Statistical Inference: A Tidy Approach

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Slides available at http://bit.ly/ness-infer
PDF slides at http://bit.ly/ness-infer-pdf

DataCamp

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R code from throughout the slides is saved as an R script here

Prior Installation

Make sure you have the (current) up-to-date R, RStudio, and R packages

- Beginner's Guide on ModernDive.com

- R (version 3.4.4)
- RStudio (version 1.1.442)
- Run this in the RStudio Console

```
pkgs <- c("tidyverse", "moderndive", "gapminder",
          "nycflights13", "fivethirtyeight", "janitor",
          "ggplot2movies", "remotes")

install.packages(pkgs)
remotes::install_github("andrewpbray/infer")
```

Freely available information

ModernDive

A Modern Dive into Data with R

- Webpage: http://moderndive.com
- Developmental version at https://moderndive.netlify.com
- GitHub Repo
- Please signup for our mailing list!

Slides available at http://bit.ly/ness-infer

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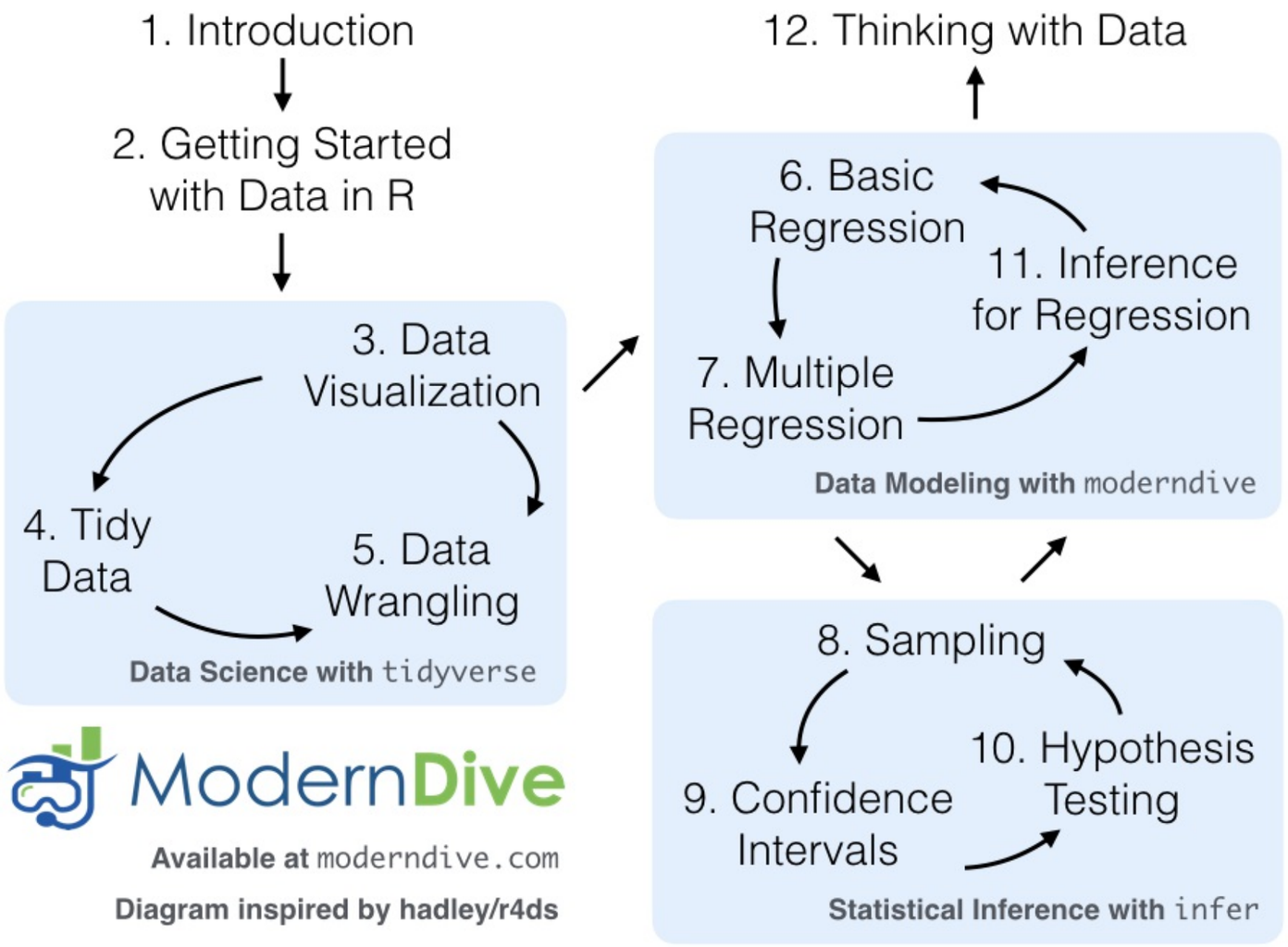
1. Introduction
2. Getting Started with Data in R
3. Data Visualization
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Data Science with tidyverse
6. Basic Regression
7. Multiple Regression
11. Inference for Regression
Data Modeling with moderndive
8. Sampling
9. Confidence Intervals
10. Hypothesis Testing
Statistical Inference with infer
12. Thinking with Data
ModernDive
Available at moderndive.com
Diagram inspired by hadley/r4ds

Designed for the novice / Nice for the practioner

For much of this book, we will assume that you are using R via RStudio. First time users often confuse the two. At its simplest:

- R is like a car's engine
- RStudio is like a car's dashboard

R: Engine	RStudio: Dashboard
	

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Designed for the novice / Nice for the practioner

A good analogy for R packages is they are like apps you can download onto a mobile phone:

R: A new phone	R Packages: Apps you can download
	

R Data Types

The bare minimum needed for understanding today

Vector/variable

- Type of vector (`int`, `num` or `dbl`, `chr`, `lgl`, `date`)

The bare minimum needed for understanding today

Vector/variable

- Type of vector (`int`, `num` or `dbl`, `chr`, `lgl`, `date`)

Data frame

- Vectors of (potentially) different types
- Each vector has the same number of rows

The bare minimum needed for understanding today

```
library(tibble)
library(lubridate)
ex1 <- data_frame(
    vec1 = c(1980, 1990, 2000, 2010),
    vec2 = c(1L, 2L, 3L, 4L),
    vec3 = c("low", "low", "high", "high"),
    vec4 = c(TRUE, FALSE, FALSE, FALSE),
    vec5 = ymd(c("2017-05-23", "1776/07/04",
                 "1983-05/31", "1908/04-01"))
  )
ex1
```

The bare minimum needed for understanding today

```
library(tibble)
library(lubridate)
ex1 <- data_frame(
    vec1 = c(1980, 1990, 2000, 2010),
    vec2 = c(1L, 2L, 3L, 4L),
    vec3 = c("low", "low", "high", "high"),
    vec4 = c(TRUE, FALSE, FALSE, FALSE),
    vec5 = ymd(c("2017-05-23", "1776/07/04",
                 "1983-05/31", "1908/04-01"))
  )
ex1
```

```
# A tibble: 4 x 5
   vec1  vec2 vec3  vec4  vec5
  <dbl> <int> <chr> <lgl> <date>
1 1980.     1 low   TRUE  2017-05-23
2 1990.     2 low   FALSE 1776-07-04
3 2000.     3 high  FALSE 1983-05-31
4 2010.     4 high  FALSE 1908-04-01
```

Welcome to the tidyverse!

The `tidyverse` is a collection of R packages that share common philosophies and are designed to work together.

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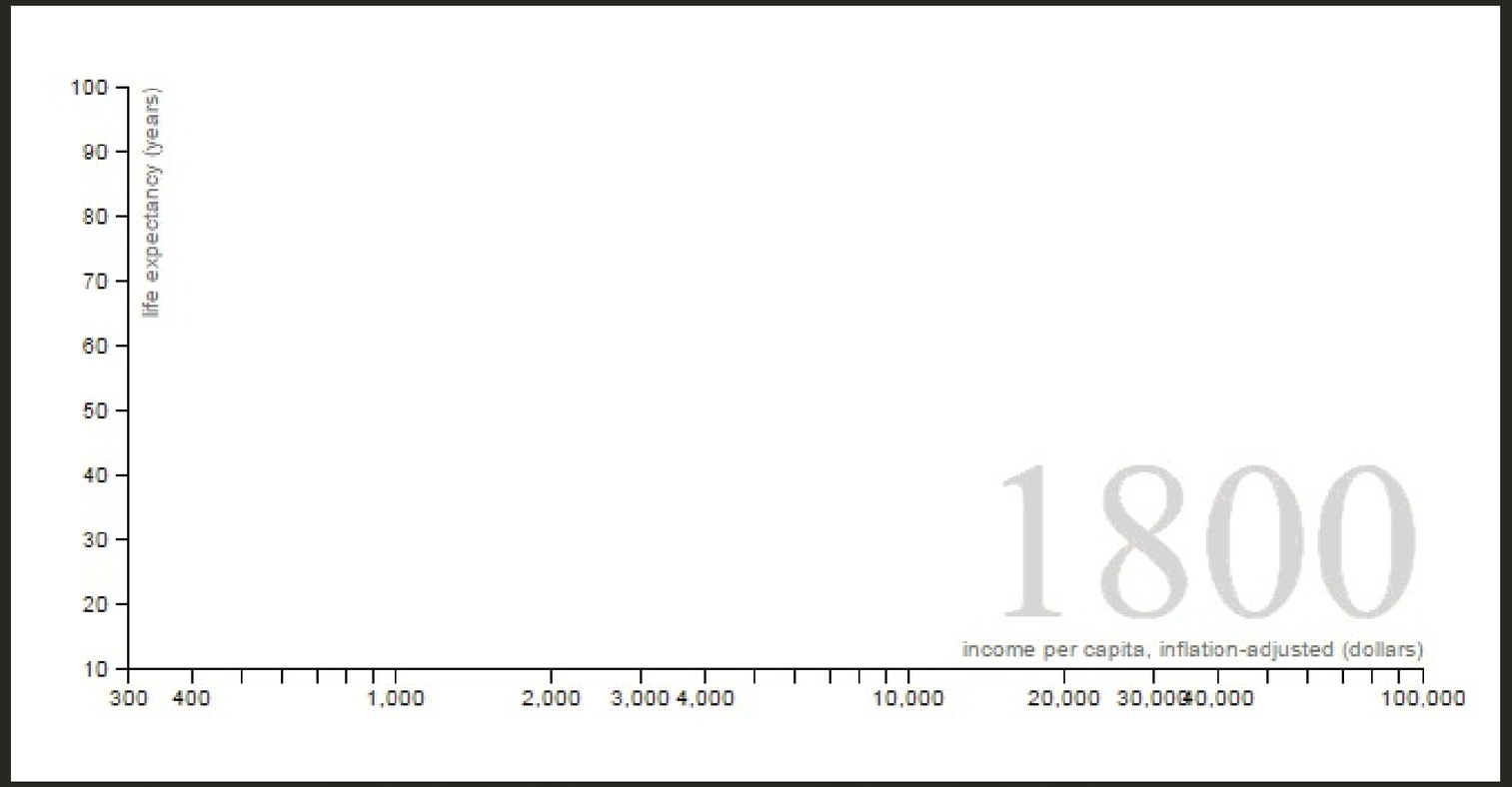
First motivating example for today



- Inspired by the late, great Hans Rosling

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Data Wrangling

The `gapminder` package

```
library(gapminder)
gapminder
```

```
# A tibble: 1,704 x 6
   country     continent  year lifeExp      pop gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
 1 Afghanistan Asia       1952    28.8  8425333      779.
 2 Afghanistan Asia       1957    30.3  9240934      821.
 3 Afghanistan Asia       1962    32.0 10267083      853.
 4 Afghanistan Asia       1967    34.0 11537966      836.
 5 Afghanistan Asia       1972    36.1 13079460      740.
 6 Afghanistan Asia       1977    38.4 14880372      786.
 7 Afghanistan Asia       1982    39.9 12881816      978.
 8 Afghanistan Asia       1987    40.8 13867957      852.
 9 Afghanistan Asia       1992    41.7 16317921      649.
10 Afghanistan Asia       1997    41.8 22227415      635.
# ... with 1,694 more rows
```

Base R versus the `tidyverse`

- The mean life expectancy across all years for Asia

Base R versus the `tidyverse`

- The mean life expectancy across all years for Asia

```
# Base R
asia <- gapminder[gapminder$continent == "Asia", ]
mean(asia$lifeExp)
```

```
[1] 60.065
```

Base R versus the `tidyverse`

- The mean life expectancy across all years for Asia

```
# Base R
asia <- gapminder[gapminder$continent == "Asia", ]
mean(asia$lifeExp)
```

```
[1] 60.065
```

```
library(dplyr)
gapminder %>% filter(continent == "Asia") %>%
  summarize(mean_exp = mean(lifeExp))
```

```
[1] 60.065
```

The pipe `%>%`

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The pipe `%>%`

- A way to chain together commands
- Can be read as "and then" when reading over code

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- A way to chain together commands
- Can be read as "and then" when reading over code

```
library(dplyr)
gapminder %>% filter(continent == "Asia") %>%
  summarize(mean_exp = mean(lifeExp))
```

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The Five Main Verbs (5MV) of data wrangling

- `filter()`
- `summarize()`
- `group_by()`
- `mutate()`
- `arrange()`

`filter()`

- Select a subset of the rows of a data frame.
- Arguments are "filters" that you'd like to apply.

`filter()`

- Select a subset of the rows of a data frame.
- Arguments are "filters" that you'd like to apply.

```
library(gapminder); library(dplyr)
gap_2007 <- gapminder %>% filter(year == 2007)
head(gap_2007, 4)
```

```
# A tibble: 4 x 6
  country     continent  year lifeExp      pop gdpPercap
  <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
1 Afghanistan Asia       2007    43.8 31889923      975.
2 Albania     Europe     2007    76.4  3600523     5937.
3 Algeria     Africa     2007    72.3 33333216     6223.
4 Angola      Africa     2007    42.7 12420476     4797.
```

- Use `==` to compare a variable to a value

Logical operators

- Use `|` to check for any in multiple filters being true:

Logical operators

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```
gapminder %>%
  filter(year == 2002 | continent == "Asia") %>%
  sample_n(8)
```

Logical operators

- Use `|` to check for any in multiple filters being true:

```
gapminder %>%
  filter(year == 2002 | continent == "Asia") %>%
  sample_n(8)
```

```
# A tibble: 8 x 6
  country     continent  year lifeExp      pop gdpPercap
  <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
1 Iraq        Asia       1997    58.8 20775703     3076.
2 Korea, Rep. Asia       1997    74.6 46173816    15994.
3 Bangladesh  Asia       1952    37.5 46886859      684.
4 France      Europe     2002    79.6 59925035    28926.
5 Kuwait      Asia       1957    58.0   212846   113523.
6 Iran        Asia       1962    49.3 22874000     4187.
7 Myanmar     Asia       1982    58.1 34680442      424.
8 Canada      Americas   2002    79.8 31902268    33329.
```

Logical operators

- Use `,` to check for all of multiple filters being true:

Logical operators

- Use `,` to check for all of multiple filters being true:

```
gapminder %>%
  filter(year == 2002, continent == "Asia")
```

```
# A tibble: 8 x 6
  country          continent  year lifeExp        pop gdpPercap
  <fct>            <fct>     <int>   <dbl>      <int>     <dbl>
1 Afghanistan      Asia       2002    42.1   25268405      727.
2 Bahrain          Asia       2002    74.8     656397    23404.
3 Bangladesh       Asia       2002    62.0  135656790     1136.
4 Cambodia         Asia       2002    56.8   12926707      896.
5 China            Asia       2002    72.0 1280400000     3119.
6 Hong Kong, China Asia       2002    81.5    6762476    30209.
7 India            Asia       2002    62.9 1034172547     1747.
8 Indonesia        Asia       2002    68.6  211060000     2874.
```

Logical operators

- Use `%in%` to check for any being true (shortcut to using `|` repeatedly with `==`)

Logical operators

- Use `%in%` to check for any being true (shortcut to using `|` repeatedly with `==`)

```
gapminder %>%
  filter(country %in% c("Argentina", "Belgium", "Mexico"),
         year %in% c(1987, 1992))
```

Logical operators

- Use `%in%` to check for any being true (shortcut to using `|` repeatedly with `==`)

```
gapminder %>%
  filter(country %in% c("Argentina", "Belgium", "Mexico"),
         year %in% c(1987, 1992))
```

```
# A tibble: 6 x 6
  country   continent  year lifeExp      pop gdpPercap
  <fct>     <fct>     <int>   <dbl>    <int>     <dbl>
1 Argentina Americas   1987    70.8 31620918     9140.
2 Argentina Americas   1992    71.9 33958947     9308.
3 Belgium   Europe     1987    75.4  9870200    22526.
4 Belgium   Europe     1992    76.5 10045622    25576.
5 Mexico    Americas   1987    69.5 80122492     8688.
6 Mexico    Americas   1992    71.5 88111030     9472.
```

`summarize()`

- Any numerical summary that you want to apply to a column of a data frame is specified within `summarize()`.

```
stats_1997 <- gapminder %>%
  filter(year == 1997) %>%
  summarize(max_exp = max(lifeExp),
            sd_exp = sd(lifeExp))
stats_1997
```

`summarize()`

- Any numerical summary that you want to apply to a column of a data frame is specified within `summarize()`.

