Uncertainty

How confident are we?

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Agenda

1. Uncertainty
2. More NBA data
3. Bootstrap Sampling

The Missing Ingrediant

- Thus far we have:

   1. Tested whether **selective** schools have **higher SAT scores**: Yes
   2. Tested Trump's theory that **polls were biased against him**: No
   3. Tested whether RDD polls **contact more Trump supporters**: No
   4. Tested whether state polls **accurately predicted the president**: No

- We want to do more than say "Yes" or "No" when answering a Research Question or making a Prediction
- We want to express our **confidence**

What is "confidence"?

- In frequentist statistics:
  - How often your conclusion would be correct if you were able to run an "experiment" many times
  - How often your conclusion would be correct if you were able to observe the world many times
- Research Question: Are NBA players in their rookie season more prone to turnovers?
  - Theory: ??
  - Hypothesis: ??
- Analysis: compare `tov` by `isRookie`

NBA Example

```
require(tidyverse)
nba <-
read_rds('https://github.com/jbisbee1/ISP_Data_Science_2024/raw/main/da
glimpse(nba %>% select(tov,isRookie))
```

```
## Rows: 530
## Columns: 2
## $ tov      <dbl> 144, 4, 135, 14, 121, 8, 33, 6, 28, 2, 72…
## $ isRookie <lgl> FALSE, FALSE, FALSE, FALSE, FALSE, TRUE, …
```

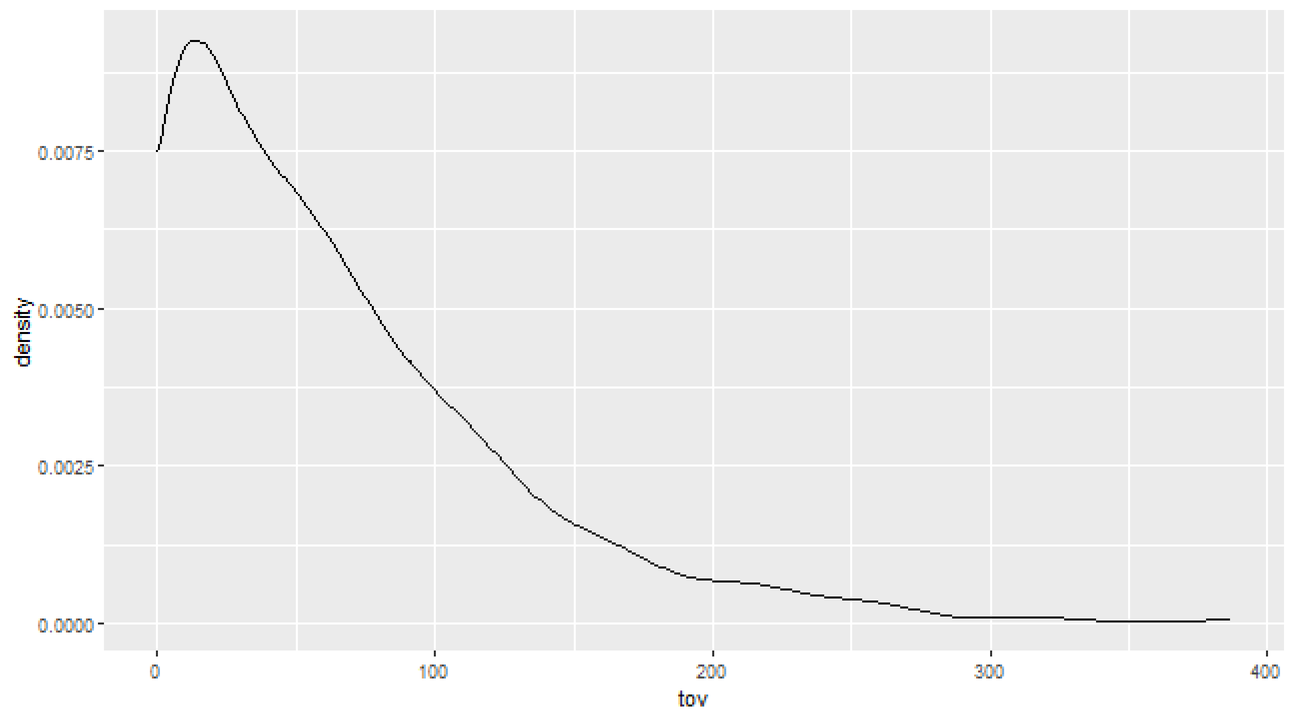
Look

```
summary(nba %>% select(tov,isRookie))
```

```
##       tov            isRookie      
##  Min.   :  0.00   Mode :logical  
##  1st Qu.: 14.25   FALSE:425      
##  Median : 47.00   TRUE :105      
##  Mean   : 62.82                  
##  3rd Qu.: 91.75                  
##  Max.   :387.00                  
```

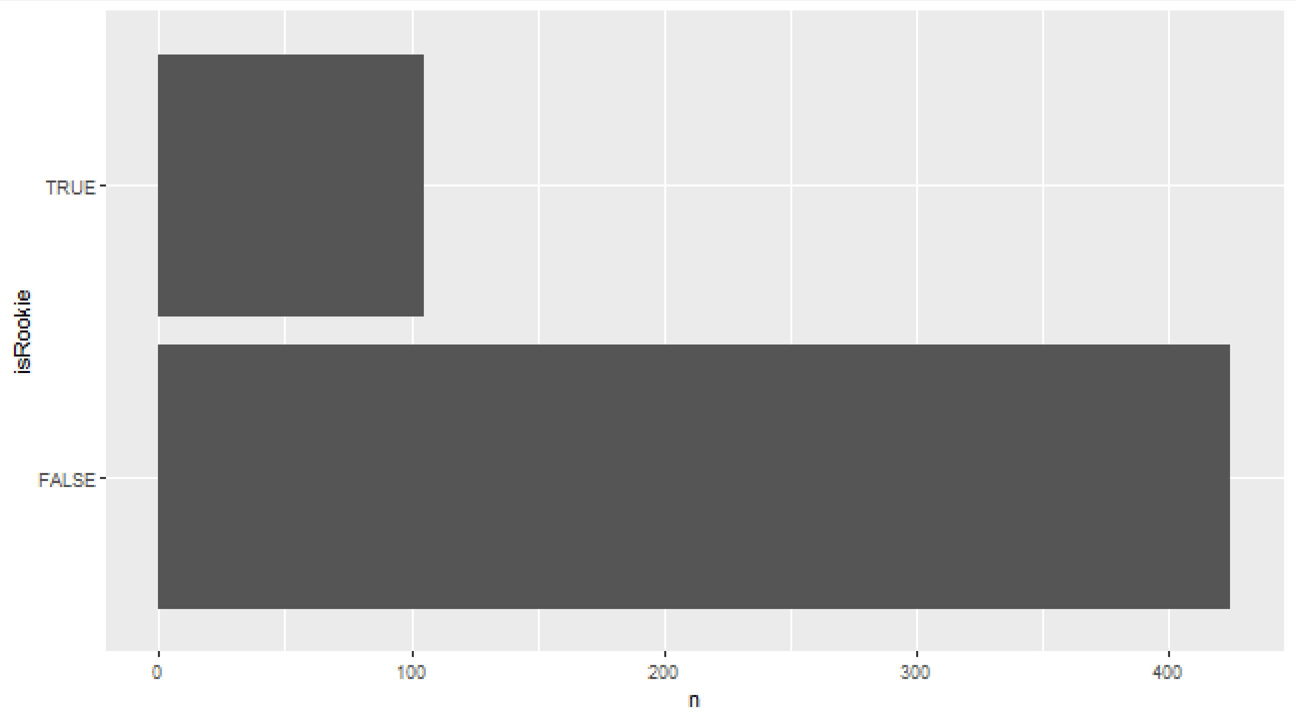
Visualize: Univariate Y

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



Visualize: Univariate X

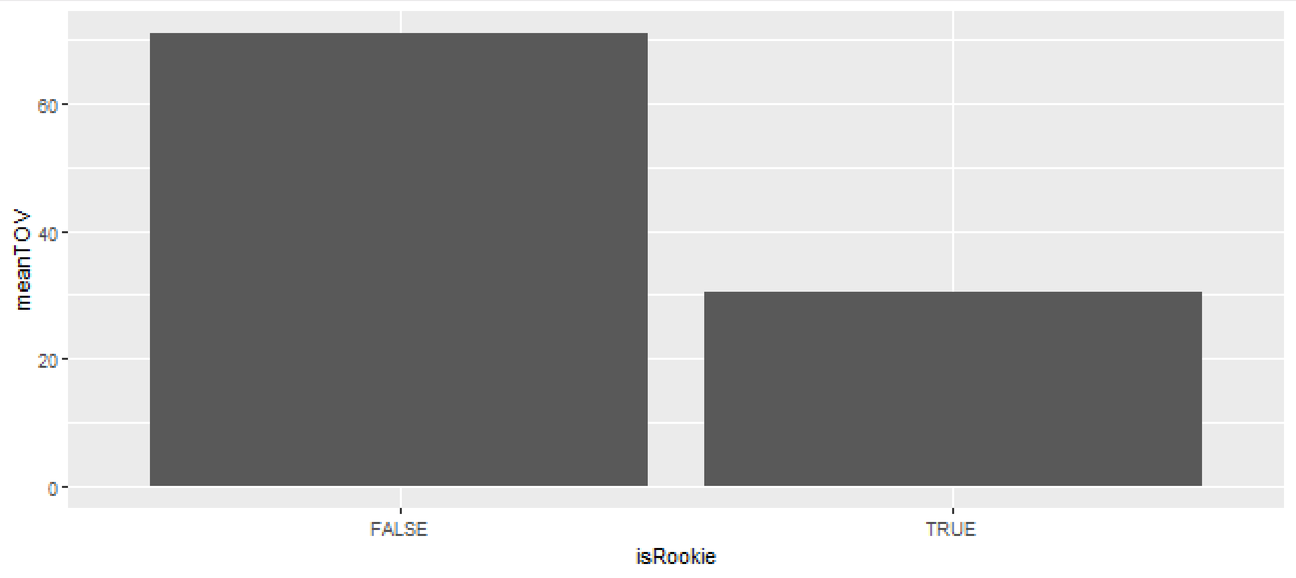
```r
nba %>%
  count(isRookie) %>%
  ggplot(aes(x = n,y = isRookie)) +
  geom_bar(stat = 'identity')
```



