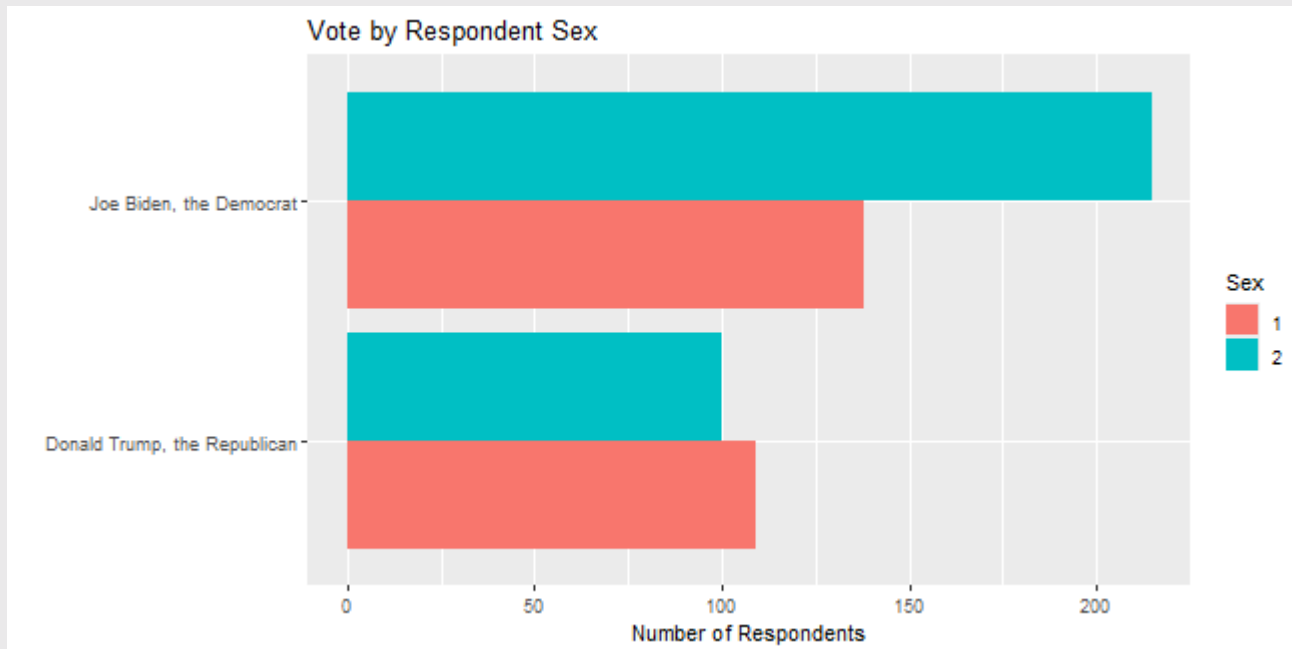
```
## [1] "numeric"
```

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

```
pVoteSex <- topplot %>%  
  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!**