```
stats_1997 <- gapminder %>%
  filter(year == 1997) %>%
  summarize(max_exp = max(lifeExp),
            sd_exp = sd(lifeExp))
stats_1997
```

```
# A tibble: 1 x 2
  max_exp sd_exp
    <dbl>  <dbl>
1    80.7   11.6
```

Combining `summarize()` with `group_by()`

When you'd like to determine a numerical summary for all levels of a different categorical variable

```
max_exp_1997_by_cont <- gapminder %>%
  filter(year == 1997) %>%
  group_by(continent) %>%
  summarize(max_exp = max(lifeExp),
            sd_exp = sd(lifeExp))
max_exp_1997_by_cont
```

Combining `summarize()` with `group_by()`

When you'd like to determine a numerical summary for all levels of a different categorical variable

```
max_exp_1997_by_cont <- gapminder %>%
  filter(year == 1997) %>%
  group_by(continent) %>%
  summarize(max_exp = max(lifeExp),
            sd_exp = sd(lifeExp))
max_exp_1997_by_cont
```

```
# A tibble: 5 x 3
  continent max_exp sd_exp
  <fct>       <dbl>  <dbl>
1 Africa       74.8  9.10
2 Americas     78.6  4.89
3 Asia         80.7  8.09
4 Europe       79.4  3.10
5 Oceania      78.8  0.905
```

`mutate()`

- Allows you to
  1. create a new variable with a specific value OR
  2. create a new variable based on other variables OR
  3. change the contents of an existing variable

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```
gap_plus <- gapminder %>% mutate(just_one = 1)
head(gap_plus, 4)
```

```
# A tibble: 4 x 7
  country     continent  year lifeExp      pop gdpPercap just_one
  <fct>       <fct>     <int>   <dbl>    <int>     <dbl>    <dbl>
1 Afghanistan Asia       1952    28.8  8425333      779.        1.
2 Afghanistan Asia       1957    30.3  9240934      821.        1.
3 Afghanistan Asia       1962    32.0 10267083      853.        1.
4 Afghanistan Asia       1967    34.0 11537966      836.        1.
```

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```
gap_w_gdp <- gapminder %>% mutate(gdp = pop * gdpPercap)
sample_n(gap_w_gdp, 4)
```

```
# A tibble: 4 x 7
  country   continent  year lifeExp      pop gdpPercap           gdp
  <fct>     <fct>     <int>   <dbl>    <int>     <dbl>         <dbl>
1 Comoros   Africa     1967    46.5   217378     1876.    407807572.
2 Paraguay  Americas   1992    68.2  4483945     4196.  18816476471.
3 Mauritius Africa     1967    61.6   789309     2475.   1953845681.
4 Chile     Americas   1997    75.8 14599929    10118. 147722858046.
```

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```
gap_weird <- gapminder %>% mutate(pop = pop + 1000)
head(gap_weird, 4)
```

```
# A tibble: 4 x 6
  country     continent  year lifeExp      pop gdpPercap
  <fct>       <fct>     <int>   <dbl>    <dbl>     <dbl>
1 Afghanistan Asia       1952    28.8  8426333.      779.
2 Afghanistan Asia       1957    30.3  9241934.      821.
3 Afghanistan Asia       1962    32.0 10268083.      853.
4 Afghanistan Asia       1967    34.0 11538966.      836.
```

`arrange()`

- Reorders the rows in a data frame based on the values of one or more variables

`arrange()`

- Reorders the rows in a data frame based on the values of one or more variables

```
gapminder %>% arrange(year, country) %>% head(10)
```

```
# A tibble: 10 x 6
   country     continent  year lifeExp      pop gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
 1 Afghanistan Asia       1952    28.8  8425333       779.
 2 Albania     Europe     1952    55.2  1282697      1601.
 3 Algeria     Africa     1952    43.1  9279525      2449.
 4 Angola      Africa     1952    30.0  4232095      3521.
 5 Argentina   Americas   1952    62.5 17876956      5911.
 6 Australia   Oceania    1952    69.1  8691212     10040.
 7 Austria     Europe     1952    66.8  6927772      6137.
 8 Bahrain     Asia       1952    50.9   120447      9867.
 9 Bangladesh  Asia       1952    37.5 46886859       684.
10 Belgium     Europe     1952    68.0  8730405      8343.
```

`arrange()`

- Can also put into descending order

`arrange()`

- Can also put into descending order

```
gapminder %>%
  filter(year > 2000) %>%
  arrange(desc(lifeExp)) %>%
  head(10)
```

```
# A tibble: 10 x 6
   country          continent  year lifeExp      pop gdpPercap
   <fct>            <fct>     <int>   <dbl>    <int>     <dbl>
 1 Japan            Asia       2007    82.6 127467972    31656.
 2 Hong Kong, China Asia       2007    82.2   6980412    39725.
 3 Japan            Asia       2002    82.0 127065841    28605.
 4 Iceland          Europe     2007    81.8    301931    36181.
 5 Switzerland      Europe     2007    81.7   7554661    37506.
 6 Hong Kong, China Asia       2002    81.5   6762476    30209.
 7 Australia        Oceania    2007    81.2  20434176    34435.
 8 Spain            Europe     2007    80.9  40448191    28821.
 9 Sweden           Europe     2007    80.9   9031088    33860.
10 Israel           Asia       2007    80.7   6426679    25523.
```

Don't mix up `arrange` and `group_by`

- `group_by` is used (mostly) with `summarize` to calculate summaries over groups
- `arrange` is used for sorting

Don't mix up `arrange` and `group_by`

This doesn't really do anything useful

```
gapminder %>% group_by(year)
```

```
# A tibble: 1,704 x 6
# Groups:   year [12]
   country     continent  year lifeExp      pop gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
 1 Afghanistan Asia       1952    28.8  8425333      779.
 2 Afghanistan Asia       1957    30.3  9240934      821.
 3 Afghanistan Asia       1962    32.0 10267083      853.
 4 Afghanistan Asia       1967    34.0 11537966      836.
 5 Afghanistan Asia       1972    36.1 13079460      740.
 6 Afghanistan Asia       1977    38.4 14880372      786.
 7 Afghanistan Asia       1982    39.9 12881816      978.
 8 Afghanistan Asia       1987    40.8 13867957      852.
 9 Afghanistan Asia       1992    41.7 16317921      649.
10 Afghanistan Asia       1997    41.8 22227415      635.
# ... with 1,694 more rows
```

Don't mix up `arrange` and `group_by`

But this does

```
gapminder %>% arrange(year)
```

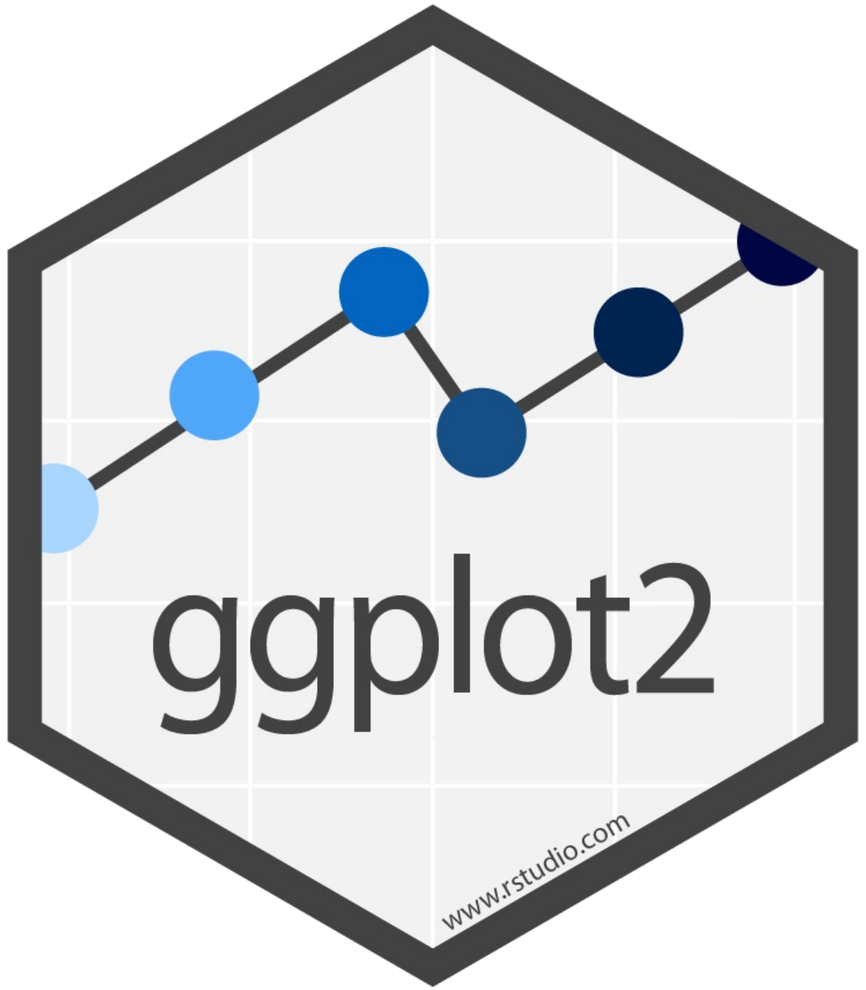
```
# A tibble: 1,704 x 6
   country     continent  year lifeExp      pop gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
 1 Afghanistan Asia       1952    28.8  8425333      779.
 2 Albania     Europe     1952    55.2  1282697     1601.
 3 Algeria     Africa     1952    43.1  9279525     2449.
 4 Angola      Africa     1952    30.0  4232095     3521.
 5 Argentina   Americas   1952    62.5 17876956     5911.
 6 Australia   Oceania    1952    69.1  8691212    10040.
 7 Austria     Europe     1952    66.8  6927772     6137.
 8 Bahrain     Asia       1952    50.9   120447     9867.
 9 Bangladesh  Asia       1952    37.5 46886859      684.
10 Belgium     Europe     1952    68.0  8730405     8343.
# ... with 1,694 more rows
```

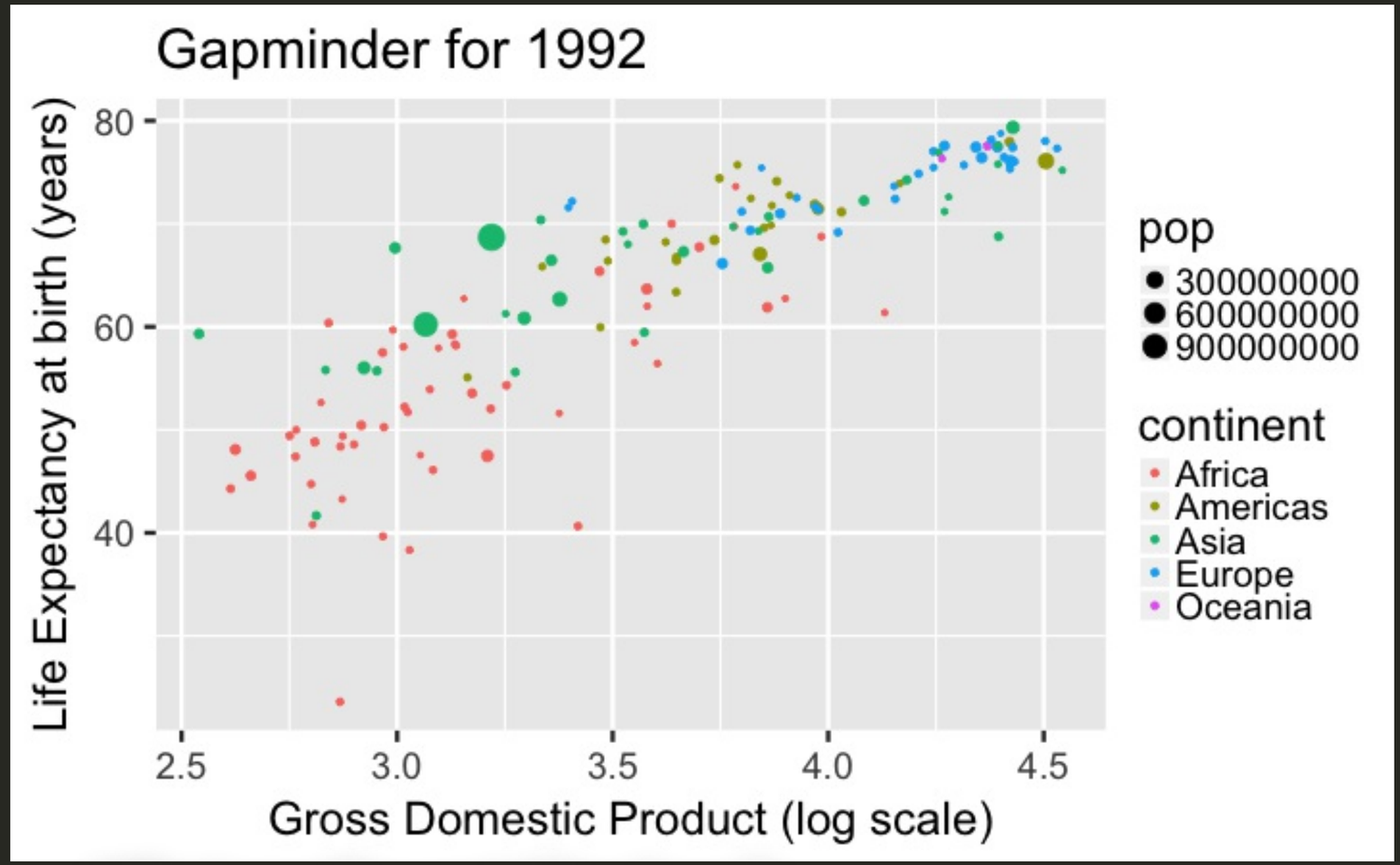
Practice

Use the 5MV to answer problems from R data packages, e.g., [`nycflights13::weather`]

1. What is the maximum arrival delay for each carrier departing JFK? [`nycflights13::flights`]
2. Calculate for each movie the domestic return on investment for 2013 scaled data descending by ROI [`fivethirtyeight::bechdel`]

Data Visualization





- What are the variables here?
- What is the observational unit?
- How are the variables mapped to aesthetics?

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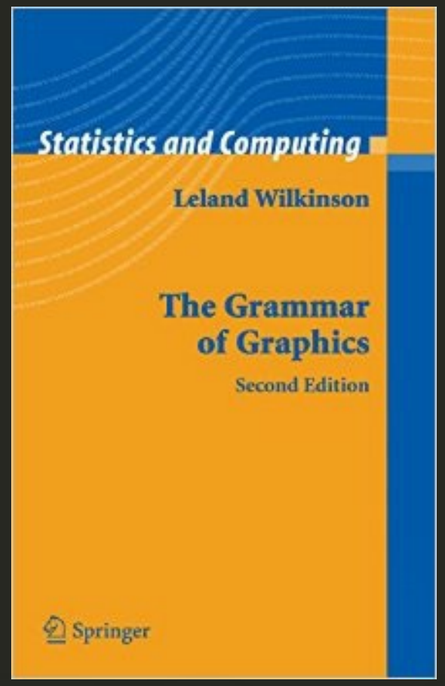
Grammar of Graphics

Wilkinson (2005) laid out the proposed "Grammar of Graphics"



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Grammar of Graphics in R

Wickham implemented the grammar in R
in the `ggplot2` package

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What is a statistical graphic?

What is a statistical graphic?

A `mapping` of
`data` variables

What is a statistical graphic?

A `mapping` of
`data` variables

to
`aes()`thetic attributes

What is a statistical graphic?

A `mapping` of
`data` variables

to
`aes()`thetic attributes

of
`geom_`etric objects.

Back to Basics

Old school

- Sketch the graphics below on paper, where the `x`-axis is variable `A` and the `y`-axis is variable `B`

```
# A tibble: 4 x 4
      A     B     C D
  <dbl> <dbl> <dbl> <chr>
1 1980.    1.    3. cold
2 1990.    2.    2. cold
3 2000.    3.    1. hot
4 2010.    4.    2. hot
```

1. A scatter plot
2. A scatter plot where the `color` of the points corresponds to `D`
3. A scatter plot where the `size` of the points corresponds to `C`

Reproducing the plots in `ggplot2`

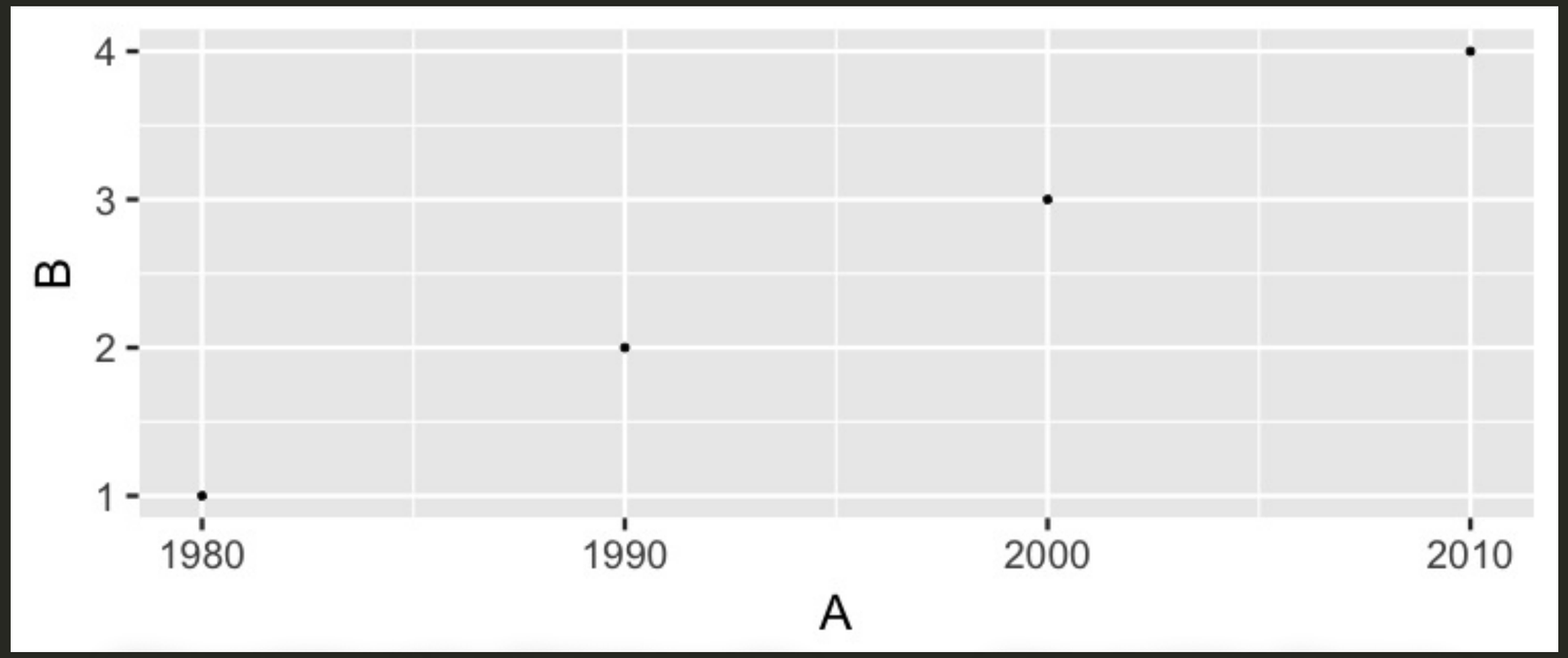
1. A scatterplot

```
library(ggplot2)
ggplot(data = simple_ex, mapping = aes(x = A, y = B)) +
  geom_point()
```

Reproducing the plots in `ggplot2`

1. A scatterplot

```
library(ggplot2)
ggplot(data = simple_ex, mapping = aes(x = A, y = B)) +
  geom_point()
```



Reproducing the plots in `ggplot2`

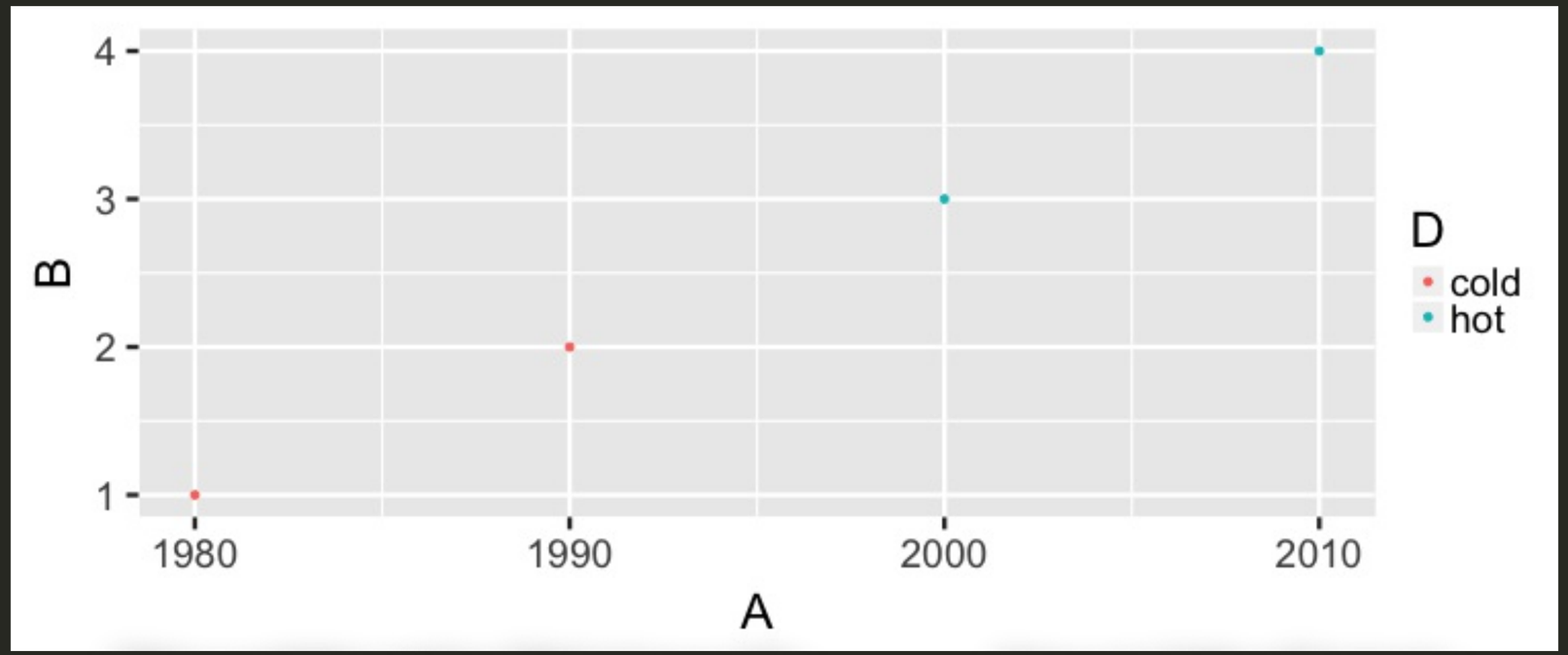
2. A scatter plot where the `color` of the points corresponds to `D`

```
library(ggplot2)
ggplot(data = simple_ex, mapping = aes(x = A, y = B)) +
  geom_point(mapping = aes(color = D))
```