Visualize: Multivariate

- Option #1: `summarise()` data prior to plotting

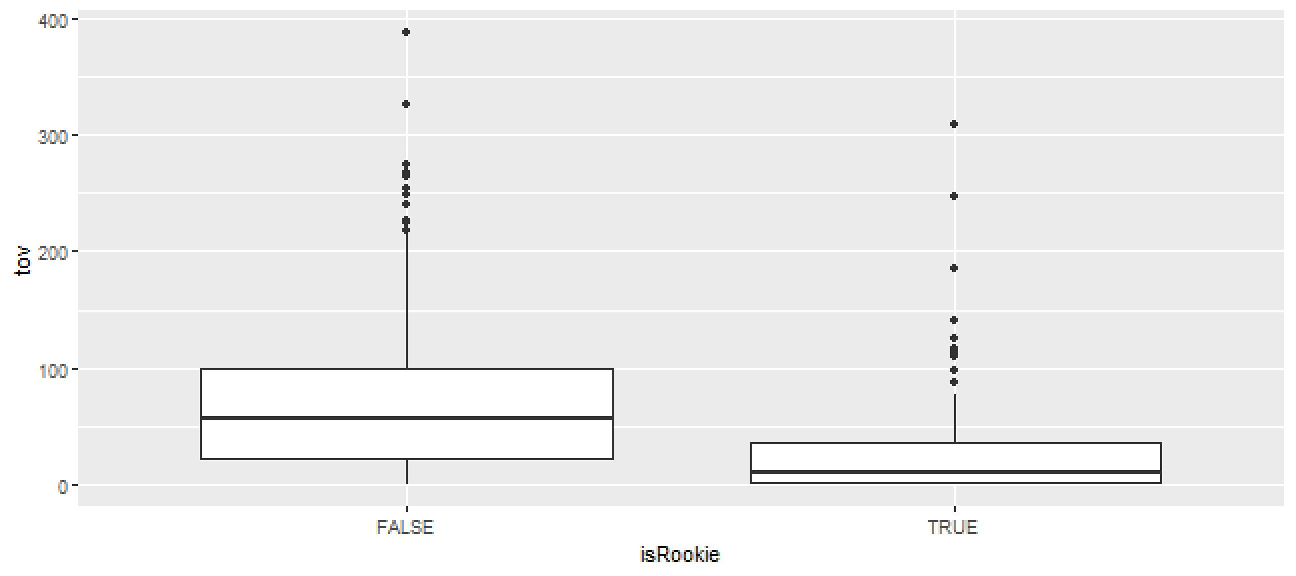
```
nba %>%
  group_by(isRookie) %>%
  summarise(meanTOV = mean(tov,na.rm=T)) %>%
  ggplot(aes(x = isRookie,y = meanTOV)) +
  geom_bar(stat = 'identity')
```



Visualize: Multivariate

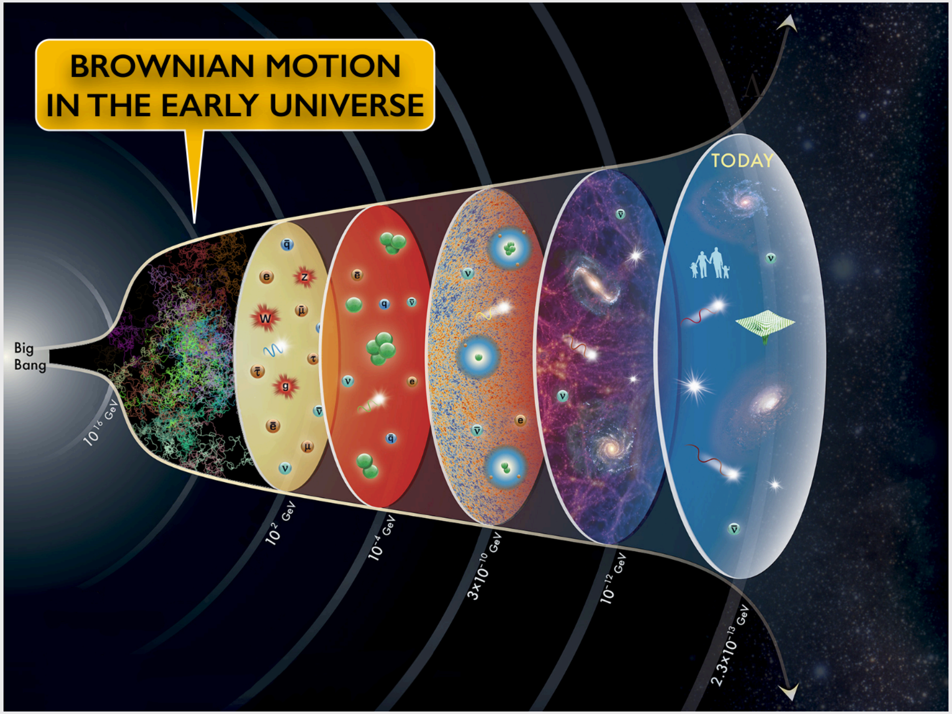
- Option #2: plot raw data

```
nba %>%
  ggplot(aes(x = isRookie,y = tov)) +
  geom_boxplot()
```



Uncertainty

- Are rookies **better** than more senior players?
- Big philosophical step back
    - We live in a stochastic universe!



Uncertainty

- Are rookies **better** than more senior players?
- Populations versus samples
  - Intro stats: uncertainty due to **sample**

Uncertainty

- Big philosophical step back
  - We live in a stochastic universe!
- What does **better** mean?
  - Theory: An innate quality in greater abundance
  - Prediction: If we had to bet on who turns over the ball less, who do we choose?
- How **confident** would we be with this bet?

Uncertainty

- If the universe is inherently stochastic, we are inherently uncertain
    - We THINK rookies are more careful passers, but not 100% certain
- How to measure this?
    - Run 100 experimental seasons
    - Record turnovers for rookies and non-rookies for each season
    - Calculate how many times rookies turned the ball over less than non-rookies
- 90 seasons out of 100 → 90% confident / certainty
- 100 seasons out of 100 → 100%?
- **FUNDAMENTAL STOCHASTIC NATURE OF REALITY (FSNoR)**

Uncertainty

- Running 100 experimental seasons is impossible
    1. We are not Adam Silver
    2. Even if we were Adam Silver, 100 seasons = a century of basketball!

Uncertainty

- Running 100 experimental seasons is impossible

  1. We are not Adam Silver
  2. Even if we were Adam Silver, 100 seasons = a century of basketball!
  3. If we were God? 100 seasons with the same players?

- *STILL wouldn't be 100% certain due to* ***FSNoR***

  - (**F**undamental **S**tochastic **N**ature **o**f **R**eality)

Uncertainty

- But we are data scientists
- Take 1 season of basketball but sample it randomly
- **Bootstrap sampling**
- Theory: By mimicking the sampling process, we can simulate a God experiment
    - (NB: this goes much deeper. Uncertainty from bootstrap combines FSNoR + sampling uncertainty.)
- Practice: `sample_n()` + `for()` loops

Bootstrap Demo Step 1

- One randomly sampled player via `sample_n(size,replace)`
  - `size`: how many samples (from 1 to all observations)
  - `replace`: whether to put the sample back (`TRUE` or `FALSE`)

```
set.seed(123) # Ensure we can reproduce results exactly

nba %>%
  sample_n(size = 1,replace = T) %>%
  select(namePlayer,slugSeason,isRookie,tov)
```

```
## # A tibble: 1 × 4
##   namePlayer    slugSeason isRookie   tov
##   <chr>         <chr>      <lgl>    <dbl>
## 1 Moritz Wagner 2018-19    TRUE        39
```

Bootstrap Demo Step 2

- Two randomly sampled players

```
set.seed(123)
nba %>%
  sample_n(size = 1,replace = T) %>%
select(namePlayer,slugSeason,isRookie,tov)
```

```
## # A tibble: 1 × 4
##   namePlayer     slugSeason isRookie   tov
##   <chr>          <chr>      <lgl>    <dbl>
## 1 Moritz Wagner 2018-19    TRUE        39
```

```
nba %>%
  sample_n(size = 1,replace = T) %>%
select(namePlayer,slugSeason,isRookie,tov)
```

```
## # A tibble: 1 × 4
##   namePlayer slugSeason isRookie   tov
##   <chr>      <chr>      <lgl>    <dbl>
## 1 Sam Dekker 2018-19    FALSE       24
```

Bootstrap Demo Step 2

- OR two randomly sampled players

```
set.seed(123)

nba %>%
  sample_n(size = 2,replace = T) %>%
select(namePlayer,slugSeason,isRookie,tov)
```

```
## # A tibble: 2 × 4
##   namePlayer     slugSeason isRookie   tov
##   <chr>          <chr>      <lgl>    <dbl>
## 1 Moritz Wagner 2018-19    TRUE        39
## 2 Sam Dekker    2018-19    FALSE       24
```

Bootstrap Demo Step 3

- Randomly sample all players: `size = nrow(nba)` (or `nrow(.)`)

```
set.seed(123)

nba %>%
  sample_n(size = nrow(nba),replace = T) %>% # Same as nrow(.)
  select(namePlayer,slugSeason,isRookie,tov)
```

```
## # A tibble: 530 × 4
##    namePlayer         slugSeason isRookie   tov
##    <chr>              <chr>      <lgl>    <dbl>
##  1 Moritz Wagner      2018-19    TRUE        39
##  2 Sam Dekker         2018-19    FALSE       24
##  3 Joe Harris         2018-19    FALSE      121
##  4 Jonas Valanciunas  2018-19    FALSE       90
##  5 John Holland       2018-19    FALSE        0
##  6 Angel Delgado      2018-19    TRUE         0
##  7 Donovan Mitchell   2018-19    FALSE      218
##  8 Damian Jones       2018-19    FALSE       16
##  9 Luke Kornet        2018-19    FALSE       25
## 10 Justin Anderson    2018-19    FALSE       23
## # ℹ 520 more rows
```

Bootstrap Demo Step 4

- Linking to **confidence**: Do we draw the same conclusion twice?

```
set.seed(123)

# Bootstrapped Season #1
bsSeason1 <- nba %>%
  sample_n(size = nrow(.),replace = T) %>%
  select(isRookie,tov) %>%
  mutate(bsSeason = 1)

# Bootstrapped Season #2
bsSeason2 <- nba %>%
  sample_n(size = nrow(.),replace = T) %>%
  select(isRookie,tov) %>%
  mutate(bsSeason = 2)
```

Bootstrap Demo Step 4

- Linking to **confidence**: Do we draw the same conclusion twice?

```
bsSeason1 %>%
  group_by(isRookie) %>%
  summarise(mean_tov = mean(tov))
```

```
## # A tibble: 2 × 2
##   isRookie mean_tov
##   <lgl>       <dbl>
## 1 FALSE        68.6
## 2 TRUE         36.9
```

```
bsSeason2 %>%
  group_by(isRookie) %>%
  summarise(mean_tov = mean(tov))
```

```
## # A tibble: 2 × 2
##   isRookie mean_tov
##   <lgl>       <dbl>
## 1 FALSE        65.6
## 2 TRUE         28.5
```

Bootstrap Demo Step 5

- Want to do this 100 times!
- Use a `for()` loop to make it cleaner
- A `for()` loop repeats the same code multiple times
  - Benefit: don't need to copy and paste a chunk of code 100 times
  - Just put a chunk of code in a loop that repeats 100 times!

```
set.seed(123) # Ensure you'll get the same results each time
bsSeasons <- NULL # Instantiate empty object
for(bsSeason in 1:100) { # Repeat 100 times
  tmpSeason <- nba %>%
    sample_n(size = nrow(.),replace = T) %>% # Sample the data
    select(isRookie,tov) %>% # Select variables of interest
    mutate(bsSeasonNumber = bsSeason) # Save the simulation ID
  bsSeasons <- bind_rows(bsSeasons,tmpSeason) # Append to the empty
object!
}
```

Bootstrap to measure Confidence

- Compare rookie versus non-rookie turnovers each season

```
bsSeasons %>%
  group_by(bsSeasonNumber,isRookie) %>%
  summarise(mean_tov = mean(tov),.groups = 'drop')
```

```
## # A tibble: 200 × 3
##    bsSeasonNumber isRookie mean_tov
##             <int> <lgl>       <dbl>
##  1              1 FALSE        68.6
##  2              1 TRUE         36.9
##  3              2 FALSE        65.6
##  4              2 TRUE         28.5
##  5              3 FALSE        62.5
##  6              3 TRUE         26.5
##  7              4 FALSE        67.5
##  8              4 TRUE         29.9
##  9              5 FALSE        74.8
## 10              5 TRUE         31.3
## # ℹ 190 more rows
```

Bootstrap to measure Confidence

- Compare rookie versus non-rookie turnovers each season

```
bsSeasons %>%
  group_by(bsSeasonNumber,isRookie) %>%
  summarise(mean_tov = mean(tov),.groups = 'drop') %>%
  spread(isRookie,mean_tov)
```

```
## # A tibble: 100 × 3
##    bsSeasonNumber `FALSE` `TRUE`
##             <int>   <dbl>  <dbl>
##  1              1    68.6   36.9
##  2              2    65.6   28.5
##  3              3    62.5   26.5
##  4              4    67.5   29.9
##  5              5    74.8   31.3
##  6              6    70.7   31.6
##  7              7    73.7   19.8
##  8              8    73.7   33
##  9              9    65.0   24.3
## 10             10    72.2   28.0
## # ℹ 90 more rows
```

Bootstrap to measure Confidence

- Compare rookie versus non-rookie turnovers each season

```
bsSeasons %>%
  group_by(bsSeasonNumber,isRookie) %>%
  summarise(mean_tov = mean(tov),.groups = 'drop') %>%
  spread(isRookie,mean_tov) %>%
  filter(complete.cases(.)) %>%
  mutate(rookieBetter = ifelse(`FALSE` > `TRUE`,1,0))
```

```
## # A tibble: 100 × 4
##    bsSeasonNumber `FALSE` `TRUE` rookieBetter
##             <int>   <dbl>  <dbl>        <dbl>
##  1              1    68.6   36.9            1
##  2              2    65.6   28.5            1
##  3              3    62.5   26.5            1
##  4              4    67.5   29.9            1
##  5              5    74.8   31.3            1
##  6              6    70.7   31.6            1
##  7              7    73.7   19.8            1
##  8              8    73.7   33              1
##  9              9    65.0   24.3            1
## 10             10    72.2   28.0            1
```

Bootstrap to measure Confidence

- Compare UVA and UT's FT percentages in each season

```
(conf <- bsSeasons %>%
  group_by(bsSeasonNumber,isRookie) %>%
  summarise(mean_tov = mean(tov),.groups = 'drop') %>%
  spread(isRookie,mean_tov) %>%
  filter(complete.cases(.)) %>%
  mutate(rookieBetter = ifelse(`FALSE` > `TRUE`,1,0)) %>%
  summarise(rookieBetter = mean(rookieBetter)))
```

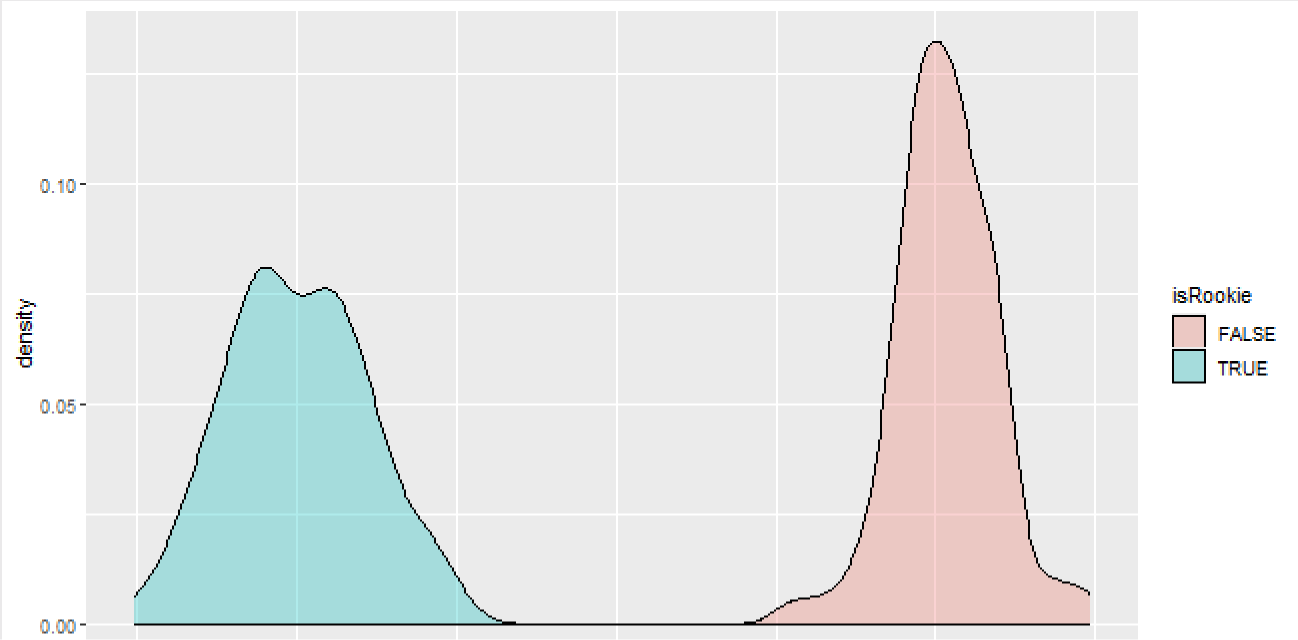
```
## # A tibble: 1 × 1
##   rookieBetter
##          <dbl>
## 1            1
```

- Rookies have fewer turnovers 100% of the time! (How much do you bet on next season?)

Other ways to use bootstraps

- Could plot the **distributions** for each school

```
bsSeasons %>%
  group_by(bsSeasonNumber,isRookie) %>%
  summarise(mean_tov = mean(tov),.groups = 'drop') %>%
  ggplot(aes(x = mean_tov,fill = isRookie)) +
  geom_density(alpha = .3)
```



Other ways to use bootstraps

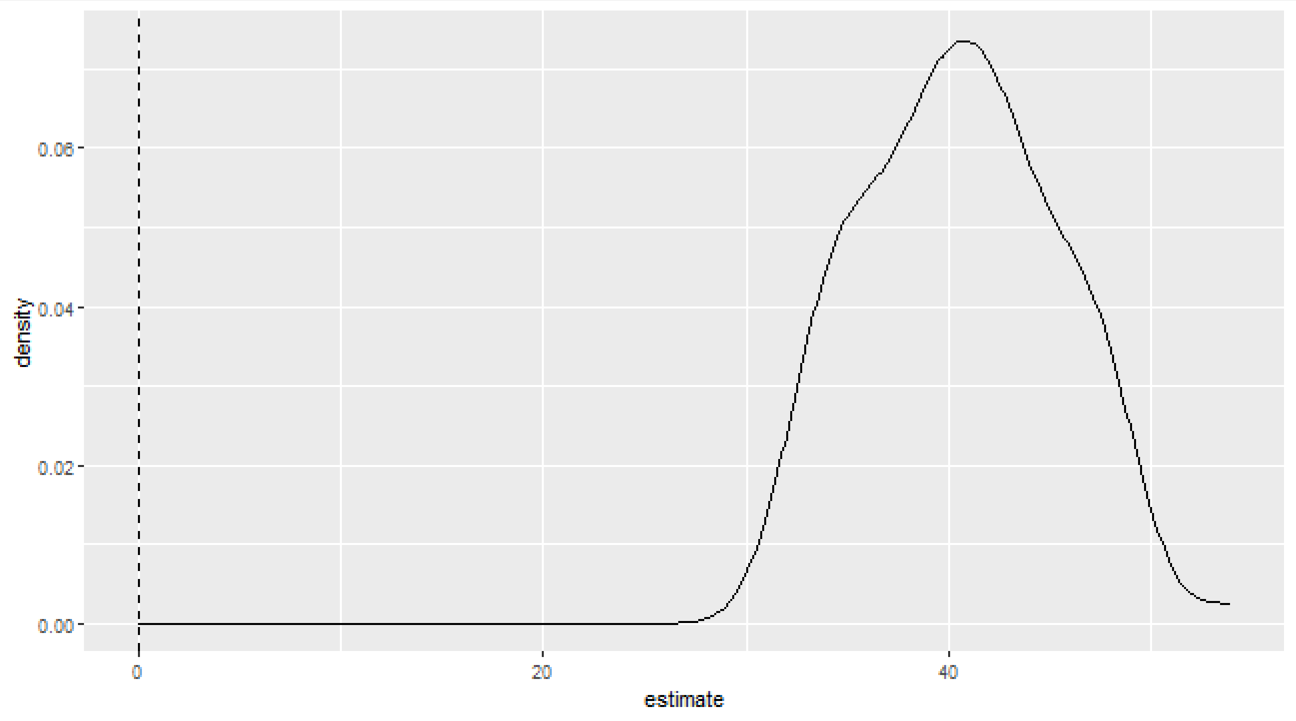
- Could plot the **distributions** of the "estimate"

```
p <- bsSeasons %>%
  group_by(bsSeasonNumber,isRookie) %>%
  summarise(mean_tov = mean(tov),.groups = 'drop') %>%
  spread(isRookie,mean_tov) %>%
  mutate(estimate = `FALSE` - `TRUE`) %>%
  ggplot(aes(x = estimate)) +
  geom_density(alpha = .3) +
  geom_vline(xintercept = 0,linetype = 'dashed')
```