Reproducing the plots in `ggplot2`

2. A scatter plot where the `color` of the points corresponds to `D`

```
library(ggplot2)
ggplot(data = simple_ex, mapping = aes(x = A, y = B)) +
  geom_point(mapping = aes(color = D))
```



Reproducing the plots in `ggplot2`

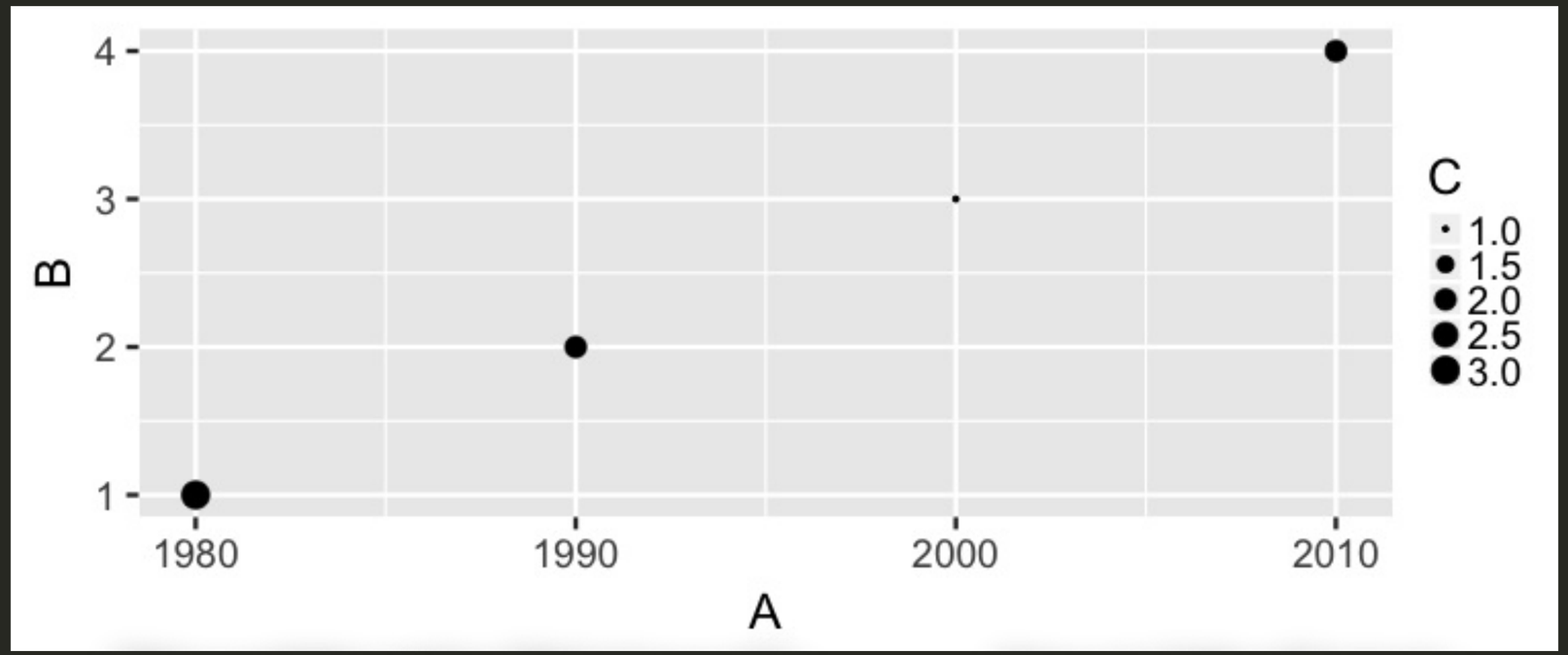
3. A scatter plot where the `size` of the points corresponds to `C`

```
library(ggplot2)
ggplot(data = simple_ex, mapping = aes(x = A, y = B, size = C)) +
  geom_point()
```

Reproducing the plots in `ggplot2`

3. A scatter plot where the `size` of the points corresponds to `C`

```
library(ggplot2)
ggplot(data = simple_ex, mapping = aes(x = A, y = B, size = C)) +
  geom_point()
```



The Five-Named Graphs

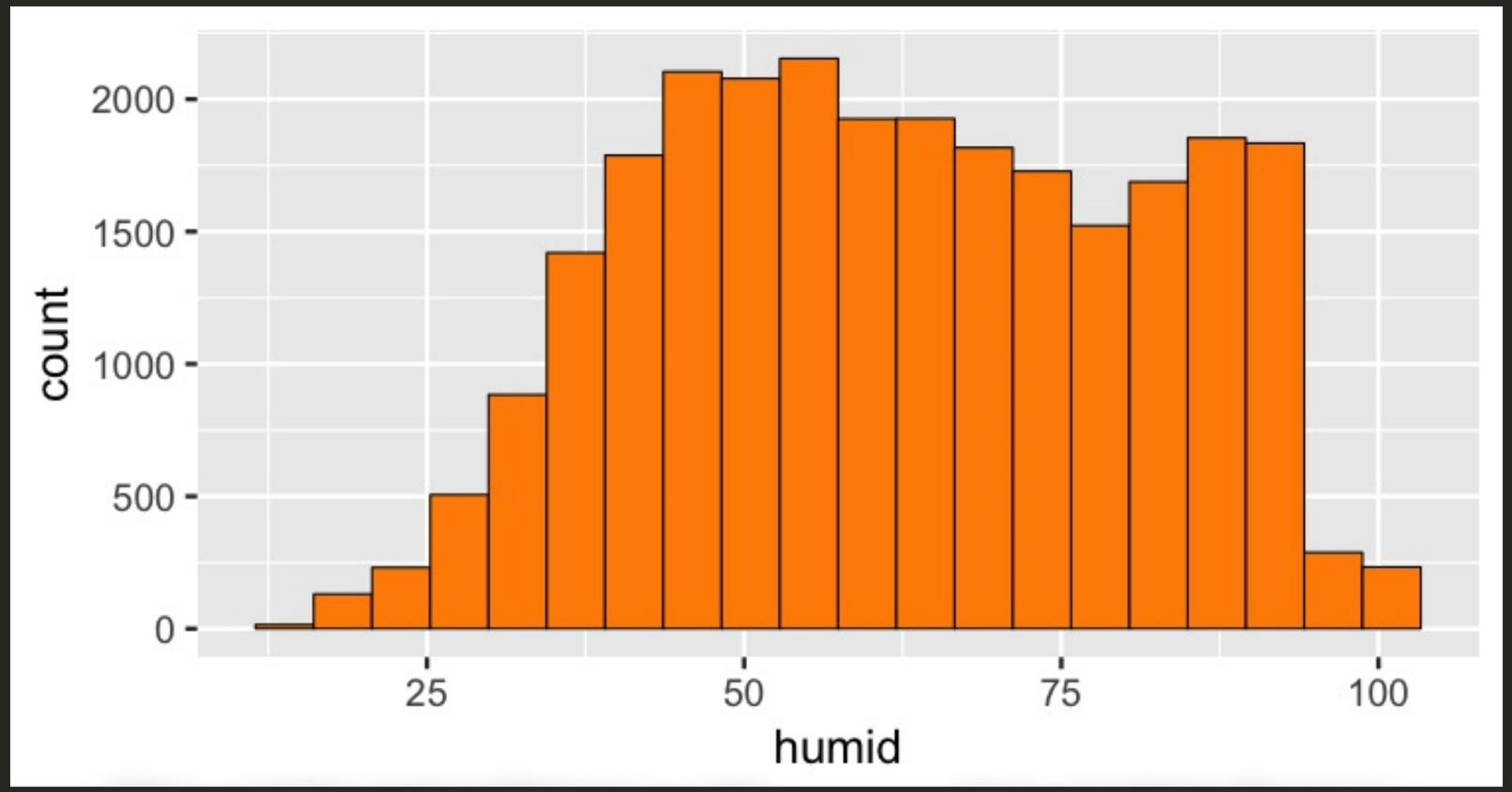
The 5NG of data viz

- Scatterplot: `geom_point()`
- Line graph: `geom_line()`
- Histogram: `geom_histogram()`
- Boxplot: `geom_boxplot()`
- Bar graph: `geom_bar()`

More examples

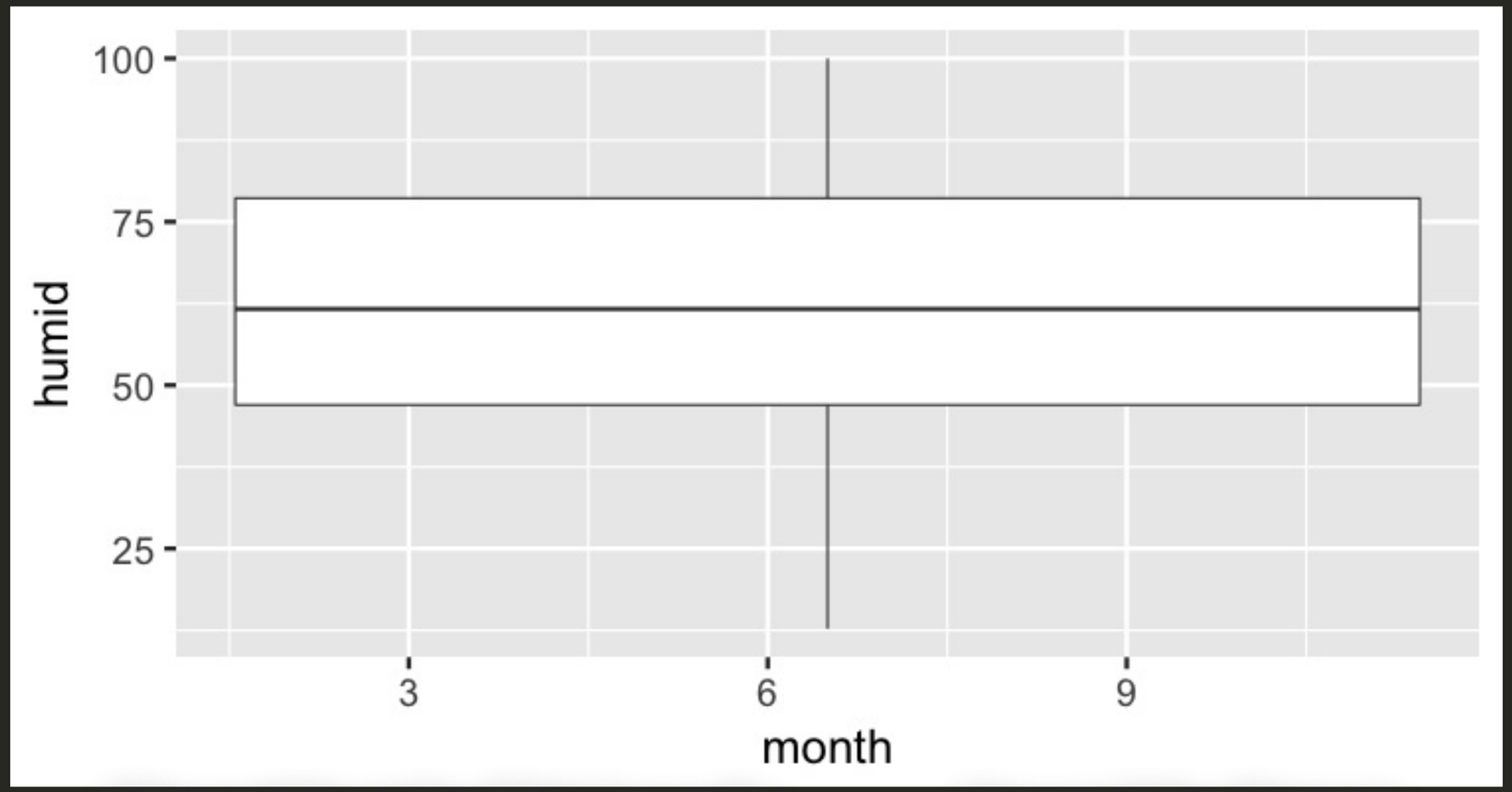
Histogram

```
library(nycflights13)
ggplot(data = weather, mapping = aes(x = humid)) +
  geom_histogram(bins = 20, color = "black", fill = "darkorange")
```



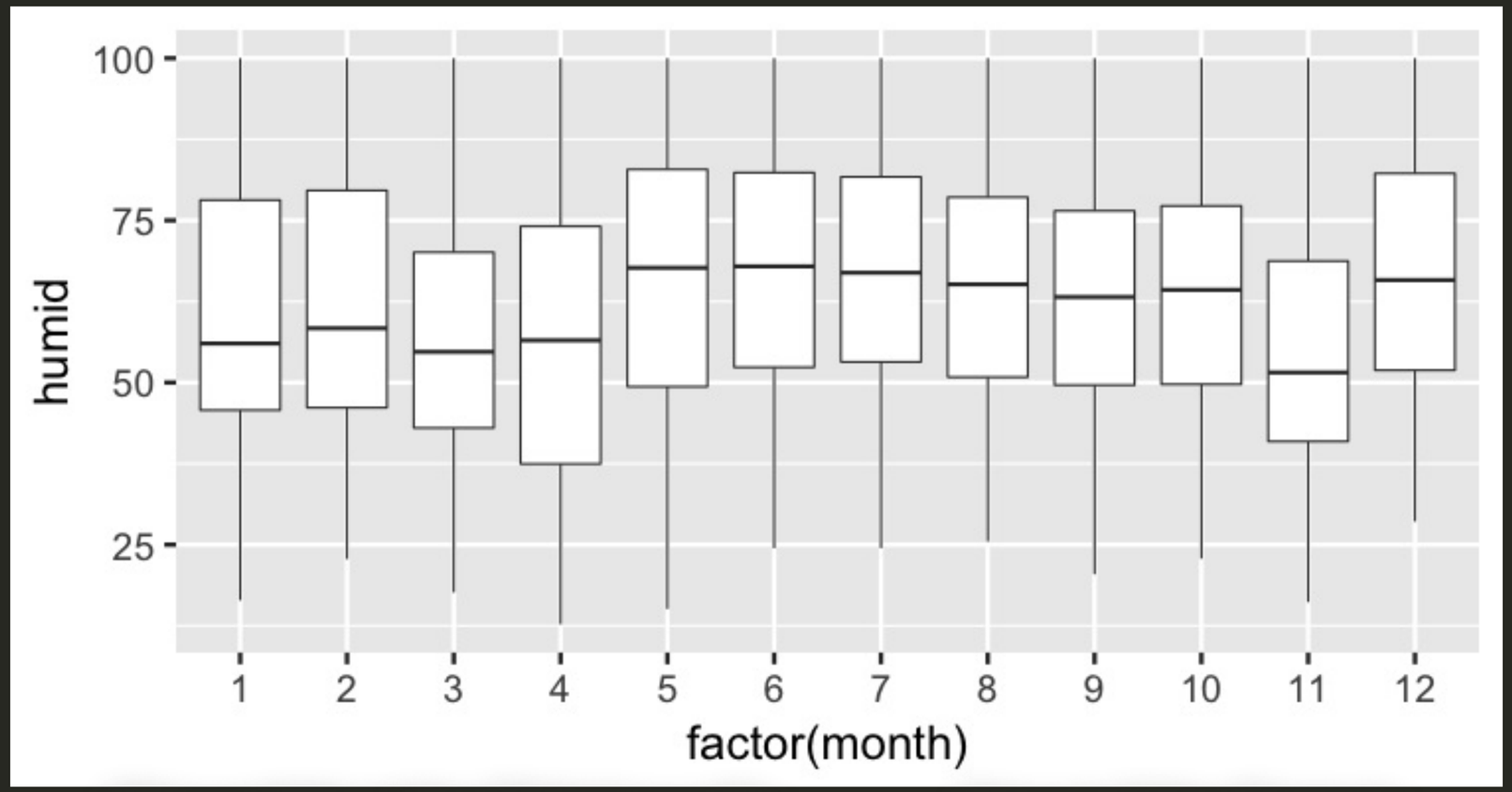
Boxplot (broken)

```
library(nycflights13)
ggplot(data = weather, mapping = aes(x = month, y = humid)) +
  geom_boxplot()
```



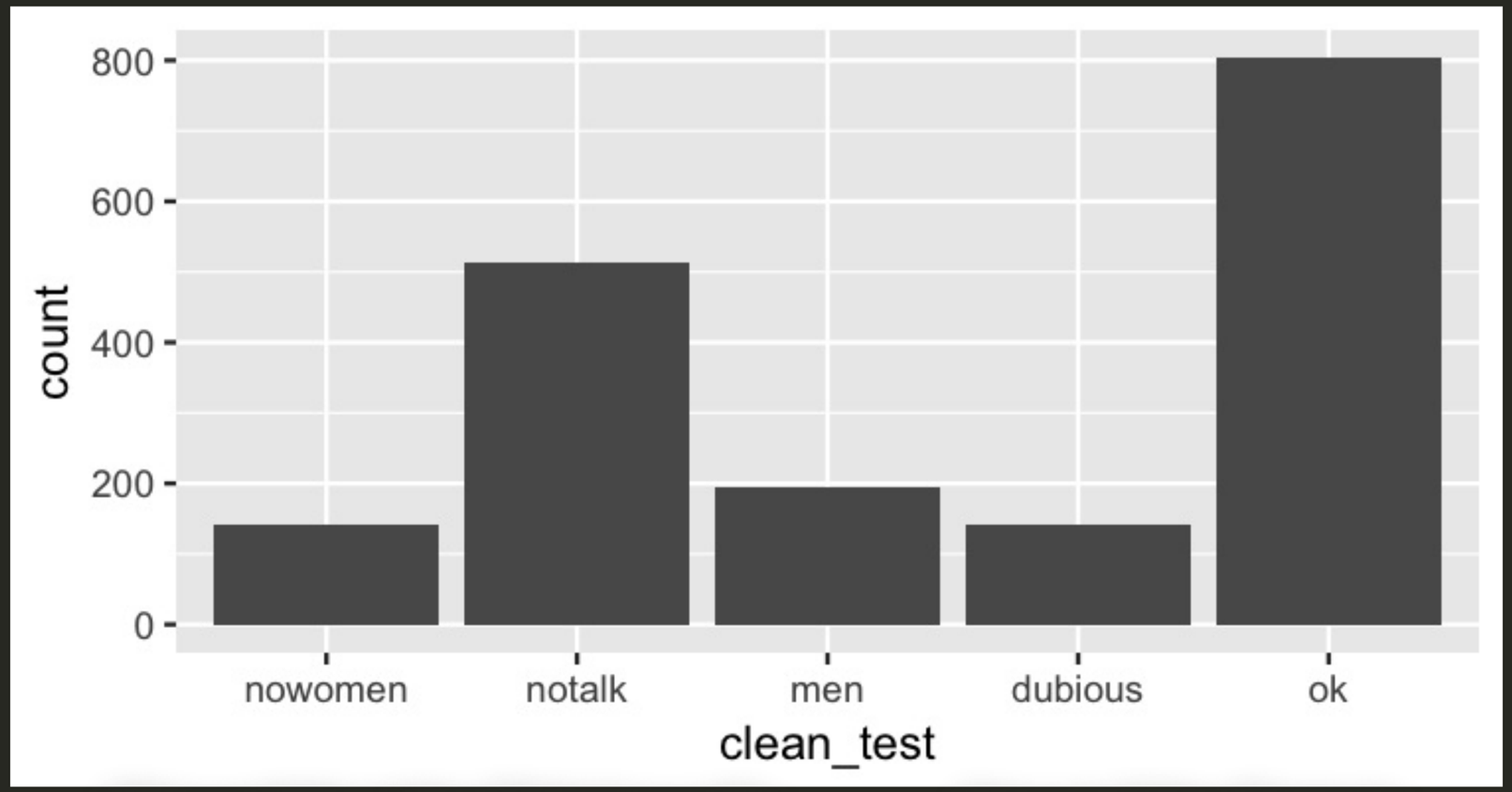
Boxplot (fixed)

```
library(nycflights13)
ggplot(data = weather, mapping = aes(x = factor(month), y = humid)) +
  geom_boxplot()
```



Bar graph

```
library(fivethirtyeight)
ggplot(data = bechdel, mapping = aes(x = clean_test)) +
  geom_bar()
```



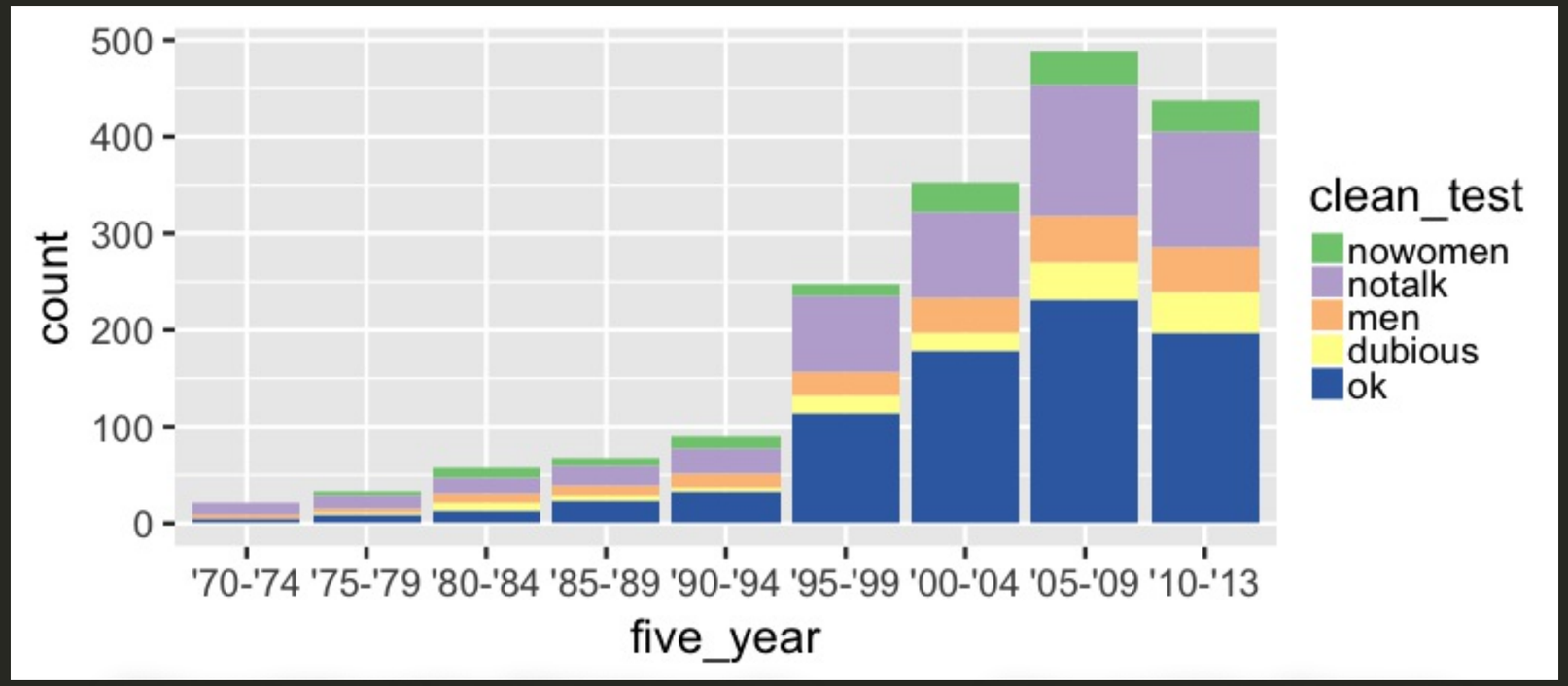
How about over time?

- One more variable to create with `dplyr`

```
library(dplyr)
year_bins <- c("'70-'74", "'75-'79", "'80-'84", "'85-'89",
               "'90-'94", "'95-'99", "'00-'04", "'05-'09",
               "'10-'13")
bechdel <- bechdel %>%
  mutate(five_year = cut(year,
                         breaks = seq(1969, 2014, 5),
                         labels = year_bins))
```

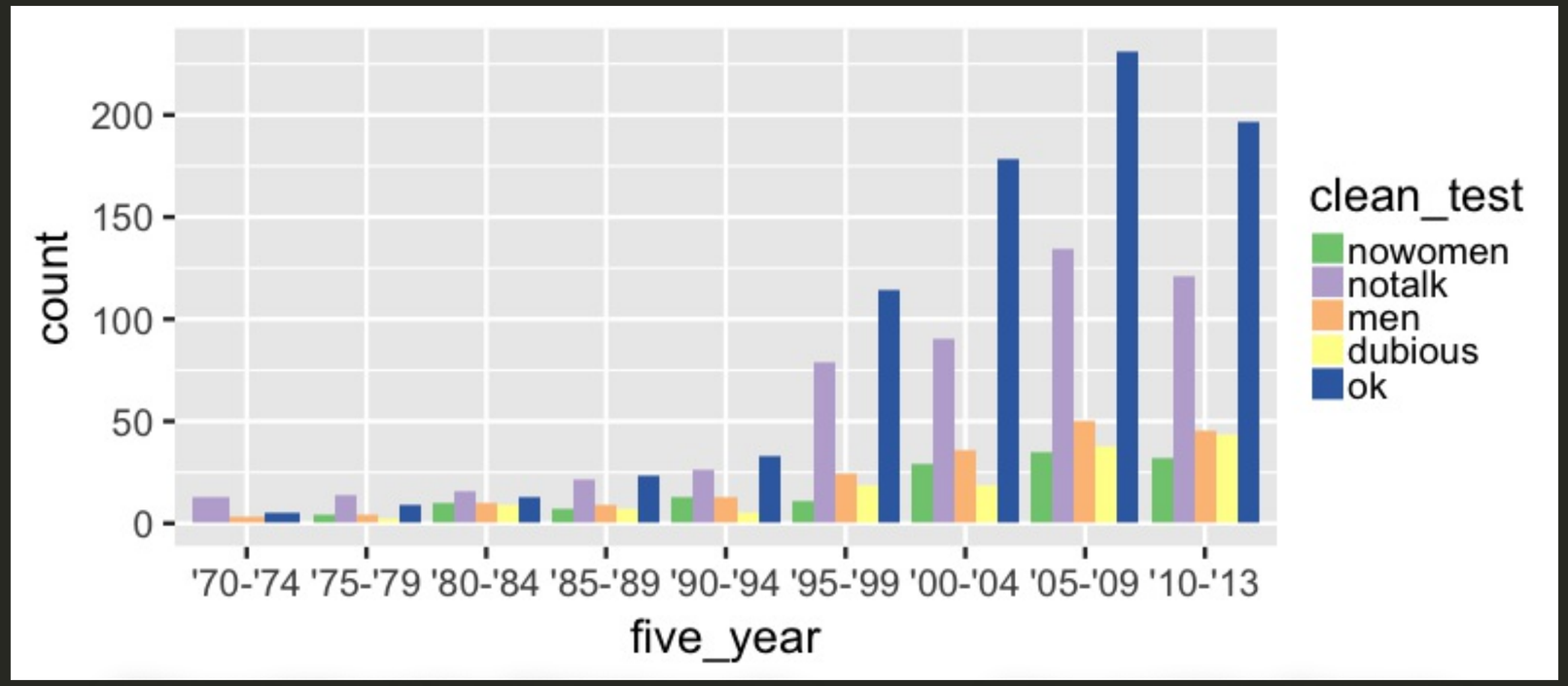
How about over time? (Stacked)

```
library(fivethirtyeight)
library(ggplot2)
ggplot(data = bechdel,
       mapping = aes(x = five_year, fill = clean_test)) +
  geom_bar() +
  scale_fill_brewer(type = "qual") # set colors
```



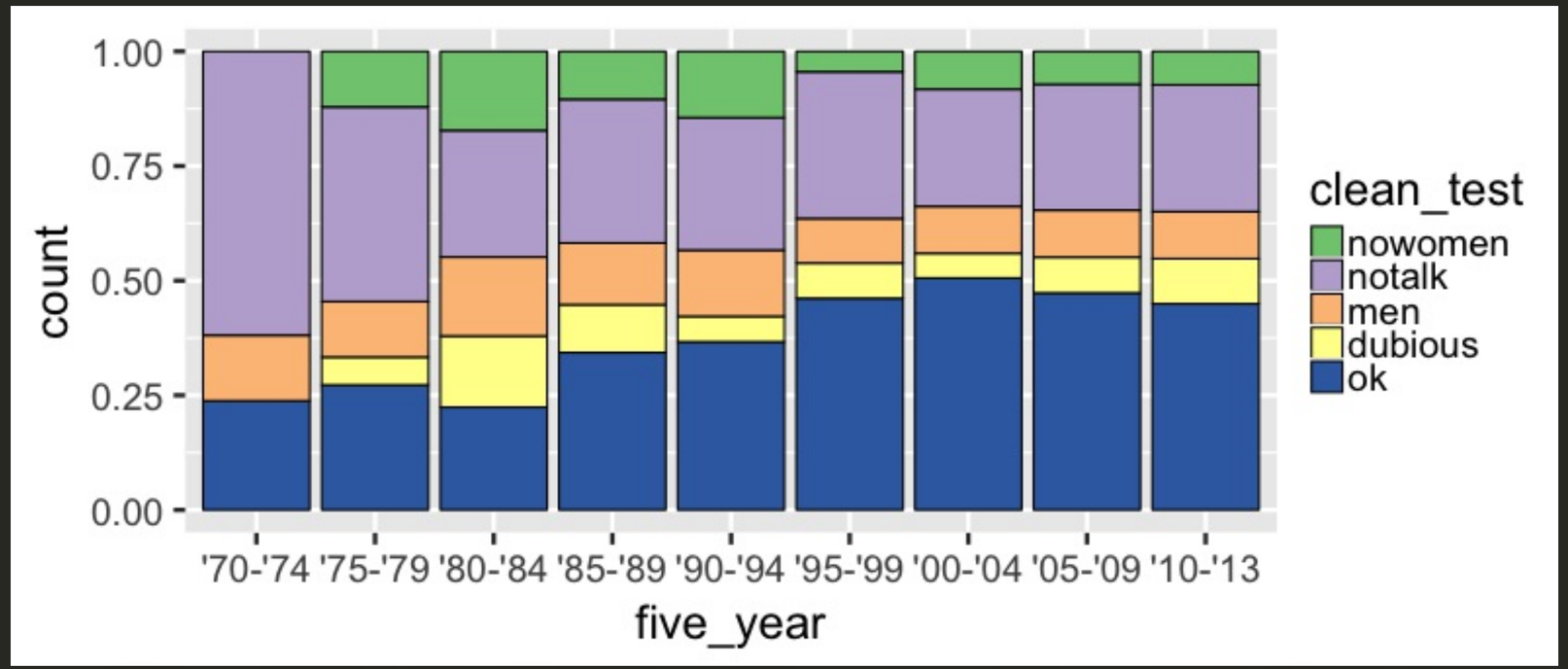
How about over time? (Side-by-side)

```
library(fivethirtyeight)
library(ggplot2)
ggplot(data = bechdel,
       mapping = aes(x = five_year, fill = clean_test)) +
  geom_bar(position = "dodge") +
  scale_fill_brewer(type = "qual")
```



How about over time? (Stacked proportional)

```
library(fivethirtyeight)
library(ggplot2)
ggplot(data = bechdel,
       mapping = aes(x = five_year, fill = clean_test)) +
  geom_bar(position = "fill", color = "black") +
  scale_fill_brewer(type = "qual")
```



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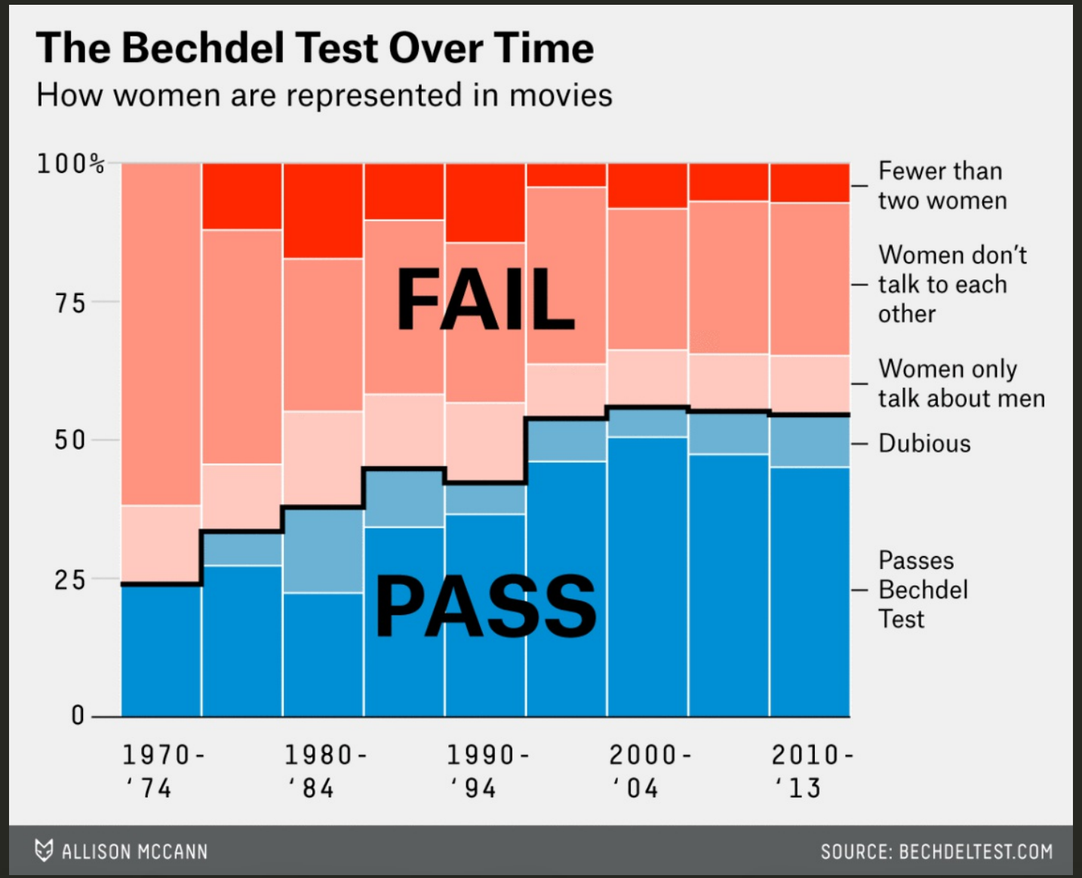
`ggplot2` is for beginners and for data science professionals!



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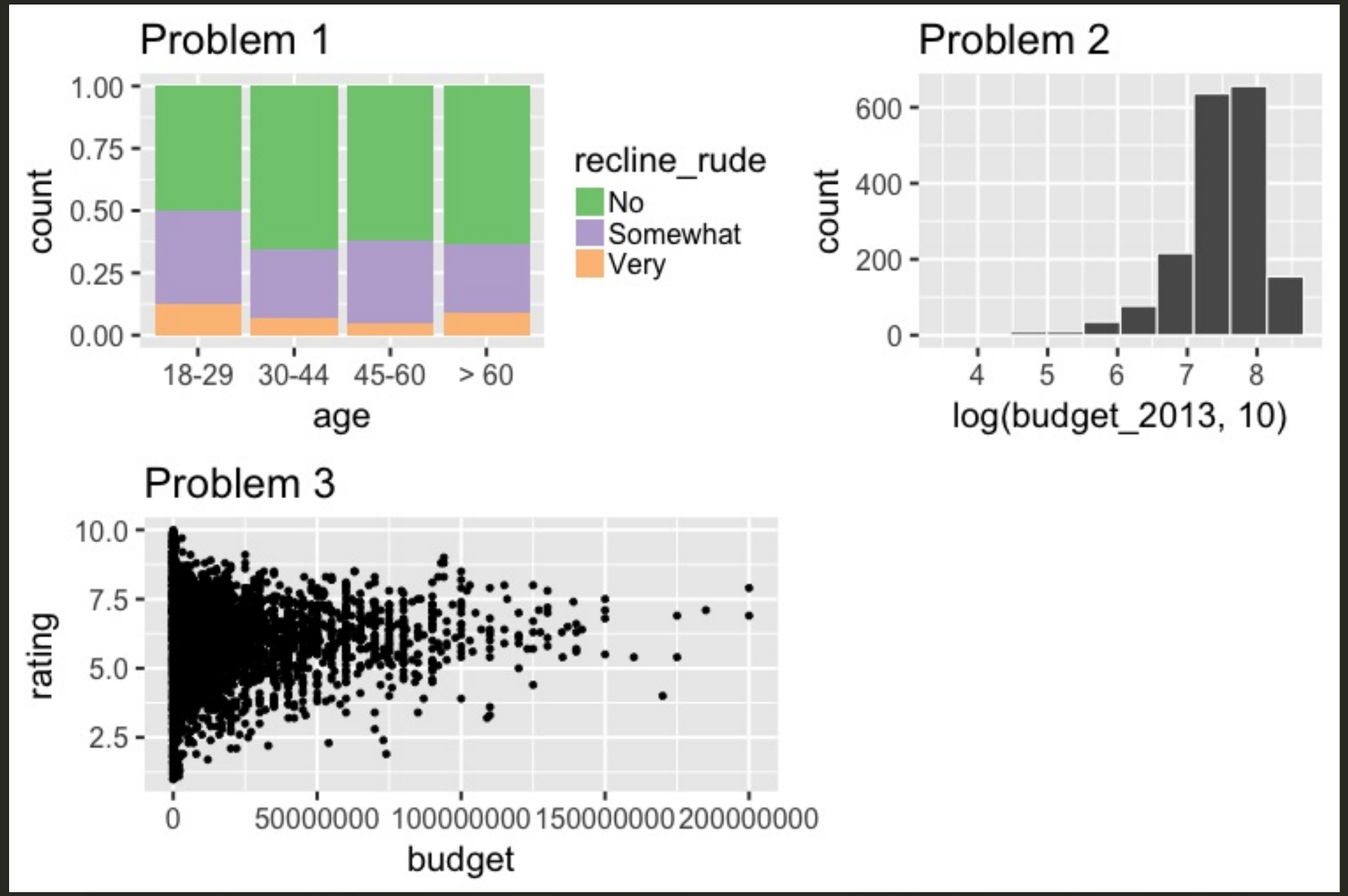
Practice

Produce appropriate 5NG with R package & data set in [ ], e.g., [`nycflights13::weather`]