Other ways to use bootstraps

- Could plot the **distributions** of the "estimate"

```
p
```



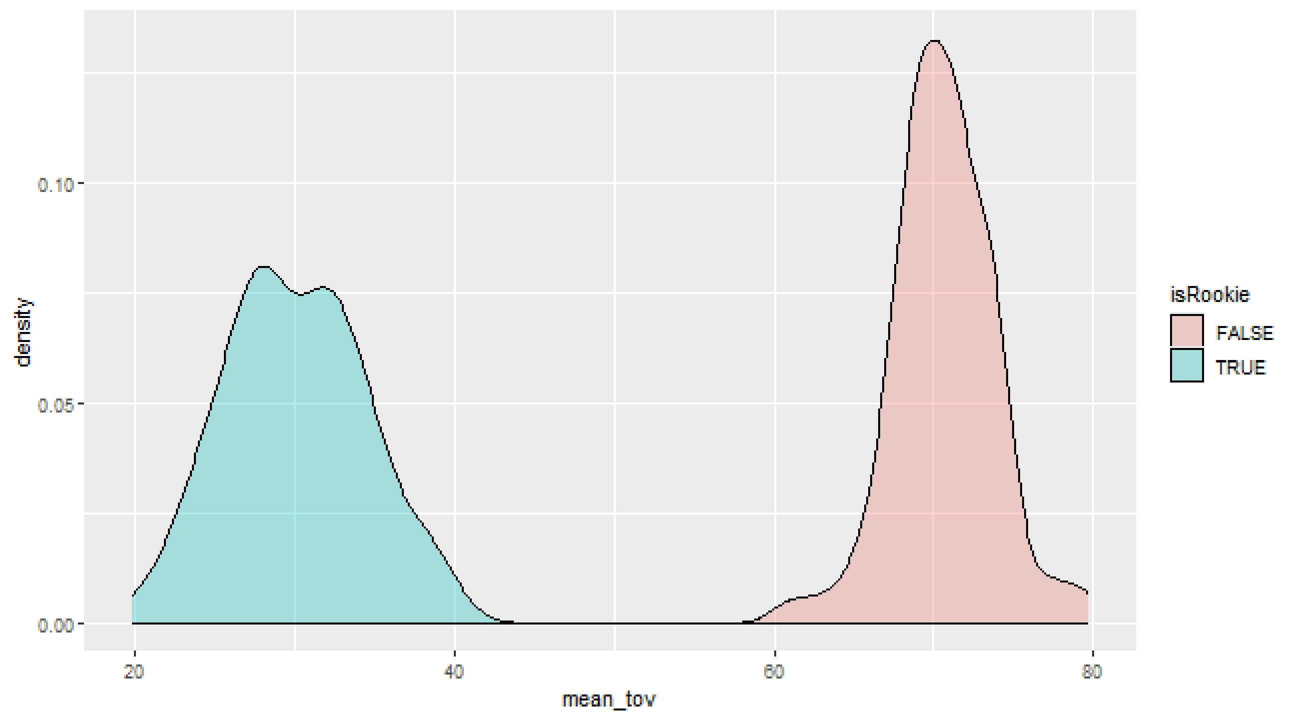
Where to calculate the "estimate"

- **First** we created a new dataset of 100 simulated seasons
- **Then** we calculate average FT % for TN and UVA for each simulation
- **Finally** we calculate proportion of times average is higher for TN
- **BUT!** It is equally valid to calculate the "estimate" *within* the `for()` loop

```
set.seed(123)
bsRes <- NULL
for(counter in 1:100) {
  tmpEst <- nba %>%
    sample_n(size = nrow(.),replace = T) %>%
    group_by(isRookie) %>%
    summarise(mean_tov = mean(tov,na.rm=T)) %>%
    mutate(bsSeason = counter)

  bsRes <- bind_rows(bsRes,tmpEst)
}
```

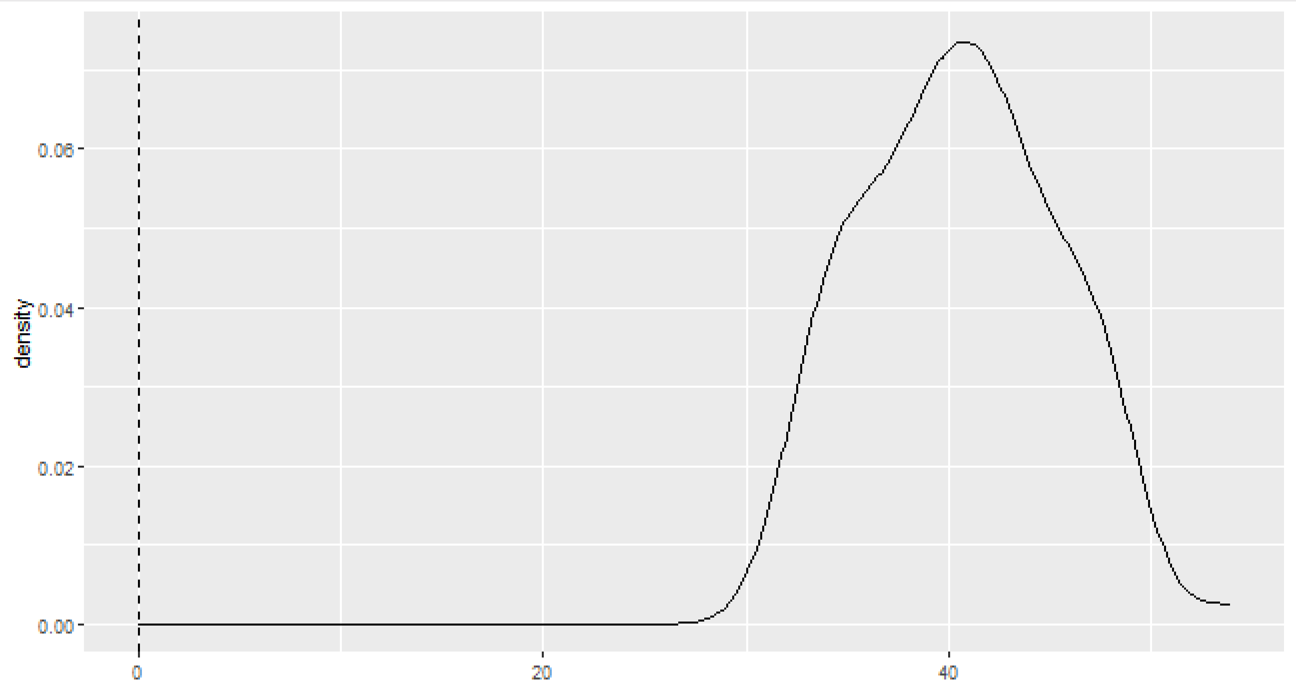
Where to calculate the "estimate"

```
bsRes %>%
  ggplot(aes(x = mean_tov,fill = isRookie)) +
  geom_density(alpha = .3)
```



Where to calculate the "estimate"

```
bsRes %>%
  spread(isRookie,mean_tov) %>%
  mutate(rookieBetter = `FALSE` - `TRUE`) %>%
  ggplot(aes(x = rookieBetter)) +
  geom_density(alpha = .3) +
  geom_vline(xintercept = 0,linetype = 'dashed')
```



Where to calculate the "estimate"

- Same confidence measure

```
bsRes %>%
  spread(key = isRookie,value = mean_tov) %>%
  mutate(rookieBetter = ifelse(`FALSE` > `TRUE`,1,0)) %>%
  summarise(confidence = mean(rookieBetter,na.rm=T))
```

```
## # A tibble: 1 × 1
##   confidence
##        <dbl>
## 1          1
```

Interpreting Confidence

- **Is this high?**
  - What value reflects the minimum confidence?
  - A coin flip → 50%
- What does a confidence level of 0.1 (or 10%) mean?
  - We are 100% confident?

Do we believe this?

- Why might this conclusion be **spurious**?
- Rookies get less playing time
- Therefore fewer opportunities to turn the ball over
- Solution? Turnovers per minute (or hour)

Re-evaluating

```
nba <- nba %>%
  mutate(tov_hr = tov*60 / minutes)

nba %>%
  group_by(isRookie) %>%
  summarise(tov_hr = mean(tov_hr))
```

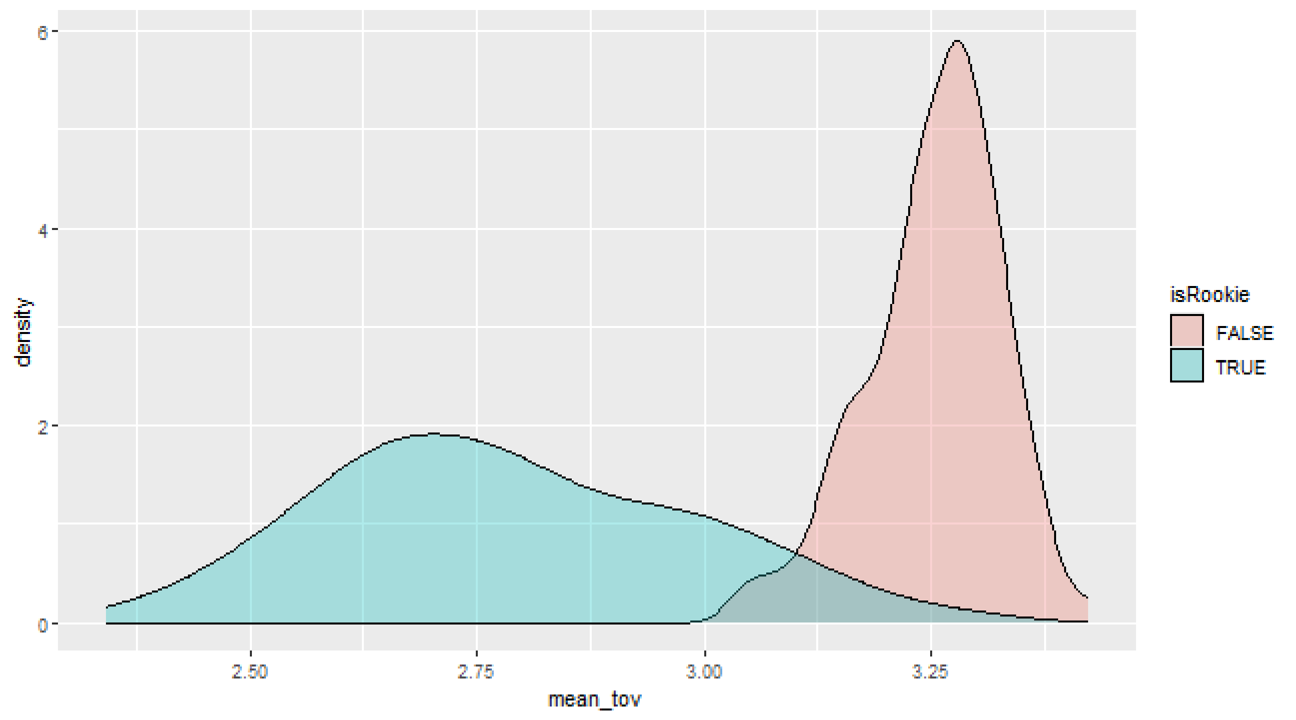
```
## # A tibble: 2 × 2
##   isRookie tov_hr
##   <lgl>     <dbl>
## 1 FALSE      3.24
## 2 TRUE       2.78
```

Re-evaluating

```
set.seed(123)
bsRes <- NULL
for(counter in 1:100) {
  tmpEst <- nba %>%
    sample_n(size = nrow(.),replace = T) %>%
    group_by(isRookie) %>%
    summarise(mean_tov = mean(tov_hr,na.rm=T)) %>%
    mutate(bsSeason = counter)

  bsRes <- bind_rows(bsRes,tmpEst)
}
```

Re-evaluating

```
bsRes %>%
  ggplot(aes(x = mean_tov,fill = isRookie)) +
  geom_density(alpha = .3)
```



Re-Evaluating

```
bsRes %>%
  mutate(isRookie = ifelse(isRookie == TRUE,'Rookie','Not Rookie'))
%>%
  spread(isRookie,mean_tov) %>%
  summarise(conf = mean(`Not Rookie` > Rookie))
```

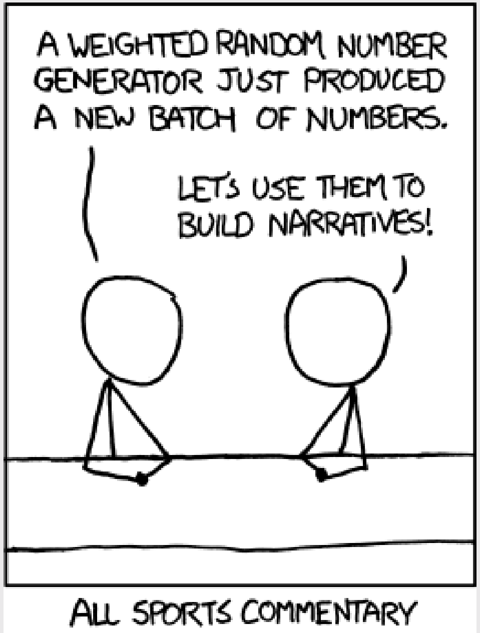
```
## # A tibble: 1 × 1
##    conf
##   <dbl>
## 1  0.99
```

Other Applications

- Could do the same to express **confidence** in conclusions about:
  - The relationship between SAT scores and selective admissions
  - The relationship between MSM polls and anti-Trump bias
  - Whether state polls are good at predicting the 2020 president

Conclusion

- Anyone can spit stats



- Data scientists are comfortable with **uncertainty**

BREAK

Sports Analytics

- Previously, we looked at players
  - Specifically, `isRookie` and `pts`
  - But could try **many** other ideas
- Useful if we want a job scouting talent
- But what if we want to advise actual games?
  - **Game Data**!