1. How does `age` predict `recline_rude`?
   [`fivethirtyeight::flying`]
2. Distribution of log base 10 scale of `budget_2013`
   [`fivethirtyeight::bechdel`]
3. How does `budget` predict `rating`?
   [`ggplot2movies::movies`]

HINTS



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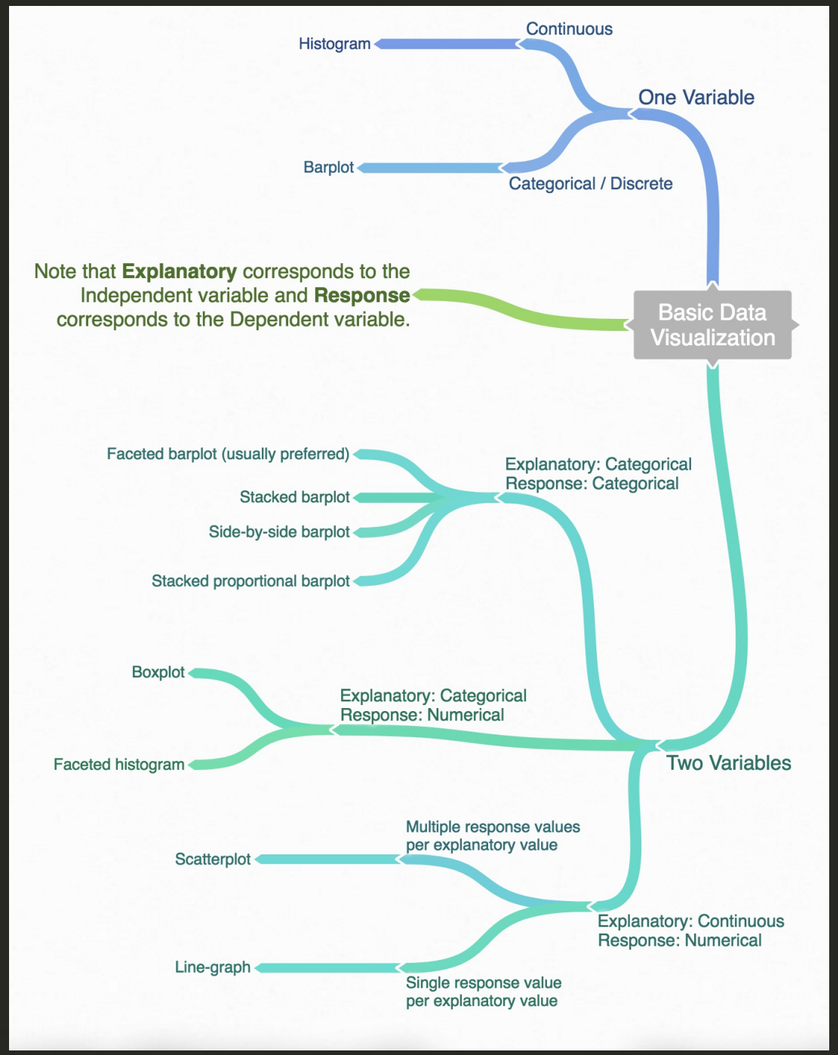
DEMO in RStudio

Determining the appropriate plot



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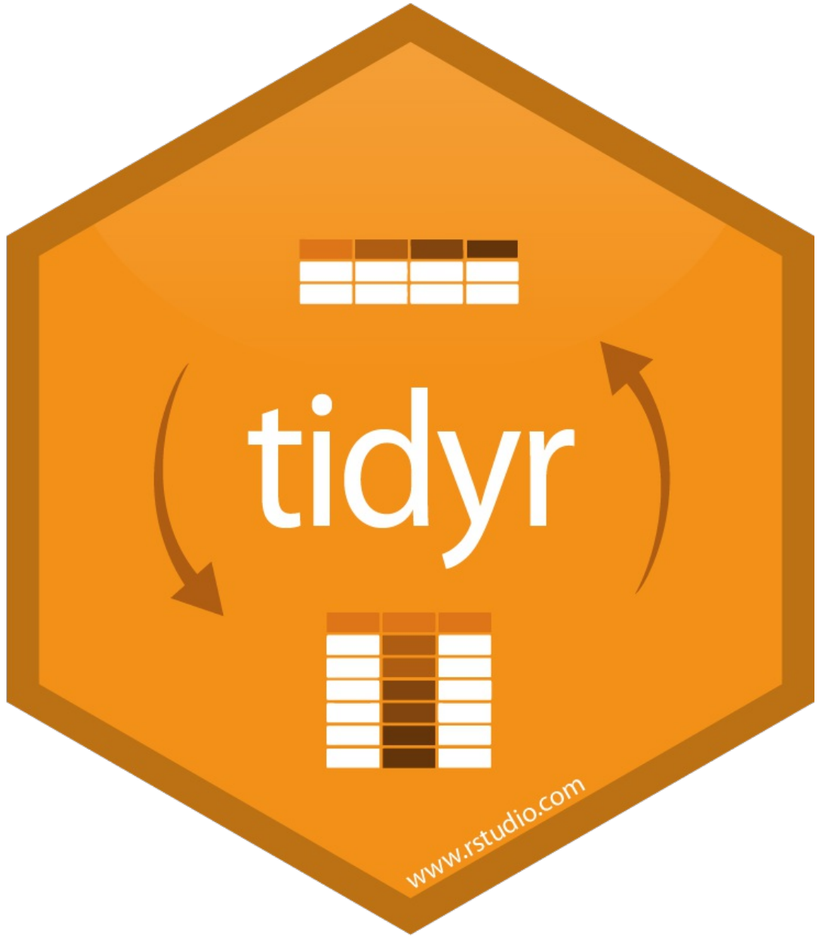
Data Tidying



Tidy Data?

1. Each variable forms a column.
2. Each observation forms a row.
3. Each type of observational unit forms a table.

The third point means we don't mix apples and oranges.

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What is Tidy Data?

1. Each observation forms a row. In other words, each row corresponds to a single instance of an observational unit
2. Each variable forms a column:
    - Some variables may be used to identify the observational units.
    - For organizational purposes, it's generally better to put these in the left-hand columns
3. Each type of observational unit forms a table.

Differentiating between neat data and tidy data

- Colloquially, they mean the same thing
- But in our context, one is a subset of the other.

Neat data is

- easy to look at,
- organized nicely, and
- in table form.

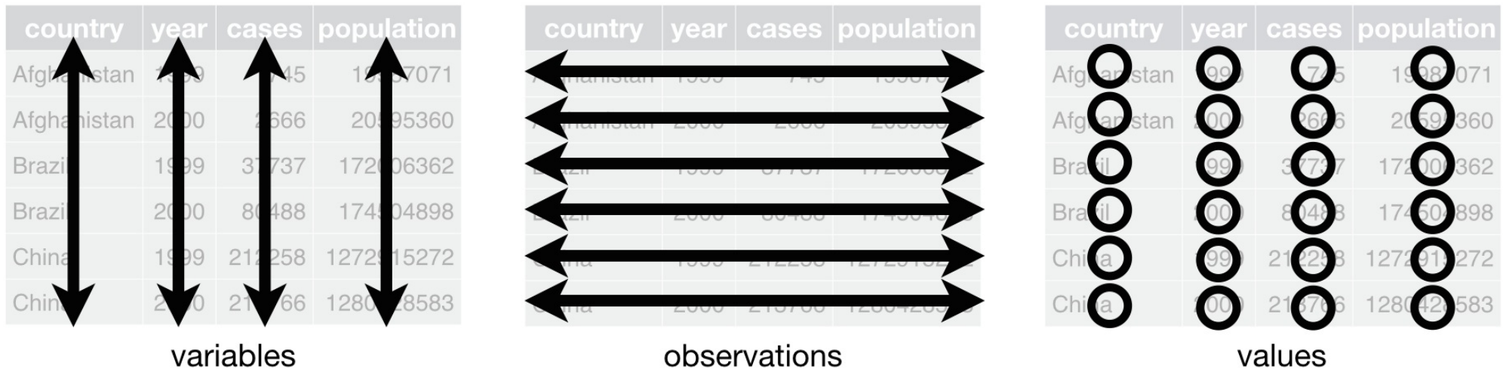
Differentiating between neat data and tidy data

- Colloquially, they mean the same thing
- But in our context, one is a subset of the other.

Neat data is

- easy to look at,
- organized nicely, and
- in table form.

Tidy data is neat but also abides by a set of three rules.



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Is this tidy?

```
# A tibble: 12 x 4
    year title                          clean_test budget_2013
   <int> <chr>                          <ord>             <int>
 1  1995 Apollo 13                      ok             99370665
 2  2005 Brokeback Mountain             notalk         16583160
 3  2010 Diary of a Wimpy Kid           ok             16023478
 4  1984 Dune                           dubious       100864980
 5  1984 Ghostbusters                   notalk         67243320
 6  2003 How to Lose a Guy in 10 Days   men            63304348
 7  2011 Iris                           ok              5696299
 8  2004 Sideways                       ok             20964279
 9  2000 Songcatcher                    ok              2435235
10  2004 Team America: World Police     men            24663858
11  2010 Tron Legacy                    notalk        213646368
12  2011 War Horse                      notalk         72498355
```

How about this? Is this tidy?

```
# A tibble: 12 x 13
   country     `1952` `1957` `1962` `1967` `1972` `1977` `1982` `1987`
   <chr>        <int>  <int>  <int>  <int>  <int>  <int>  <int>  <int>
 1 Albania         -9     -9     -9     -9     -9     -9     -9     -9
 2 Argentina       -9     -1     -1     -9     -9     -9     -8      8
 3 Armenia         -9     -7     -7     -7     -7     -7     -7     -7
 4 Australia       10     10     10     10     10     10     10     10
 5 Austria         10     10     10     10     10     10     10     10
 6 Azerbaijan      -9     -7     -7     -7     -7     -7     -7     -7
 7 Belarus         -9     -7     -7     -7     -7     -7     -7     -7
 8 Belgium         10     10     10     10     10     10     10     10
 9 Bhutan         -10    -10    -10    -10    -10    -10    -10    -10
10 Bolivia         -4     -3     -3     -4     -7     -7      8      9
11 Brazil           5      5      5     -9     -9     -4     -3      7
12 Bulgaria        -7     -7     -7     -7     -7     -7     -7     -7
# ... with 4 more variables: `1992` <int>, `1997` <int>,
#   `2002` <int>, `2007` <int>
```

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Why is tidy data important?

- Think about trying to plot democracy score across years in the simplest way possible with the data on the previous slide.

Why is tidy data important?

- Think about trying to plot democracy score across years in the simplest way possible with the data on the previous slide.
- It would be much easier if the data looked like what follows instead so we could put
  - `year` on the `x`-axis and
  - `dem_score` on the `y`-axis.

Tidy is good

```
library(tidyr)
dem_score_tidy <- dem_score %>%
  gather(-country, key = "year", value = "dem_score") %>%
  mutate(year = as.integer(year))
dem_score_tidy %>% sample_n(10) %>% arrange(country)
```

Tidy is good

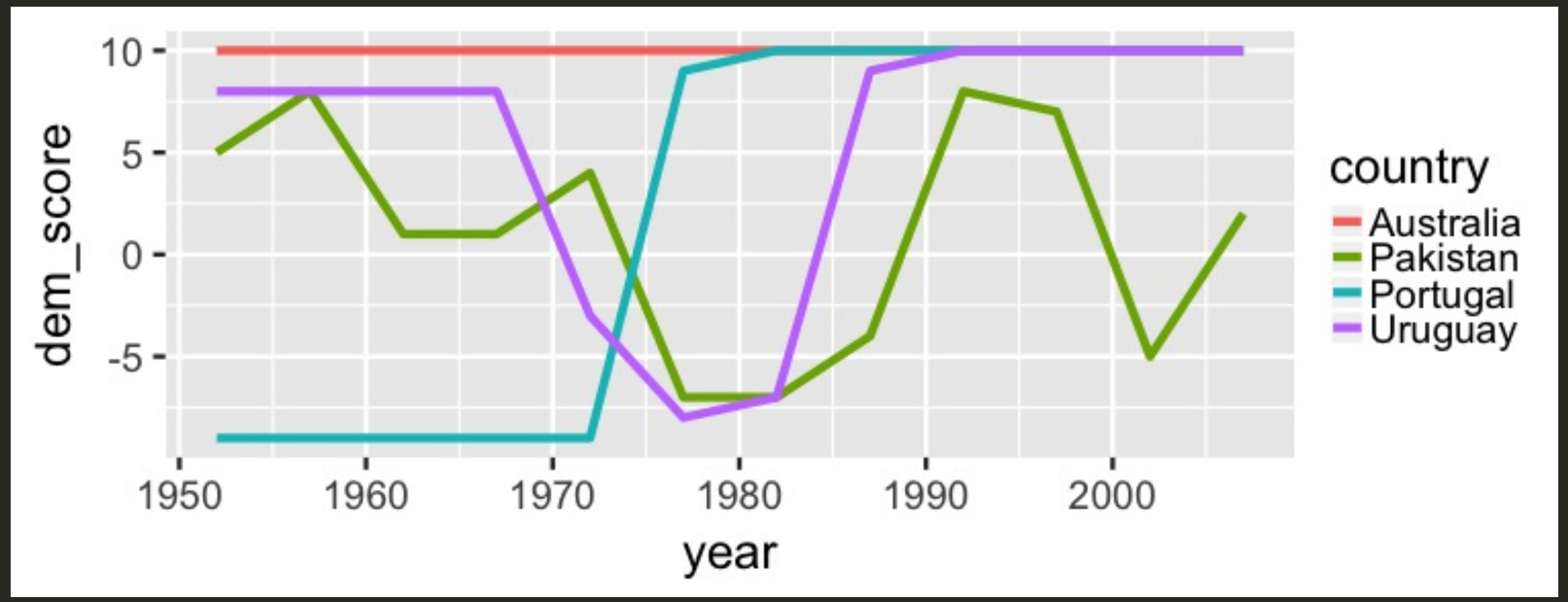
```
library(tidyr)
dem_score_tidy <- dem_score %>%
  gather(-country, key = "year", value = "dem_score") %>%
  mutate(year = as.integer(year))
dem_score_tidy %>% sample_n(10) %>% arrange(country)
```

```
# A tibble: 10 x 3
   country     year dem_score
   <chr>      <int>     <int>
 1 Canada      1997        10
 2 Costa Rica  1962        10
 3 Denmark     2002        10
 4 Georgia     1977        -7
 5 Montenegro  1972        -7
 6 Norway      2007        10
 7 Panama      1962         4
 8 Sweden      1972        10
 9 Taiwan      1952        -8
10 Taiwan      1987        -1
```

Let's plot it

- Plot the line graph for 4 countries using `ggplot`

```
dem_score4 <- dem_score_tidy %>%
  filter(country %in% c("Australia", "Pakistan", "Portugal", "Uruguay"))
ggplot(data = dem_score4, mapping = aes(x = year, y = dem_score)) +
  geom_line(mapping = aes(color = country), size = 2)
```



Beginning steps

Frequently the first thing to do when given a dataset is to

- check that the data is tidy (if not, convert it!)
- identify the observational unit,
- specify the variables, and
- give the types of variables you are presented with.

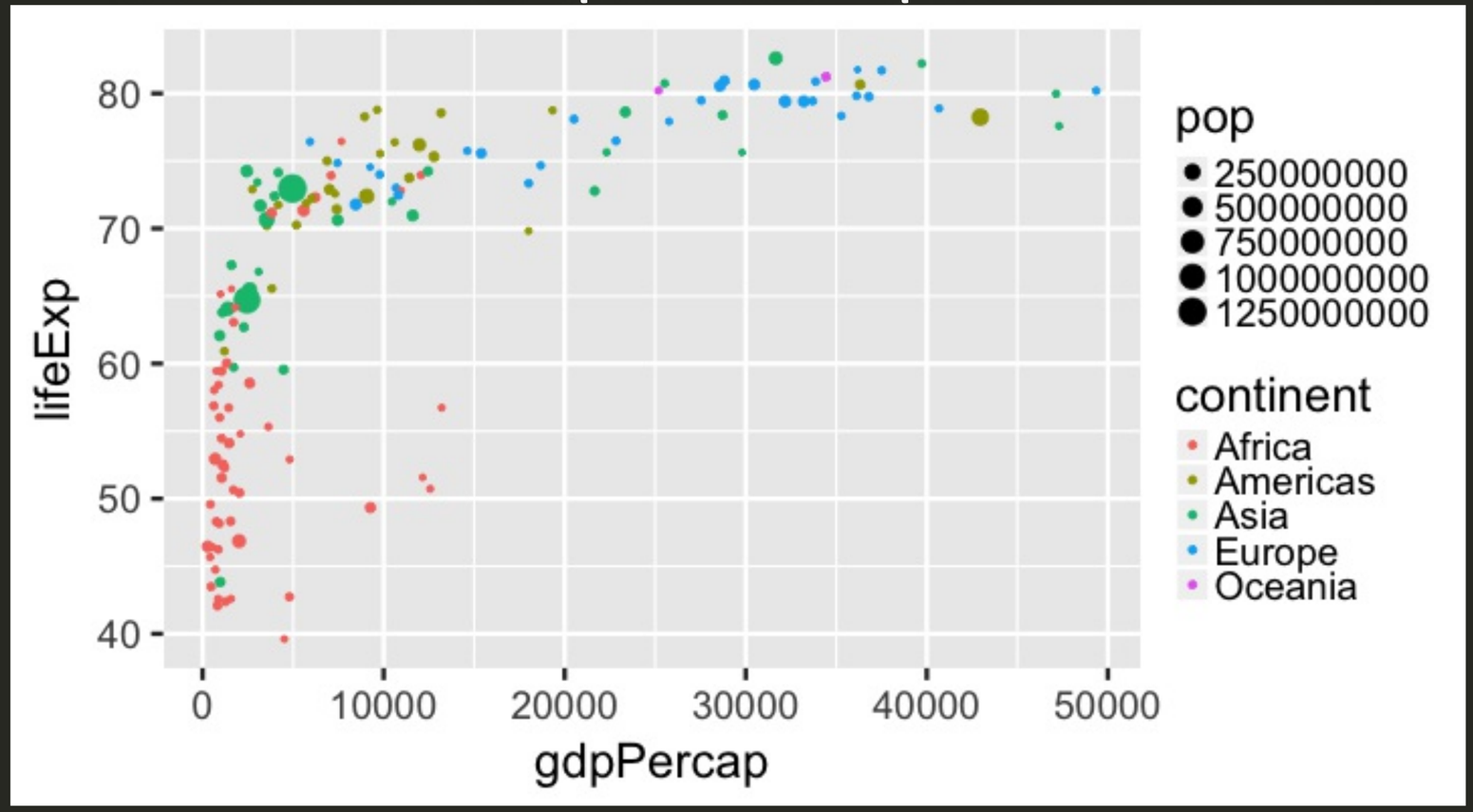
This will help with

- choosing the appropriate plot,
- summarizing the data, and
- understanding which inferences can be applied.

Sampling Distributions

Review

- Write the code to produce this plot for 2007 data



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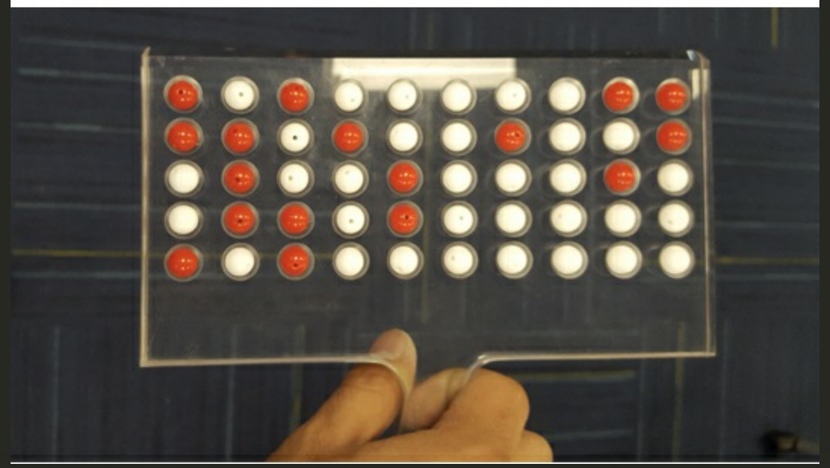
Extending this knowledge to something new

- How can we now learn about sampling distributions?

Extending this knowledge to something new

- How can we now learn about sampling distributions?



```
library(moderndive)
bowl
```

```
# A tibble: 2,400 x 2
   ball_ID color
     <int> <chr>
 1       1 white
 2       2 white
 3       3 white
 4       4 red
 5       5 white
 6       6 white
 7       7 red
 8       8 white
 9       9 red
10      10 white
# ... with 2,390 more rows
```

One virtual scoop of 50 balls (one sample)

```
set.seed(8675309)
( jennys_sample <- bowl %>% sample_n(size = 50) )
```

```
# A tibble: 50 x 2
   ball_ID color
     <int> <chr>
 1     383 red
 2    1148 red
 3    1834 white
 4    1845 white
 5     644 white
 6    1612 white
 7    2344 red
 8    2026 red
 9    2050 white
10    1065 white
# ... with 40 more rows
```

Proportion that are red

```
jennys_sample %>%
  summarize(prop_red = mean(color == "red")) %>%
  pull()
```

```
[1] 0.38
```

Proportion that are red

```
jennys_sample %>%
  summarize(prop_red = mean(color == "red")) %>%
  pull()
```

```
[1] 0.38
```

Is this how many are in the full bowl?

Sampling variability

What does `rep_bowl_samples` look like?

```
library(moderndive)
rep_bowl_samples <- bowl %>%
  rep_sample_n(size = 50, reps = 10000)
```

Sampling variability

What does `rep_bowl_samples` look like?

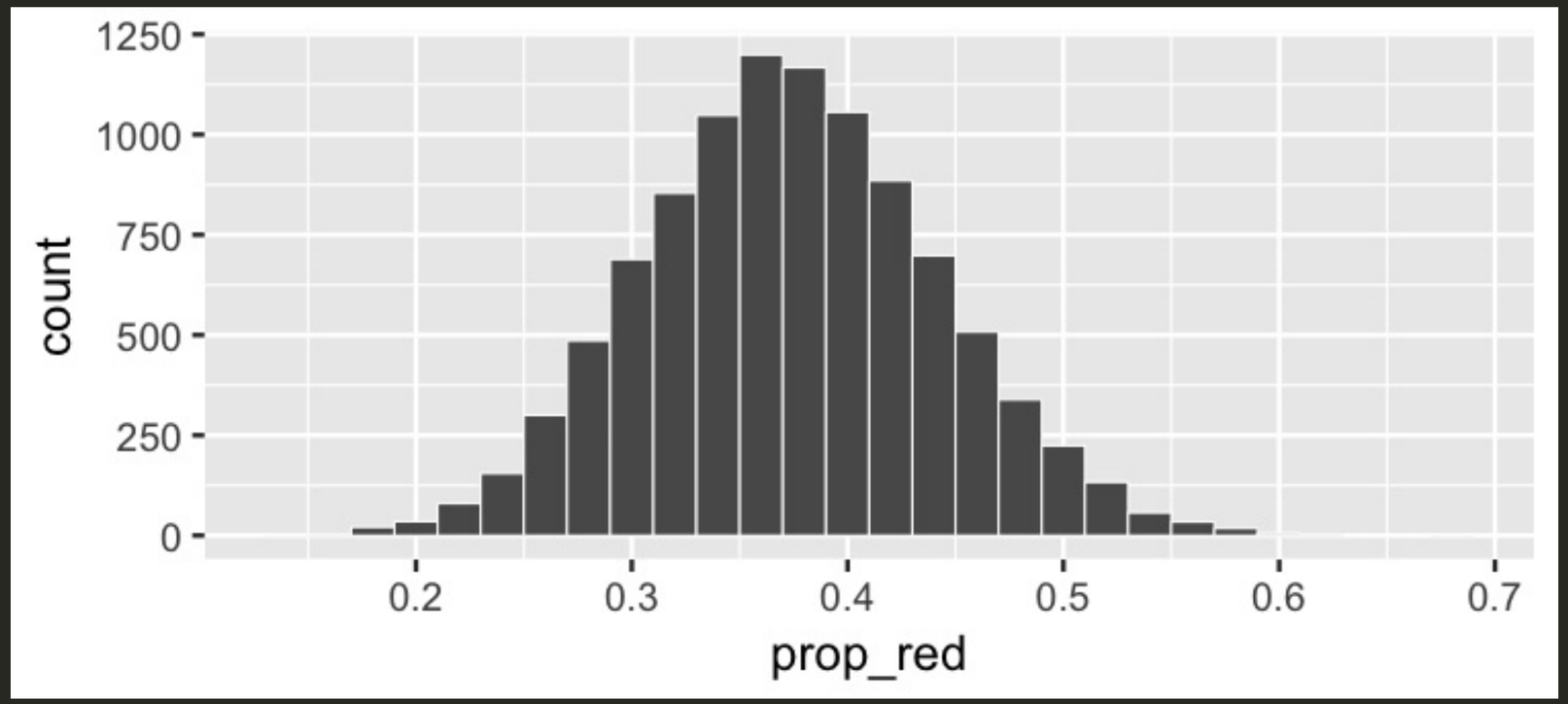
```
library(moderndive)
rep_bowl_samples <- bowl %>%
  rep_sample_n(size = 50, reps = 10000)
```

How about `bowl_props`?

```
bowl_props <- rep_bowl_samples %>%
  group_by(replicate) %>%
  summarize(prop_red = mean(color == "red"))
```

The sampling distribution

```
ggplot(data = bowl_props, mapping = aes(x = prop_red)) +
  geom_histogram(binwidth = 0.02, color = "white")
```



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Practice

- Let's estimate the mean age of pennies
- Create a sampling distribution of 10,000 samples each of size 100 from `moderndive::pennies`

Shifting focus

What about if all we had was the one sample of balls (not the whole bowl)?

```
jennys_sample %>% count(color)
```

```
# A tibble: 2 x 2
  color     n
  <chr> <int>
1 red      19
2 white    31
```

Shifting focus

What about if all we had was the one sample of balls (not the whole bowl)?

```
jennys_sample %>% count(color)
```

```
# A tibble: 2 x 2
  color     n
  <chr> <int>
1 red      19
2 white    31
```

How could we use this sample to make a guess about the sampling variability from other samples?

Building up to statistical inference!

```
library(infer)
jennys_sample %>%
  specify(formula = color ~ NULL, success = "red")
```

```
Response: color (factor)
# A tibble: 50 x 1
   color
   <fct>
 1 red
 2 red
 3 white
 4 white
 5 white
 6 white
 7 red
 8 red
 9 white
10 white
# ... with 40 more rows
```

Bootstrapping?

```
library(infer)
( bootstrap_samples <- jennys_sample %>%
  specify(formula = color ~ NULL, success = "red") %>%
  generate(reps = 48, type = "bootstrap") )
```

```
Response: color (factor)
# A tibble: 2,400 x 2
# Groups:   replicate [48]
   replicate color
       <int> <fct>
 1         1 red
 2         1 white
 3         1 white
 4         1 red
 5         1 white
 6         1 white
 7         1 red
 8         1 red
 9         1 red
10         1 red
# ... with 2,390 more rows
```

What does `bootstrap_samples` represent?

Remember we assumed that all we had was the original sample of 19 red and 31 white to start.

What does `bootstrap_samples` represent?

Remember we assumed that all we had was the original sample of 19 red and 31 white to start.

Hope `bootstrap_samples` is close to this:

Bootstrap statistics

```
jennys_sample %>%
  specify(formula = color ~ NULL, success = "red") %>%
  generate(reps = 48, type = "bootstrap") %>%
  calculate(stat = "prop")
```

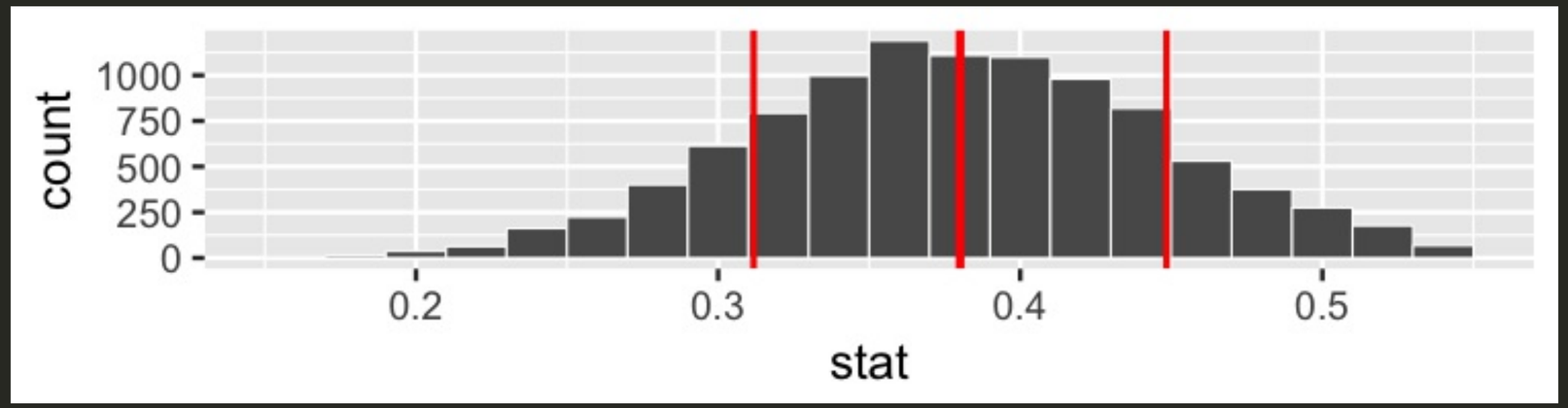
```
Response: color (factor)
# A tibble: 48 x 2
   replicate  stat
       <int> <dbl>
 1         1 0.360
 2         2 0.320
 3         3 0.420
 4         4 0.380
 5         5 0.540
 6         6 0.260
 7         7 0.380
 8         8 0.480
 9         9 0.340
10        10 0.360
# ... with 38 more rows
```

Do 10,000 reps to get a better sense for variability

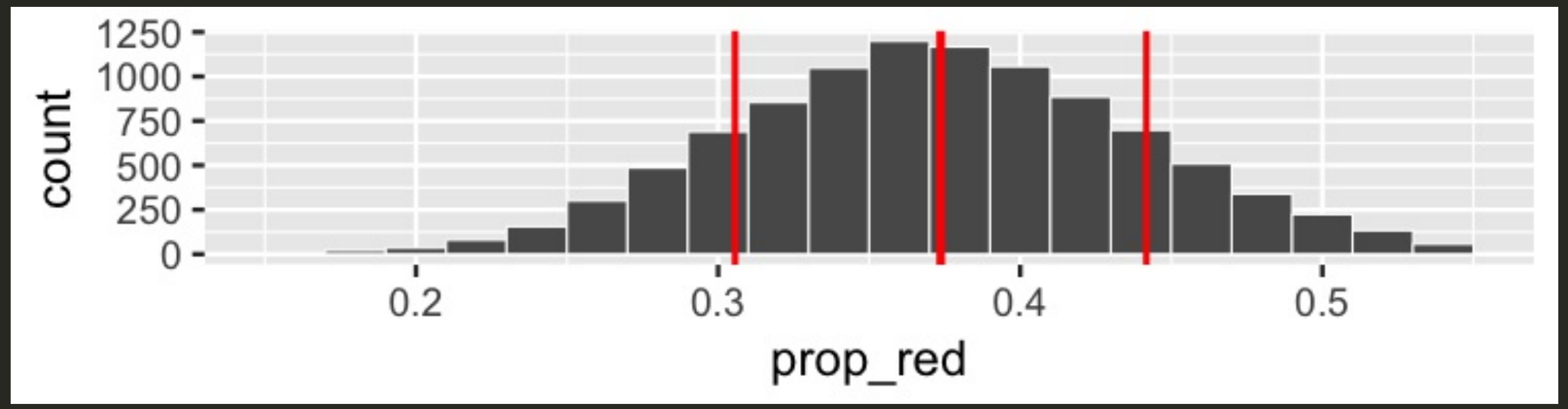
Just as we did with the sampling distribution

```
bootstrap_stats <- jennys_sample %>%
  specify(formula = color ~ NULL, success = "red") %>%
  generate(reps = 10000, type = "bootstrap") %>%
  calculate(stat = "prop")
```

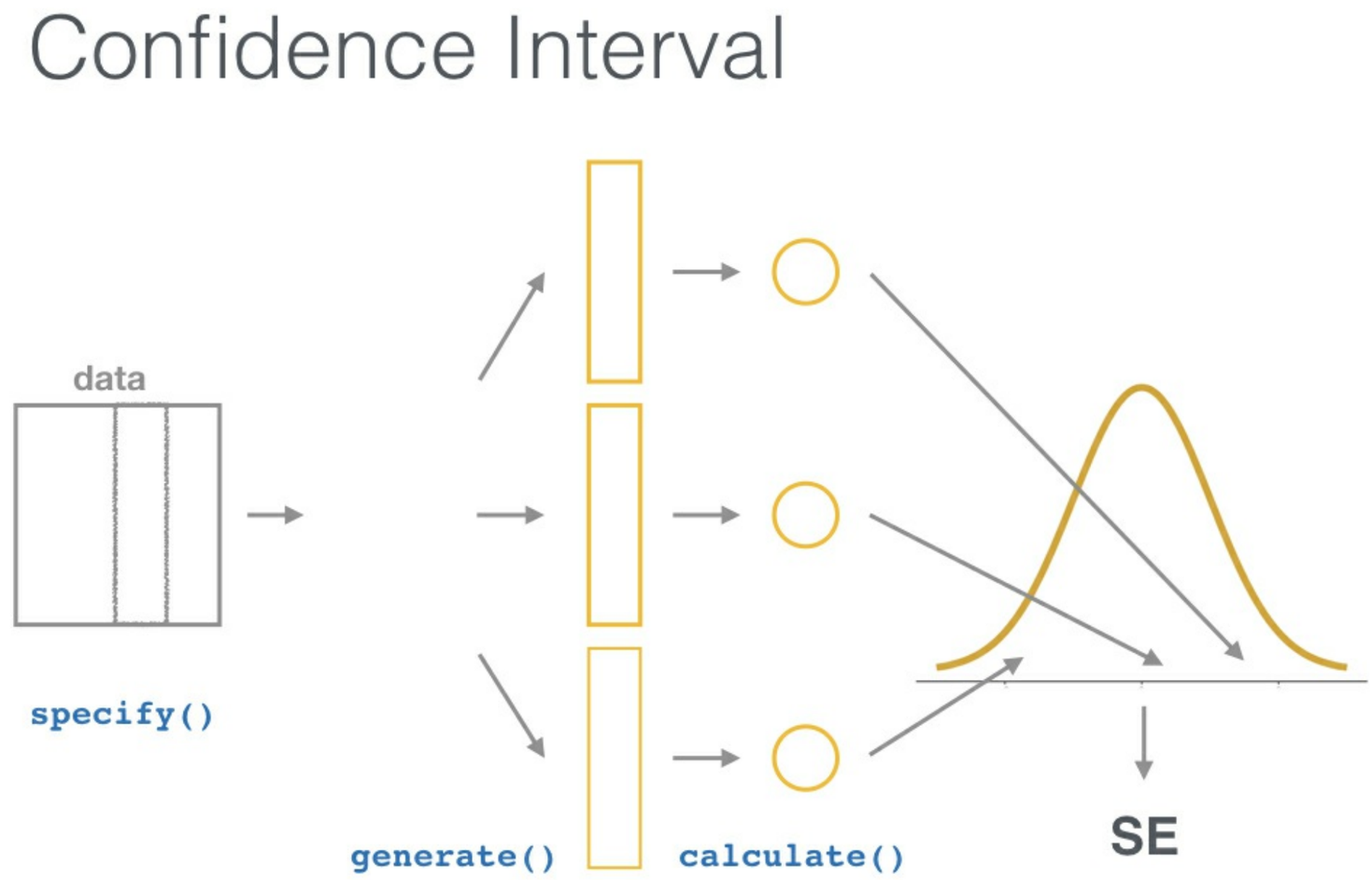
The bootstrap distribution



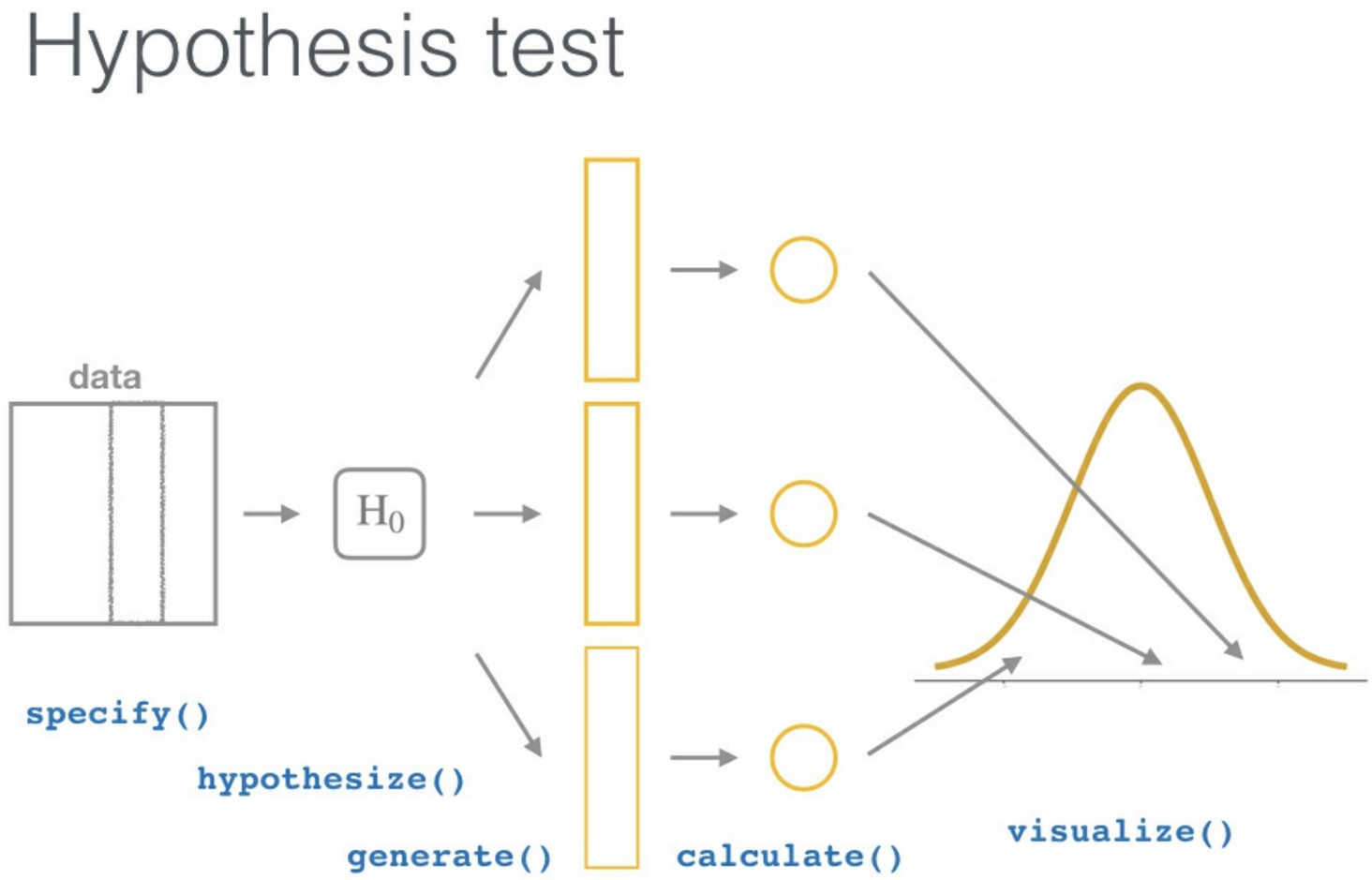
The sampling distribution



`infer` verbs



`infer` verbs


Hypothesis test
data
H_0
specify()
hypothesize()
generate()
calculate()
visualize()

Statistical Inference

`infer` hex sticker designs kindly created by Thomas Mock

Research Question

If you see someone else yawn, are you more likely to yawn?
In an episode of the show Mythbusters, they tested the myth that yawning is contagious.