Other NBA Data

- Load the `game_summary.Rds` data

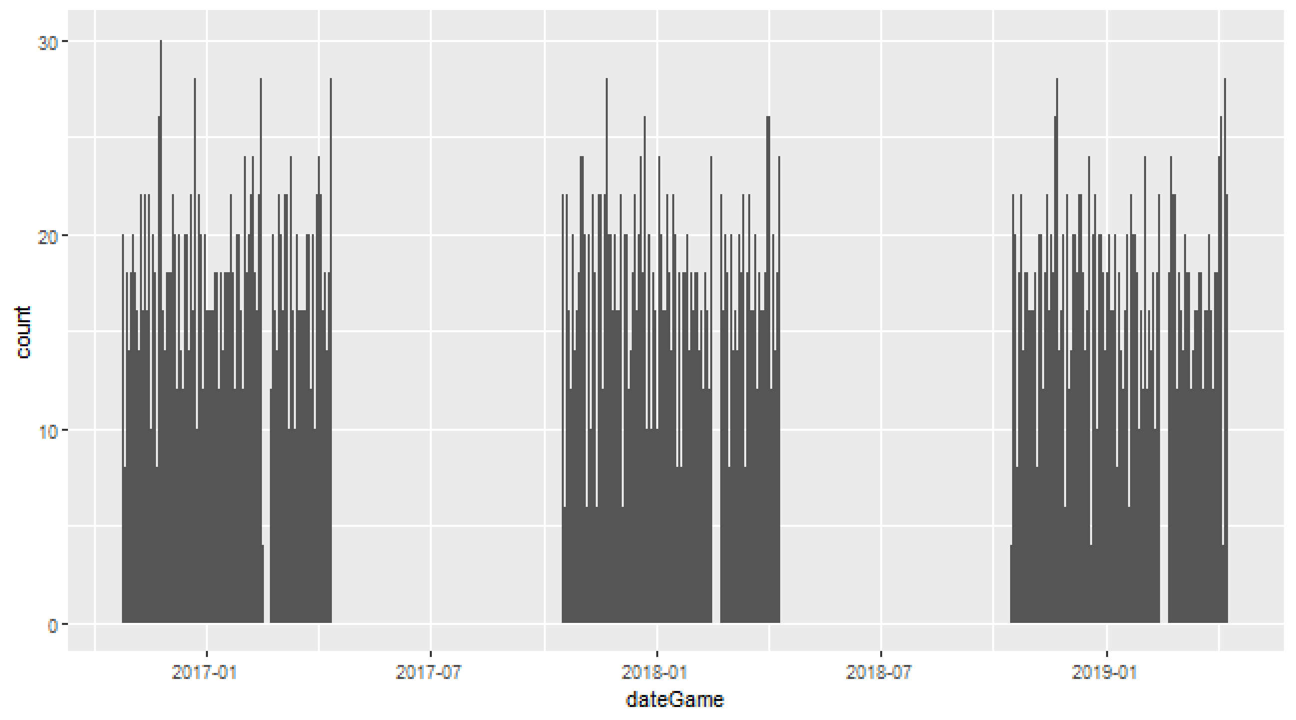
```
require(tidyverse)
gms <-
read_rds('https://github.com/jbisbee1/ISP_Data_Science_2024/raw/main/da
gms
```

```
## # A tibble: 7,380 × 16
##     idGame yearSeason dateGame   idTeam nameTeam locationGame
##      <dbl>      <int> <date>      <dbl> <chr>    <chr>
##  1 2.16e7       2017 2016-10-25 1.61e9 Clevela… H
##  2 2.16e7       2017 2016-10-25 1.61e9 New Yor… A
##  3 2.16e7       2017 2016-10-25 1.61e9 Portlan… H
##  4 2.16e7       2017 2016-10-25 1.61e9 Utah Ja… A
##  5 2.16e7       2017 2016-10-25 1.61e9 Golden … H
##  6 2.16e7       2017 2016-10-25 1.61e9 San Ant… A
##  7 2.16e7       2017 2016-10-26 1.61e9 Miami H… A
##  8 2.16e7       2017 2016-10-26 1.61e9 Orlando… H
##  9 2.16e7       2017 2016-10-26 1.61e9 Dallas … A
## 10 2.16e7       2017 2016-10-26 1.61e9 Indiana… H
## # ℹ 7,370 more rows
## # ℹ 10 more variables: tov <dbl>, pts <dbl>, treb <dbl>,
```

Other NBA Data

- Contains data on every game played between 2016 and 2019

```
gms %>%
  ggplot(aes(x = dateGame)) +
  geom_bar(stat = 'count')
```



Other NBA Data

```
glimpse(gms)
```

```
## Rows: 7,380
## Columns: 16
## $ idGame       <dbl> 21600001, 21600001, 21600002, 2160000…
## $ yearSeason   <int> 2017, 2017, 2017, 2017, 2017, 2017, 2…
## $ dateGame     <date> 2016-10-25, 2016-10-25, 2016-10-25, …
## $ idTeam       <dbl> 1610612739, 1610612752, 1610612757, 1…
## $ nameTeam     <chr> "Cleveland Cavaliers", "New York Knic…
## $ locationGame <chr> "H", "A", "H", "A", "H", "A", "A", "H…
## $ tov          <dbl> 14, 18, 12, 11, 16, 13, 10, 11, 15, 1…
## $ pts          <dbl> 117, 88, 113, 104, 100, 129, 108, 96,…
## $ treb         <dbl> 51, 42, 34, 31, 35, 55, 52, 45, 49, 5…
## $ oreb         <dbl> 11, 13, 5, 6, 8, 21, 16, 15, 10, 8, 1…
## $ pctFG        <dbl> 0.4833077, 0.3220769, 0.4310000, 0.51…
## $ pctFT        <dbl> 0.7500000, 0.8055000, 1.0000000, 1.00…
## $ teamrest     <dbl> 120, 120, 120, 120, 120, 120, 120, 12…
## $ second_game  <lgl> FALSE, FALSE, FALSE, FALSE, FALSE, FA…
## $ isWin        <lgl> TRUE, FALSE, TRUE, FALSE, FALSE, TRUE…
## $ ft_80        <dbl> 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0…
```

Codebook

Name	Description
idGame	Unique game id
yearSeason	Which season? NBA uses ending year so 2016-17 = 2017
dateGame	Date of the game
idTeam	Unique team id
nameTeam	Team Name
locationGame	Game location, H=Home, A=Away
tov	Total turnovers
pts	Total points
treb	Total rebounds
pctFG	Field Goal Percentage
teamrest	How many days since last game for team
pctFT	Free throw percentage
isWin	Won? TRUE or FALSE
ft_80	Team scored more than 80 percent of free throws

Codebook

- Which of these are categorical? Which are continuous?
  - Remember the **process**!
- `isWin` as an ordered binary

```
gms %>%
  count(isWin)
```

```
## # A tibble: 2 × 2
##   isWin     n
##   <lgl> <int>
## 1 FALSE  3690
## 2 TRUE   3690
```

Codebook

- The same number for wins and losses?

```
gms %>%
  select(idGame,nameTeam,dateGame,locationGame,isWin) %>% head()
```

```
## # A tibble: 6 × 5
##     idGame nameTeam              dateGame   locationGame isWin
##      <dbl> <chr>                 <date>     <chr>        <lgl>
## 1 21600001 Cleveland Cavaliers 2016-10-25 H            TRUE
## 2 21600001 New York Knicks     2016-10-25 A            FALSE
## 3 21600002 Portland Trail Bla… 2016-10-25 H            TRUE
## 4 21600002 Utah Jazz           2016-10-25 A            FALSE
## 5 21600003 Golden State Warri… 2016-10-25 H            FALSE
## 6 21600003 San Antonio Spurs   2016-10-25 A            TRUE
```

- Each row is a **team-game** pair
  - I.e., the Cavs hosted the Knicks on October 25, 2016 and won!

The Knicks

Science

- What predicts winning?
    - Points? (more is better)
    - Turnovers? (less is better)
    - Rebounds? (more is better)
- How confident are we?

```
gms %>%
  group_by(isWin) %>%
  summarise(avgTO = mean(tov))
```

```
## # A tibble: 2 × 2
##   isWin avgTO
##   <lgl> <dbl>
## 1 FALSE  13.9
## 2 TRUE   13.1
```

Turnovers and Winning

- On average, winning teams have ~1 fewer turnover than losing teams
- FSNoR: is this *always* the case?

```
gms %>%
  filter(yearSeason == 2017) %>%
  group_by(isWin) %>%
  summarise(avgTO = mean(tov))
```

```
## # A tibble: 2 × 2
##   isWin avgTO
##   <lgl> <dbl>
## 1 FALSE  13.8
## 2 TRUE   12.9
```

Turnovers and Winning

- On average, winning teams have ~1 fewer turnover than losing teams
- FSNoR: is this *always* the case?

```
gms %>%
  filter(yearSeason == 2018) %>%
  group_by(isWin) %>%
  summarise(avgTO = mean(tov))
```

```
## # A tibble: 2 × 2
##   isWin avgTO
##   <lgl> <dbl>
## 1 FALSE  14.1
## 2 TRUE   13.3
```

Turnovers and Winning

- On average, winning teams have ~1 fewer turnover than losing teams
- FSNoR: is this *always* the case?

```
gms %>%
  group_by(isWin,yearSeason) %>%
  summarise(avgTO = mean(tov)) %>%
  spread(isWin,avgTO,sep = '_')
```

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

```
## # A tibble: 3 × 3
##   yearSeason isWin_FALSE isWin_TRUE
##        <int>       <dbl>      <dbl>
## 1       2017        13.8       12.9
## 2       2018        14.1       13.3
## 3       2019        13.9       13.1
```

Turnovers and Winning

- On average, winning teams have ~1 fewer turnover than losing teams
- FSNoR: is this *always* the case?
  - Not literally (numbers change)
  - But practically?
- How **confident** are we in making this claim?
  - In each season, the average turnovers of winning teams are roughly 1 lower than the average turnovers of losing teams
  - Use **bootstrap sampling** to express this more concretely!