- Analysis done with Alison Hill

Participants and Procedure

Participants and Procedure

- 50 adults who thought they were being considered for an appearance on the show.

Participants and Procedure

- 50 adults who thought they were being considered for an appearance on the show.
- Each participant was interviewed individually by a show recruiter ("confederate") who either yawned or did not.

Participants and Procedure

- 50 adults who thought they were being considered for an appearance on the show.
- Each participant was interviewed individually by a show recruiter ("confederate") who either yawned or did not.
- Participants then sat by themselves in a large van and were asked to wait.

Participants and Procedure

- 50 adults who thought they were being considered for an appearance on the show.
- Each participant was interviewed individually by a show recruiter ("confederate") who either yawned or did not.
- Participants then sat by themselves in a large van and were asked to wait.
- While in the van, the Mythbusters watched to see if the unaware participants yawned.

Data

- 34 saw the confederate yawn (seed)
- 16 did not see the confederate yawn (control)
- `1` corresponds to yawn, `0` to no yawn

Data

- 34 saw the confederate yawn (seed)
- 16 did not see the confederate yawn (control)
- `1` corresponds to yawn, `0` to no yawn

```
group <- c(rep("control", 12), rep("seed", 24),
           rep("control", 4), rep("seed", 10))
yawn <- c(rep(0, 36), rep(1, 14))
yawn_myth <- data_frame(subj = seq(1, 50), group, yawn) %>%
  mutate(yawn = factor(yawn))
slice(yawn_myth, c(5, 17, 37, 49))
```

```
# A tibble: 4 x 3
   subj group   yawn
  <int> <chr>   <fct>
1     5 control 0
2    17 seed    0
3    37 control 1
4    49 seed    1
```

Results


```
library(janitor)
yawn_myth %>%
  tabyl(group, yawn) %>%
  adorn_percentages() %>%
  adorn_pct_formatting() %>%
  adorn_ns()
```

```
   group           0           1
 control 75.0% (12) 25.0%  (4)
    seed 70.6% (24) 29.4% (10)
```

Slides available at http://bit.ly/ness-infer

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Conclusion

Conclusion

Finding: CONFIRMED [1]

[1] http://www.discovery.com/tv-shows/mythbusters/mythbusters-database/yawning-contagious/

Really?

> "Though that's not an enormous increase, since they tested 50 people in the field, the gap was still wide enough for the MythBusters to confirm that yawning is indeed contagious." [1]

[1] http://www.discovery.com/tv-shows/mythbusters/mythbusters-database/yawning-contagious/

State the hypotheses

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Null hypothesis:

> There is no difference between the seed and control groups in the proportion of people who yawned.

State the hypotheses

Null hypothesis:

> There is no difference between the seed and control groups in the proportion of people who yawned.

Alternative hypothesis (directional):

> More people (relatively) yawned in the seed group than in the control group.

Test the hypothesis

Which type of hypothesis test would you conduct here?

- Independent samples t-test
- Two proportion test
- Chi-square Goodness of Fit
- Analysis of Variance

Two proportion test

Two proportion test

$$H_0 : p_{seed} - p_{control} = 0$$

Two proportion test

$$H_0 : p_{seed} - p_{control} = 0$$

$$H_A : p_{seed} - p_{control} > 0$$

The observed difference

```
yawn_myth %>%
  group_by(group) %>%
  summarize(prop = mean(yawn == 1))
```

```
# A tibble: 2 x 2
  group    prop
  <chr>   <dbl>
1 control 0.250
2 seed    0.294
```

The observed difference

```
yawn_myth %>%
  group_by(group) %>%
  summarize(prop = mean(yawn == 1))
```

```
# A tibble: 2 x 2
  group    prop
  <chr>   <dbl>
1 control 0.250
2 seed    0.294
```

```
(obs_diff <- yawn_myth %>%
  group_by(group) %>%
  summarize(prop = mean(yawn == 1)) %>%
  summarize(diff(prop)) %>%
  pull())
```

```
[1] 0.044118
```

Is this difference meaningful?

Is this difference meaningful?

Different question:

Is this difference meaningful?

Different question:

Is this difference significant?

Modeling the null hypothesis

If...

$$H_0 : p_{seed} = p_{control}$$

is true, then whether or not the participant saw someone else yawn does not matter.

Modeling the null hypothesis

If...

$$H_0 : p_{seed} = p_{control}$$

is true, then whether or not the participant saw someone else yawn does not matter.

In other words, there is no association between exposure and yawning.

Slides available at http://bit.ly/ness-infer

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Original universe

```
# A tibble: 12 x 3
    subj group   yawn
   <int> <chr>   <fct>
 1     1 control 0
 2     2 control 0
 3     3 control 0
 4     4 control 0
 5     5 control 0
 6     6 control 0
 7    15 seed    0
 8    16 seed    0
 9    17 seed    0
10    18 seed    0
11    19 seed    0
12    20 seed    0
```

```
   group  0  1 Total
 control 12  4    16
    seed 24 10    34
   Total 36 14    50
```

Slides available at http://bit.ly/ness-infer

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Original universe

```
# A tibble: 12 x 3
    subj group   yawn
   <int> <chr>   <fct>
 1     1 control 0
 2     2 control 0
 3     3 control 0
 4     4 control 0
 5     5 control 0
 6     6 control 0
 7    15 seed    0
 8    16 seed    0
 9    17 seed    0
10    18 seed    0
11    19 seed    0
12    20 seed    0
```

```
   group  0  1 Total
 control 12  4    16
    seed 24 10    34
   Total 36 14    50
```

Parallel universe

```
# A tibble: 12 x 3
    subj group   alt_yawn
   <int> <fct>   <fct>
 1     1 control 0
 2     2 control 0
 3     3 control 0
 4     4 control 0
 5     5 control 0
 6     6 control 0
 7    15 seed    0
 8    16 seed    1
 9    17 seed    1
10    18 seed    0
11    19 seed    0
12    20 seed    1
```

```
   group  0  1 Total
 control 14  2    16
    seed 22 12    34
   Total 36 14    50
```

Slides available at http://bit.ly/ness-infer

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1000 parallel universes

```
Response: yawn (factor)
Explanatory: group (factor)
Null Hypothesis:  independence
# A tibble: 1,000 x 2
   replicate    stat
       <int>   <dbl>
 1         1  0.0441
 2         2  0.0441
 3         3 -0.0478
 4         4  0.136
 5         5  0.0441
 6         6 -0.0478
 7         7  0.136
 8         8 -0.232
 9         9 -0.0478
10        10 -0.0478
# ... with 990 more rows
```

Slides available at http://bit.ly/ness-infer

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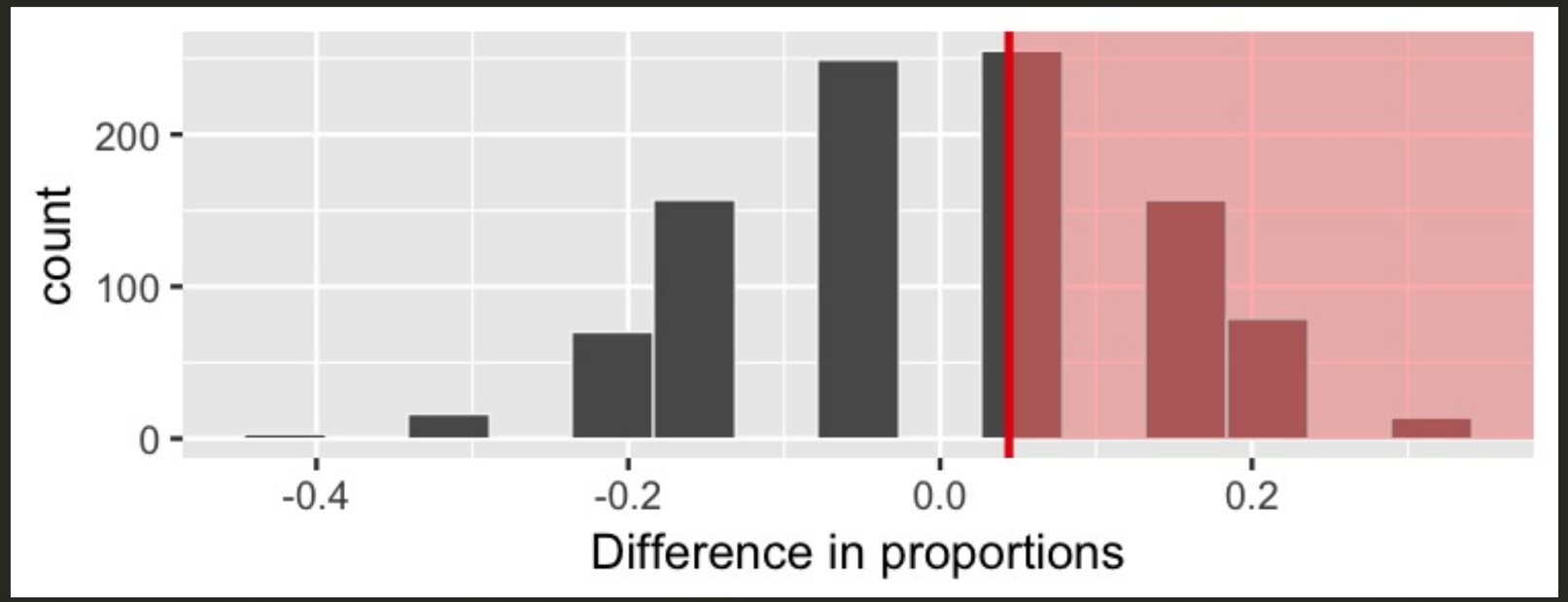
1000 parallel universes

```
Response: yawn (factor)
Explanatory: group (factor)
Null Hypothesis:  independence
# A tibble: 1,000 x 2
   replicate    stat
       <int>   <dbl>
 1         1  0.0441
 2         2  0.0441
 3         3 -0.0478
 4         4  0.136
 5         5  0.0441
 6         6 -0.0478
 7         7  0.136
 8         8 -0.232
 9         9 -0.0478
10        10 -0.0478
# ... with 990 more rows
```

```
# A tibble: 10 x 2
   replicate    stat
       <int>   <dbl>
 1       991  0.0441
 2       992 -0.0478
 3       993  0.136
 4       994 -0.232
 5       995 -0.140
 6       996 -0.140
 7       997  0.136
 8       998  0.0441
 9       999  0.136
10      1000 -0.324
```

The parallel universe distribution



The distribution of 1000 differences in proportions, if the null hypothesis were true and yawning was not contagious.

Calculating the p-value

In how many of our "parallel universes" is the difference as big or bigger than the one we observed (0.04412)?

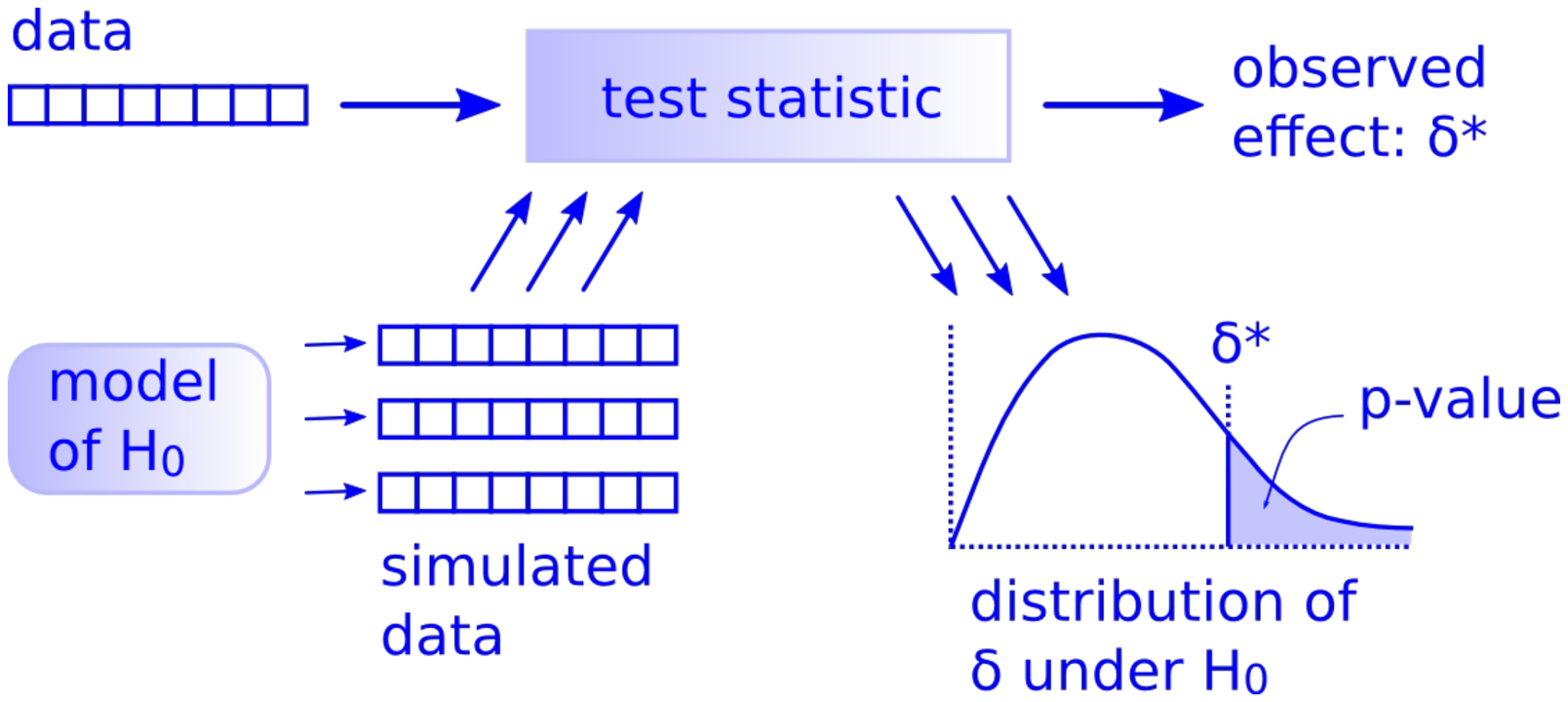
Calculating the p-value

In how many of our "parallel universes" is the difference as big or bigger than the one we observed (0.04412)?

The shaded proportion is the p-value!

```
Response: yawn (factor)
Explanatory: group (factor)
Null Hypothesis:  independence
# A tibble: 1 x 3
  n_as_big n_total p_value
     <int>   <int>   <dbl>
1      505    1000   0.505
```

There is Only One Test!

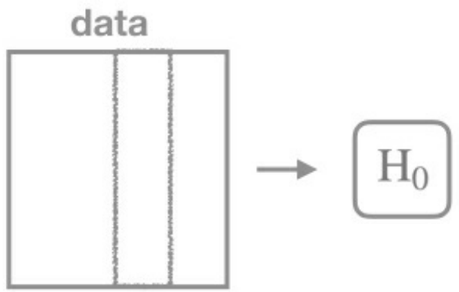


Hypothesis test

Hypothesis test

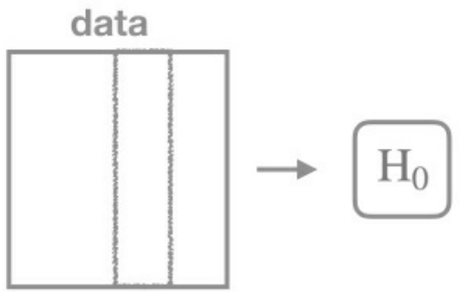

```
specify()
```

Hypothesis test



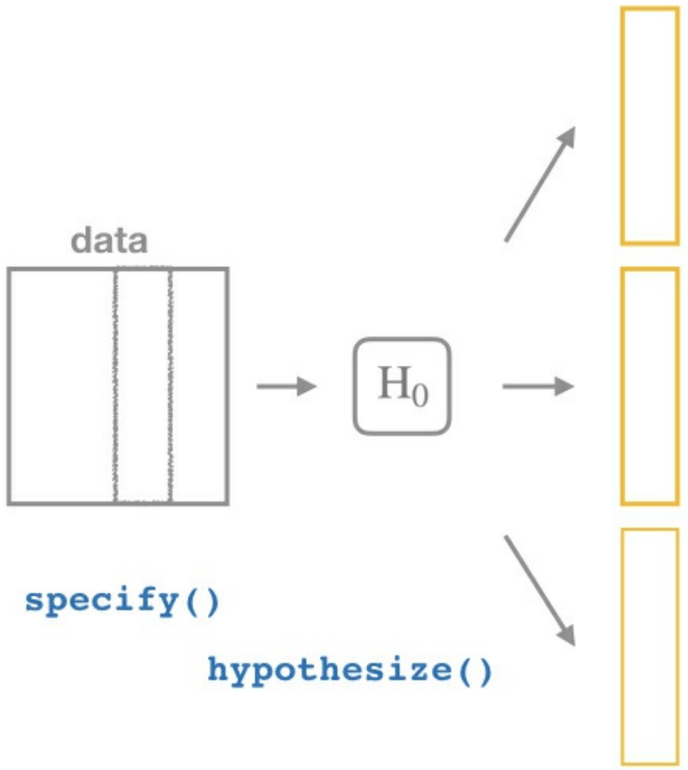

```
specify()
```

Hypothesis test

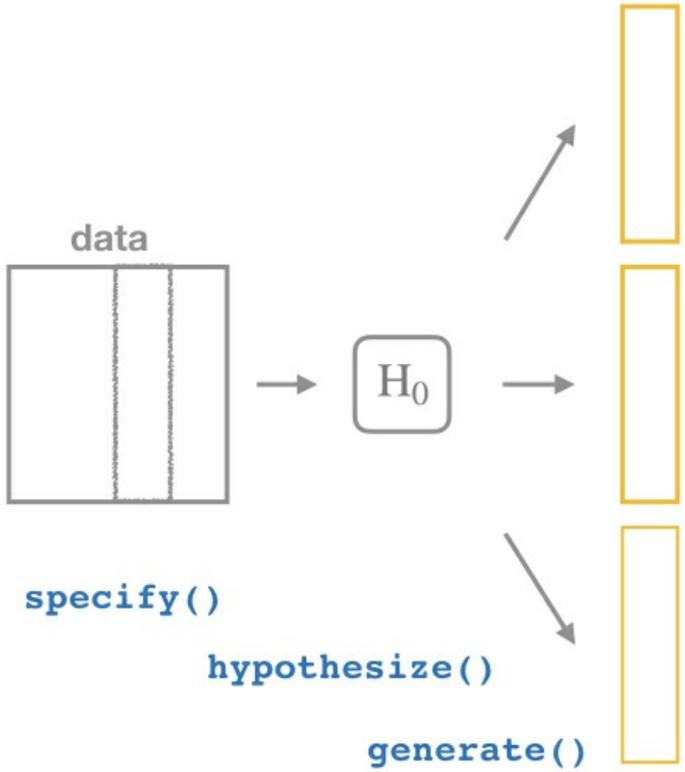



```
specify()
        hypothesize()
```