Looping

```
set.seed(123)
bs_tov <- NULL
for(i in 1:1000) {
  bs_tov <- gms %>%
    sample_n(size = 100,replace = T) %>%
    group_by(isWin) %>%
    summarise(avgTO = mean(tov)) %>%
    bind_rows(bs_tov)
}
bs_tov %>% head()
```

```
## # A tibble: 6 × 2
##   isWin avgTO
##   <lgl> <dbl>
## 1 FALSE  13.6
## 2 TRUE   13.3
## 3 FALSE  13.9
## 4 TRUE   13.0
## 5 FALSE  14.1
## 6 TRUE   13.0
```

Bootstrapped Estimates vs Data

```
bs_tov %>%
  group_by(isWin) %>%
  summarise(bs_est = mean(avgTO))
```

```
## # A tibble: 2 × 2
##   isWin bs_est
##   <lgl>  <dbl>
## 1 FALSE   13.9
## 2 TRUE    13.1
```

```
gms %>%
  group_by(isWin) %>%
  summarise(data_est = mean(tov))
```

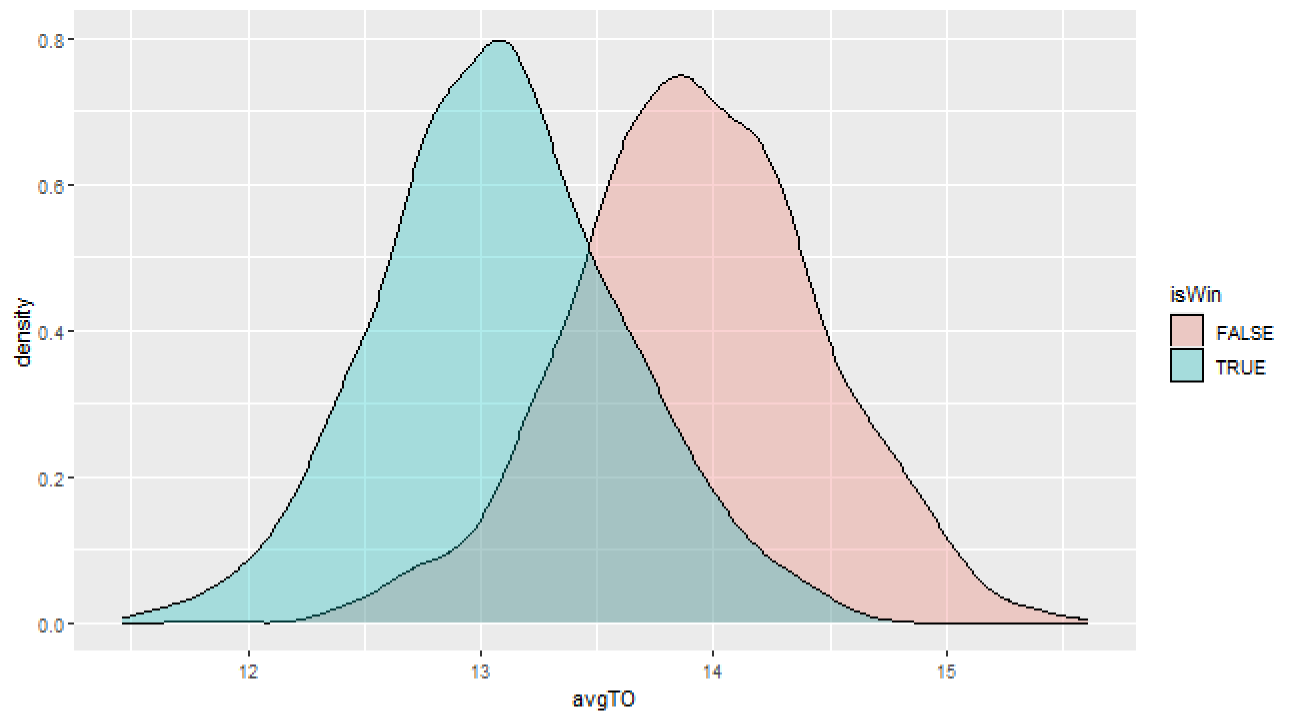
```
## # A tibble: 2 × 2
##   isWin data_est
##   <lgl>    <dbl>
## 1 FALSE     13.9
## 2 TRUE      13.1
```

Bootstrapped Estimates vs Data

- They're identical!
  - In theory, bootstrapped samples converge on true values
  - ...where "true" is the full data
- So then why bother with bootstrapping?
- **Uncertainty!**

Plot Distributions of Bootstraps

```
bs_tov %>%
  ggplot(aes(x = avgTO,fill = isWin)) +
  geom_density(alpha = .3)
```



Generalizability

- What if we only used one season?
  - Do we think our conclusions would "generalize" (i.e., apply to) other seasons?
  - For example, is the turnover-win relationship the same in the 2017 season as the 2018 season?
  - What about the 2019 season?
  - Why or why not?
- Demonstrate using the 2017 data

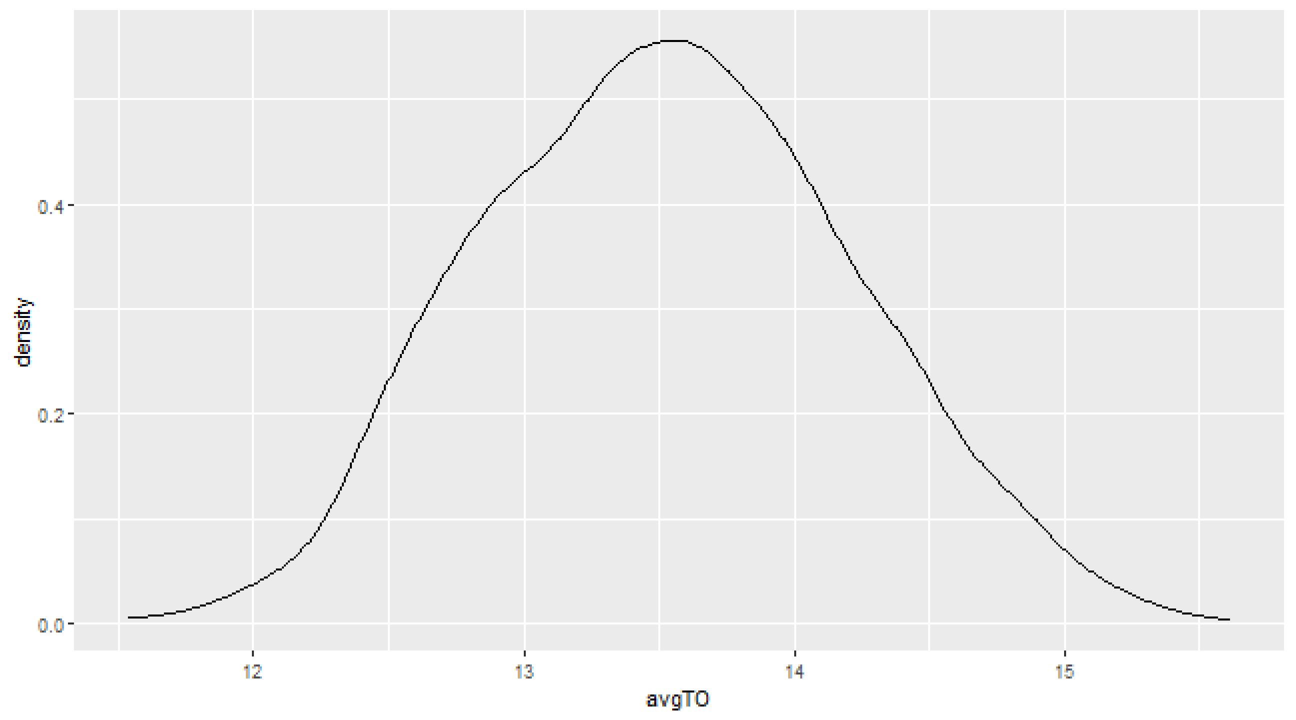
Generalizability

- Bootstrap + `group_by`

```
bsRes <- NULL

for(i in 1:500) {  # Only 500 simulations this time
  bsRes <- gms %>%
    group_by(yearSeason) %>% #<< Group by the season
    sample_n(size = 100,replace = T) %>% #<< Get 100 observations per season
    group_by(yearSeason,isWin) %>% #<< Then calculate mean tov by season AND win
    summarise(avgTO = mean(tov,na.rm=T),.groups = 'drop') %>%
    ungroup() %>%
    mutate(bsInd = i) %>%
    bind_rows(bsRes)

}
```

Plotting the results

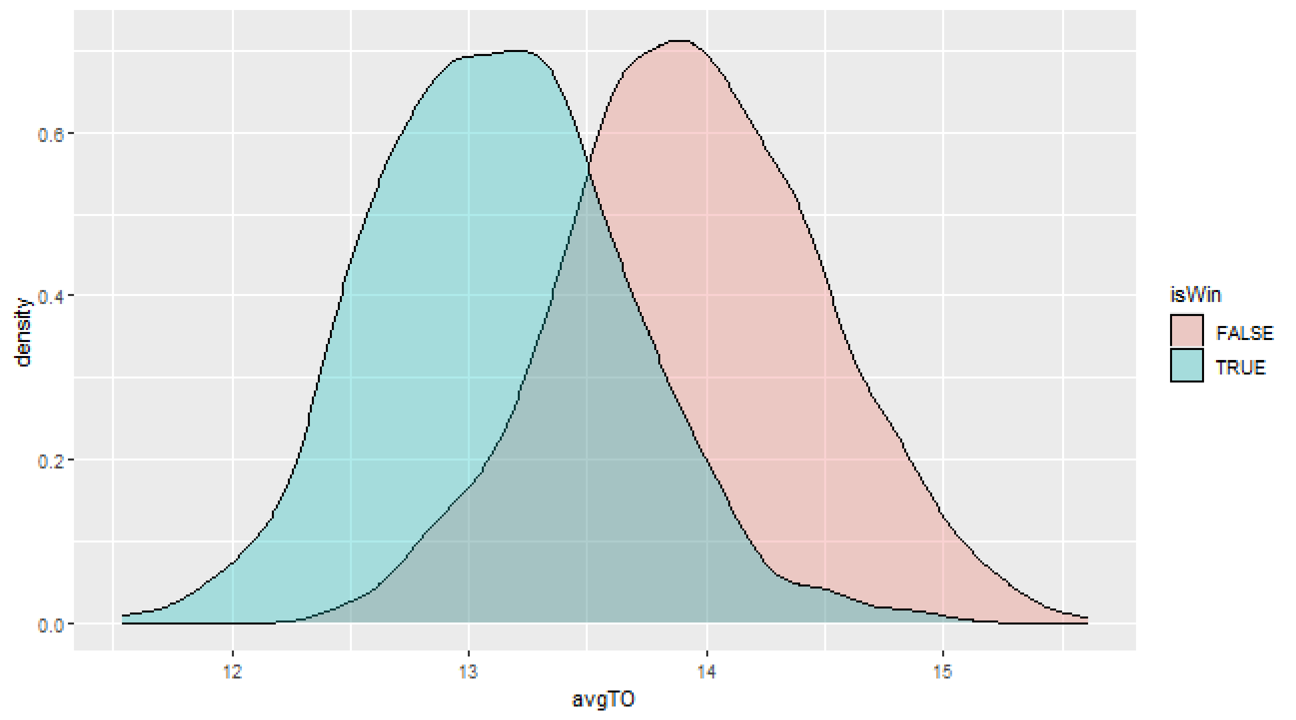
```
bsRes %>%
  ggplot(aes(x = avgTO)) +
  geom_density(alpha = .3)
```



- Is this answering our question?

Plotting the results

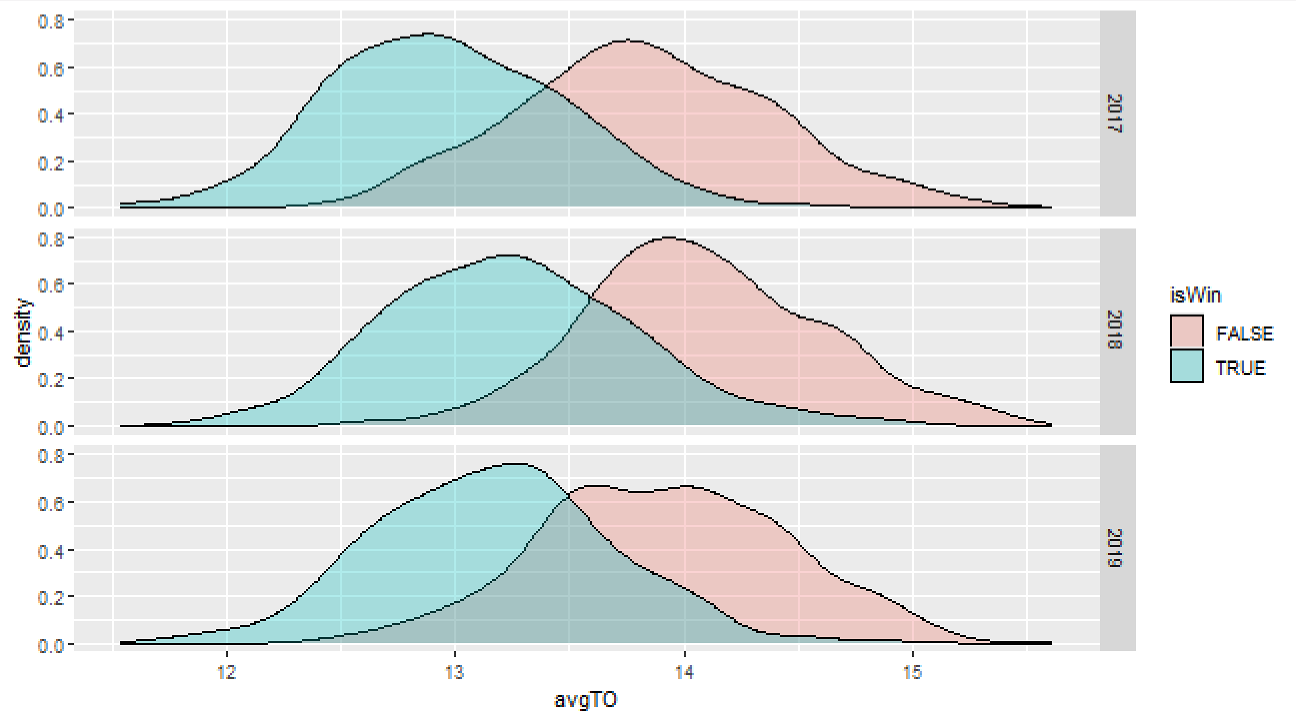
```
bsRes %>%
  ggplot(aes(x = avgTO,fill = isWin)) +
  geom_density(alpha = .3)
```



- Is this answering our question?

Plotting the results

```
bsRes %>%
  ggplot(aes(x = avgTO,fill = isWin)) +
  geom_density(alpha = .3) +
  facet_grid(yearSeason~.)
```



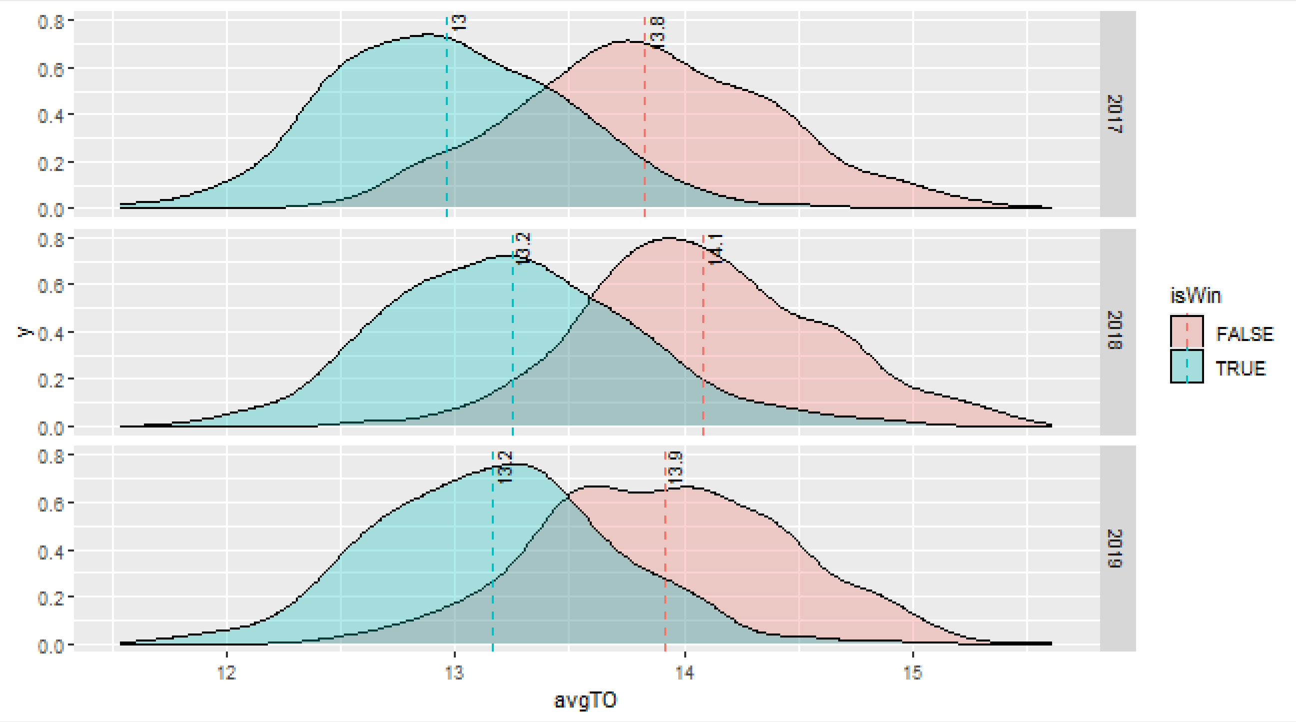
Plotting the results

```
p  <- bsRes %>%
  ggplot(aes(x = avgTO,fill = isWin)) +
  geom_density(alpha = .3) +
  geom_vline(data = bsRes %>%
               group_by(yearSeason,isWin) %>%
               summarise(avgTO = mean(avgTO,na.rm=T)),
             aes(xintercept = avgTO,color = isWin),linetype =
'dashed') +
  geom_text(data = bsRes %>%
               group_by(yearSeason,isWin) %>%
               summarise(avgTO = mean(avgTO,na.rm=T)),
             aes(x = avgTO,y = Inf,label = round(avgTO,1)),hjust =
1.1,vjust = 1.1,size = 3,angle = 90) +
  facet_grid(yearSeason~.)
```

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

Plotting the results

```
p
```



Summarizing further

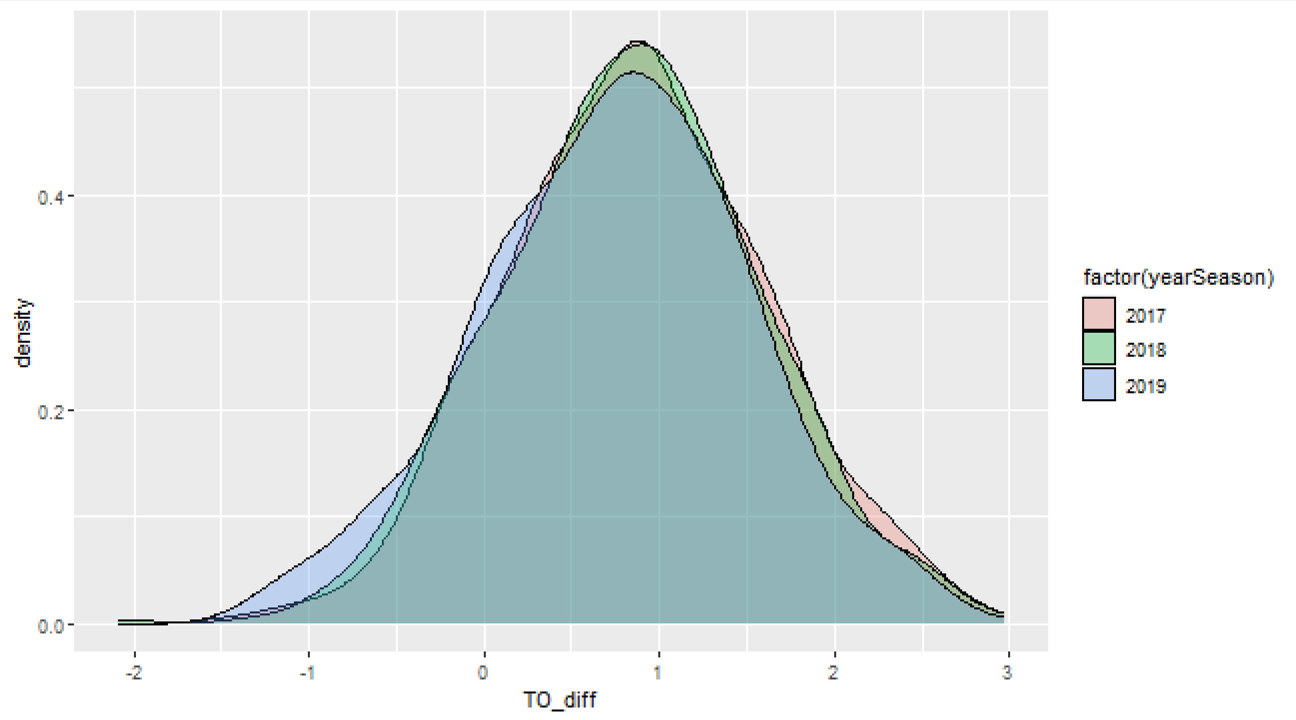
- We are *actually* interested in whether winning teams turnover the ball less
  - Science: never forget your theory / hypothesis!
- So let's actually calculate this!
- The `spread` command to create two columns

```
bsRes %>%
  spread(isWin,avgTO,sep = '_') %>%
  mutate(TO_diff = isWin_FALSE - isWin_TRUE)
```

```
## # A tibble: 1,500 × 5
##    yearSeason bsInd isWin_FALSE isWin_TRUE TO_diff
##         <int> <int>       <dbl>      <dbl>   <dbl>
##  1       2017     1        14.3       13.1  1.16
##  2       2017     2        14.1       12.5  1.60
##  3       2017     3        13.6       13.9 -0.285
##  4       2017     4        13.6       12.3  1.34
##  5       2017     5        14.1       13.4  0.739
##  6       2017     6        14.3       12.9  1.47
##  7       2017     7        13.4       13.4 -0.0161
```

Generalizability

```
bsRes %>%
  spread(isWin,avgTO,sep = '_') %>%
  mutate(TO_diff = isWin_FALSE - isWin_TRUE) %>%
  ggplot(aes(x = TO_diff,fill = factor(yearSeason))) +
  geom_density(alpha = .3)
```

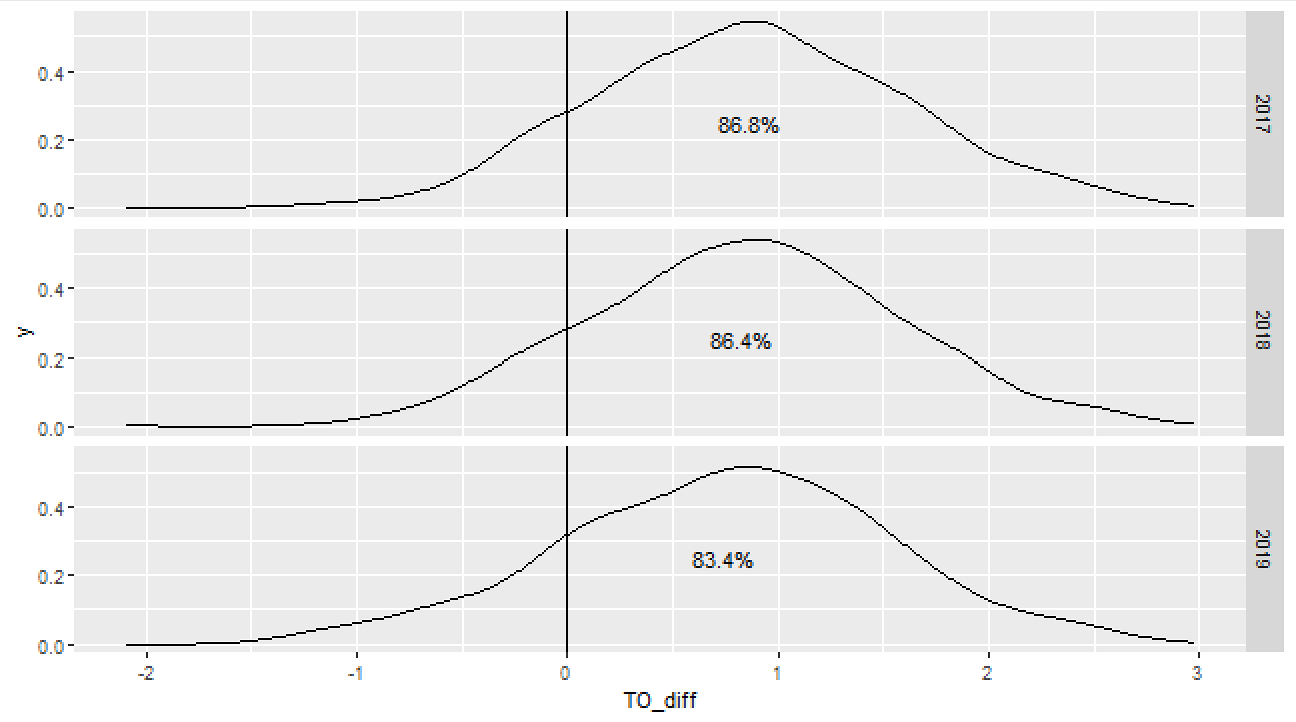


Comparing across seasons

```
p <- bsRes %>%
  spread(isWin,avgTO,sep = '_') %>%
  mutate(TO_diff = isWin_FALSE - isWin_TRUE) %>%
  ggplot(aes(x = TO_diff,group = yearSeason)) +
  geom_density(alpha = .3) +
  geom_vline(xintercept = 0) +
  geom_text(data = bsRes %>%
              spread(isWin,avgTO,sep = '_') %>%
              mutate(TO_diff = isWin_FALSE - isWin_TRUE) %>%
              group_by(yearSeason) %>%
              summarise(conf = mean(TO_diff > 0),
                        TO_diff = mean(TO_diff),
                        y = .25),
             aes(x = TO_diff,y = y,label =
paste0(round(conf*100,1),'%'))) +
  facet_grid(yearSeason ~.)
```

Comparing across seasons

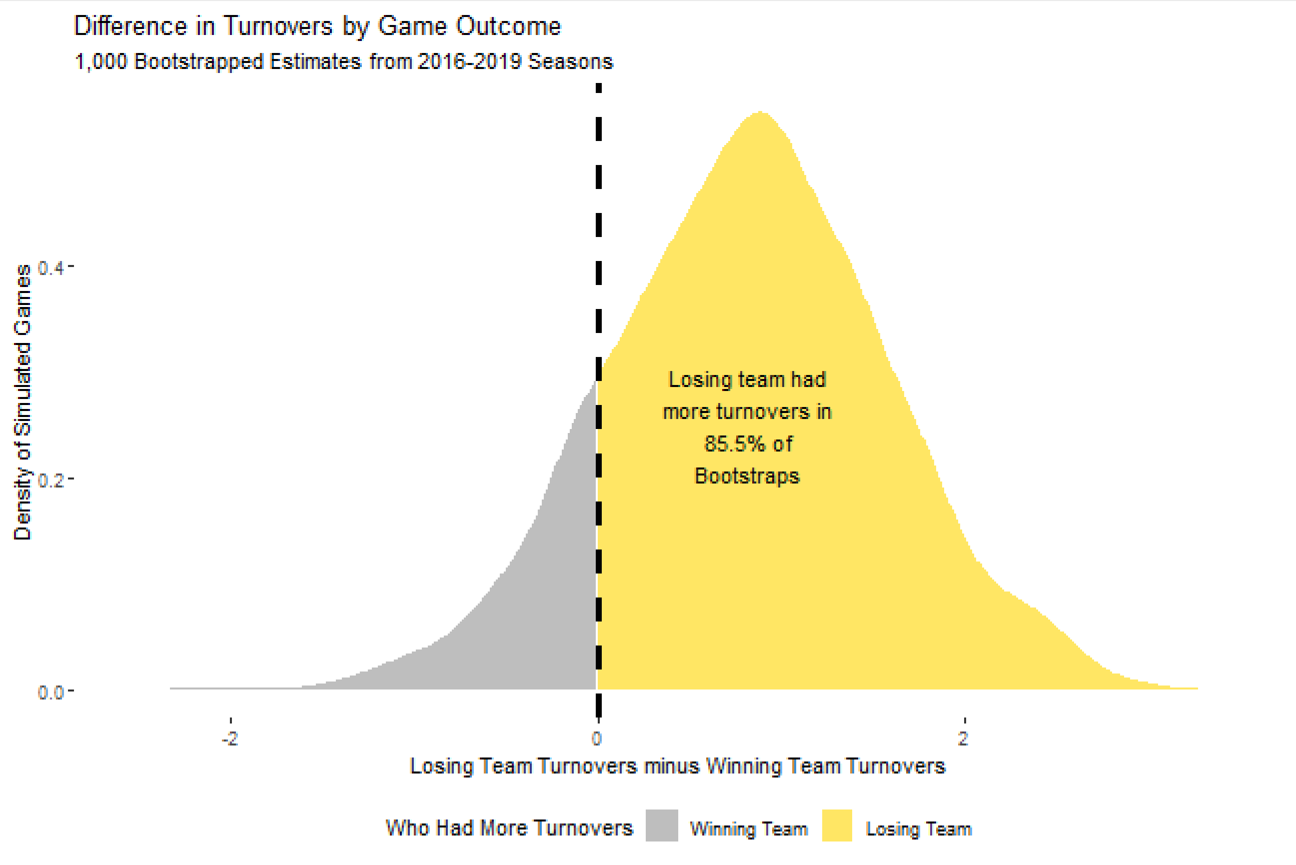
```
p
```



Visualization is **DEEP**

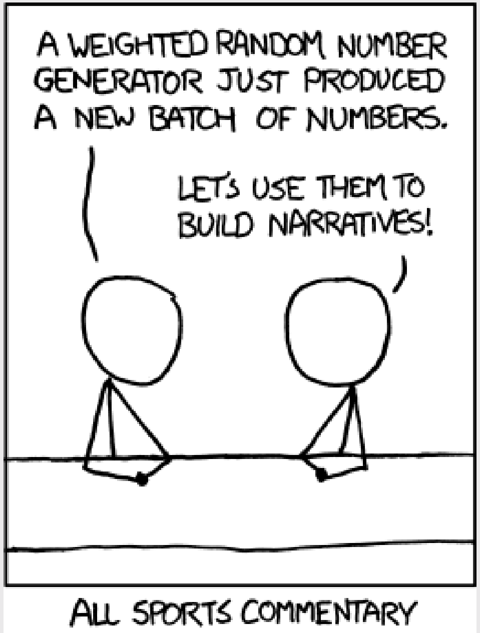
```
toplot <- bsRes %>%
  spread(isWin,avgTO,sep = '_') %>%
  mutate(TO_diff = isWin_FALSE - isWin_TRUE)

tmp <- density(toplot$TO_diff)
p <- data.frame(x = tmp$x,y = tmp$y,
           area = tmp$x >= 0) %>%
  ggplot(aes(x = x,ymin = 0,ymax = y,fill = area)) +
  geom_ribbon(alpha = .6) +
  geom_vline(xintercept = 0,linetype = 'dashed',size = 1.1) +
  annotate(geom = 'text',x = mean(toplot$TO_diff),y = .25,
           label = paste0("Losing team had\nmore turnovers
in\n",round(mean(toplot$TO_diff > 0),3)*100,"% of\nBootstraps"),
           hjust = .5) +
  labs(title = 'Difference in Turnovers by Game Outcome',
       subtitle = '1,000 Bootstrapped Estimates from 2016-2019
Seasons',
       x = 'Losing Team Turnovers minus Winning Team Turnovers',
       y = 'Density of Simulated Games') +
  scale_fill_manual(name = 'Who Had More Turnovers',
                    values = c('grey60','gold'),labels = c('Winning
Team','Losing Team')) +
  theme(panel.background = element_blank(),
```

Visualization is **DEEP**



Conclusion

- Anyone can spit stats



- Data scientists are comfortable with **uncertainty**