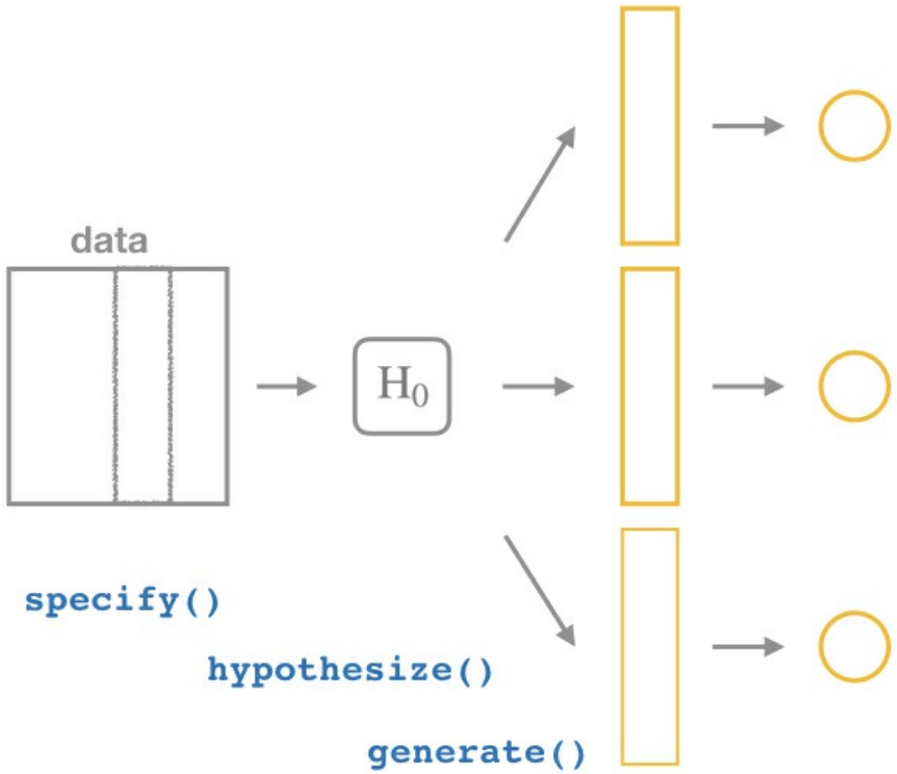
Hypothesis test



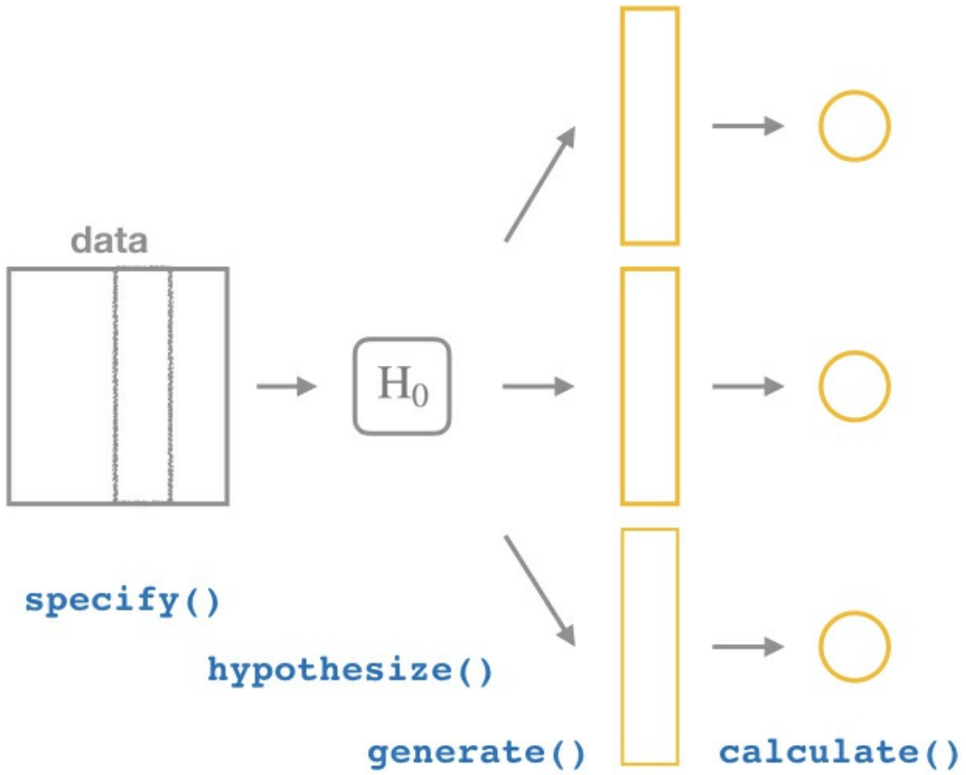
Hypothesis test



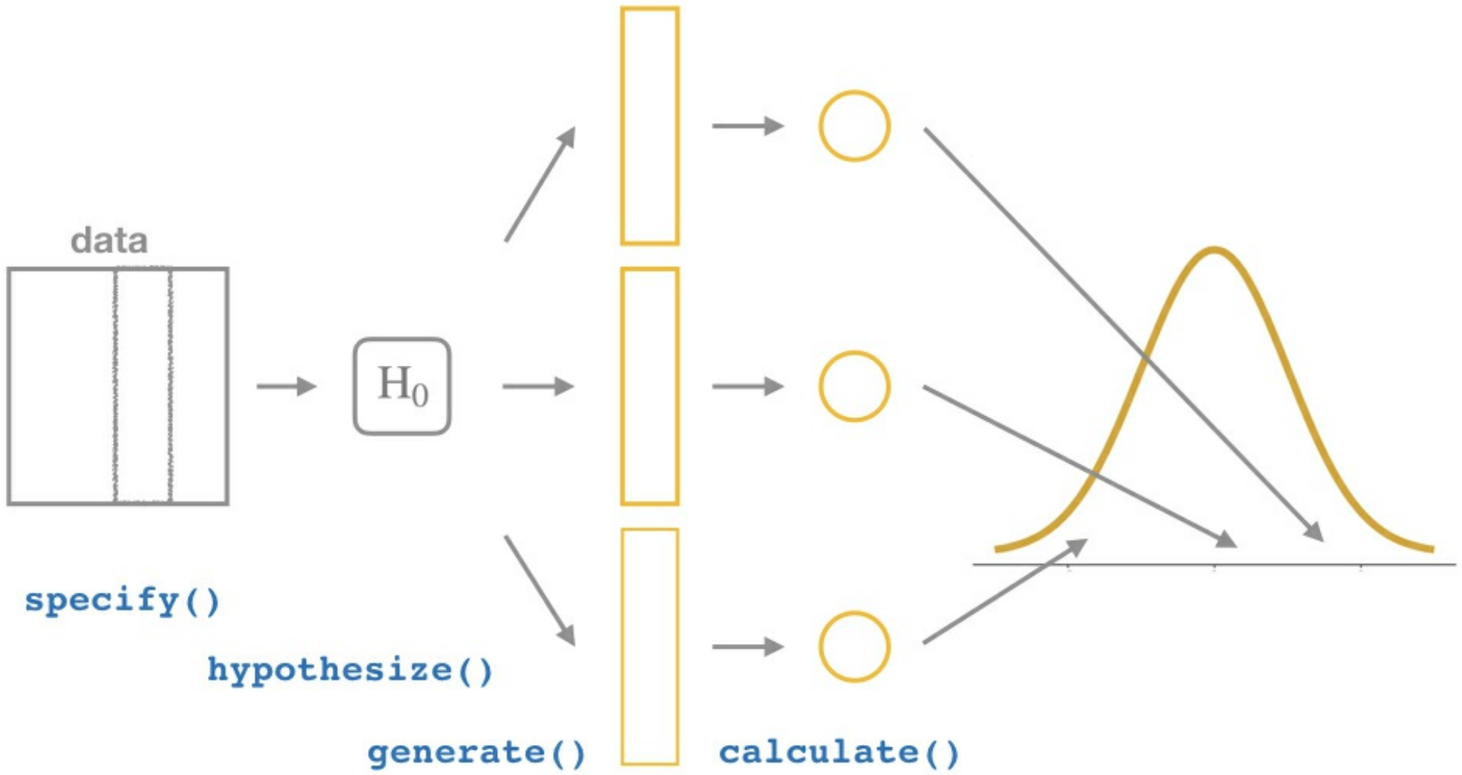
Hypothesis test



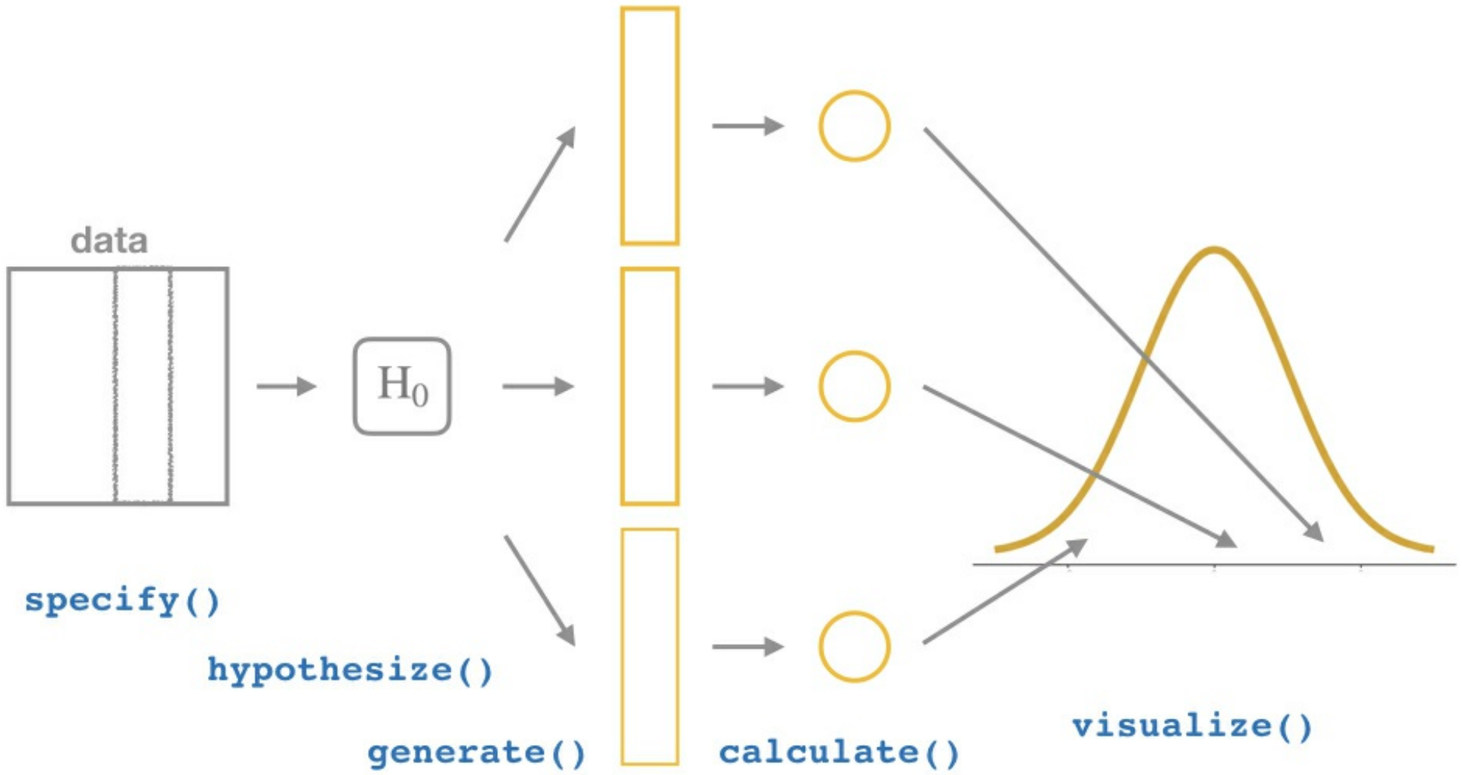
Hypothesis test



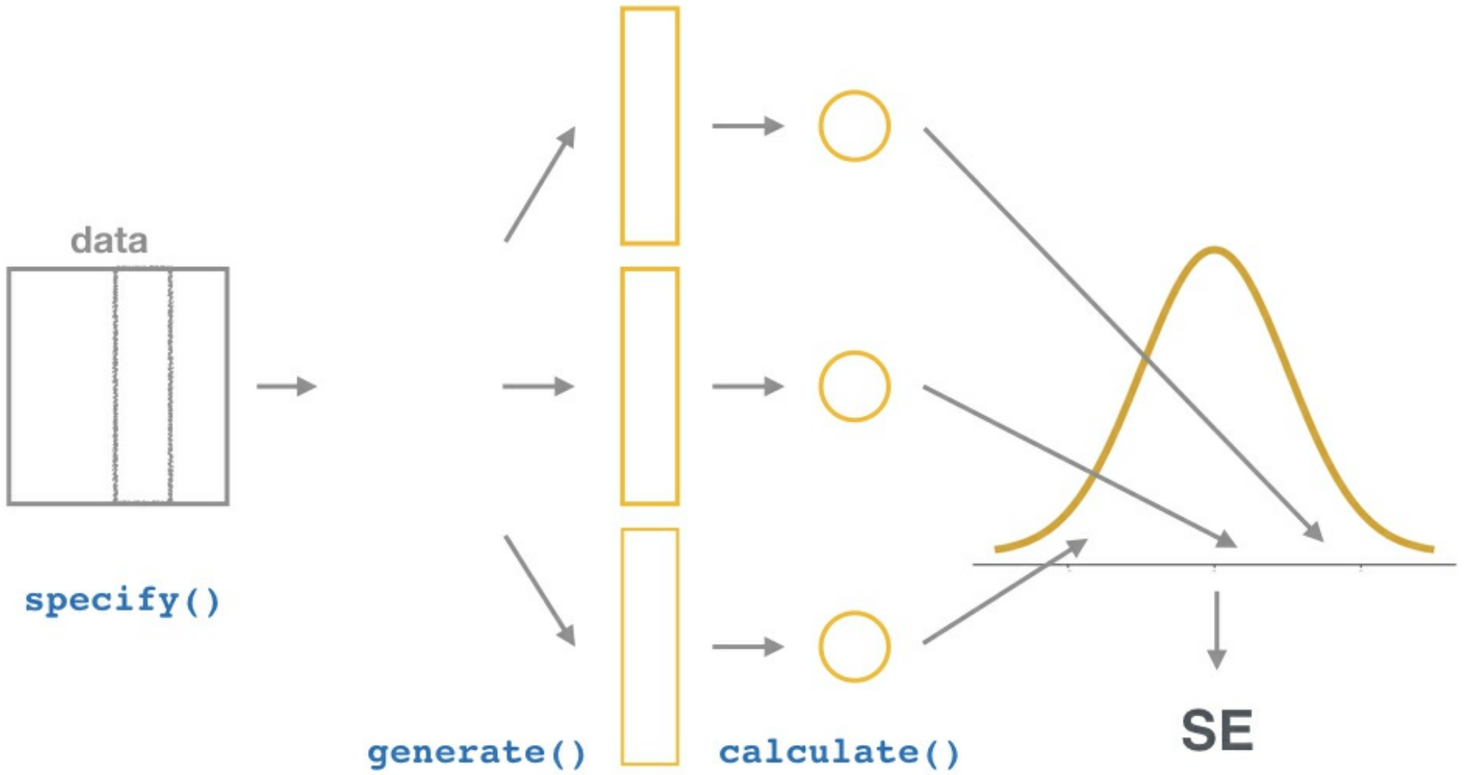
Hypothesis test



Hypothesis test



Confidence Interval



`infer`

Five functions:

- `specify()`
- `hypothesize()`
- `generate()`
- `calculate()`
- `visualize()`

`infer`

- `specify` the response and explanatory variables (`y ~ x`)
- `hypothesize` what the null hypothesis is (here, `independence` of `y` and `x`)
- `generate` new samples from parallel universes under the null hypothesis model:
    - Resample from our original data without replacement, each time shuffling the `group` (`type = "permute"`)
    - Do this a ton of times (`reps = 1000`)
- `calculate` the statistic (`stat = "diff in props"`) for each of the `reps`

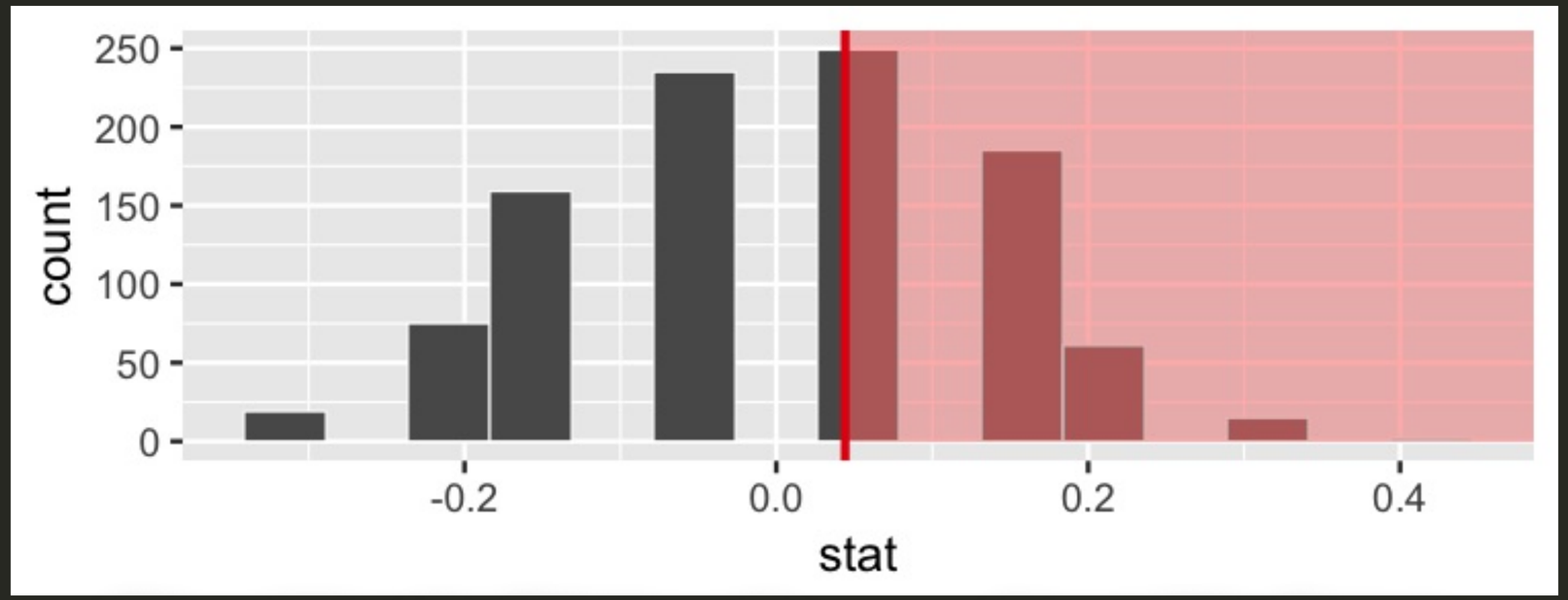
`infer` example

```
set.seed(8)
null_distn <- yawn_myth %>%
  specify(formula = yawn ~ group, success = "1") %>%
  hypothesize(null = "independence") %>%
  generate(reps = 1000, type = "permute") %>%
  calculate(stat = "diff in props", order = c("seed", "control"))
```

Visualize the null distribution

- `visualize` the distribution of the `stat` (here, `diff in props`)

```
null_distn %>%
  visualize(obs_stat = obs_diff, direction = "right")
```



Classical inference

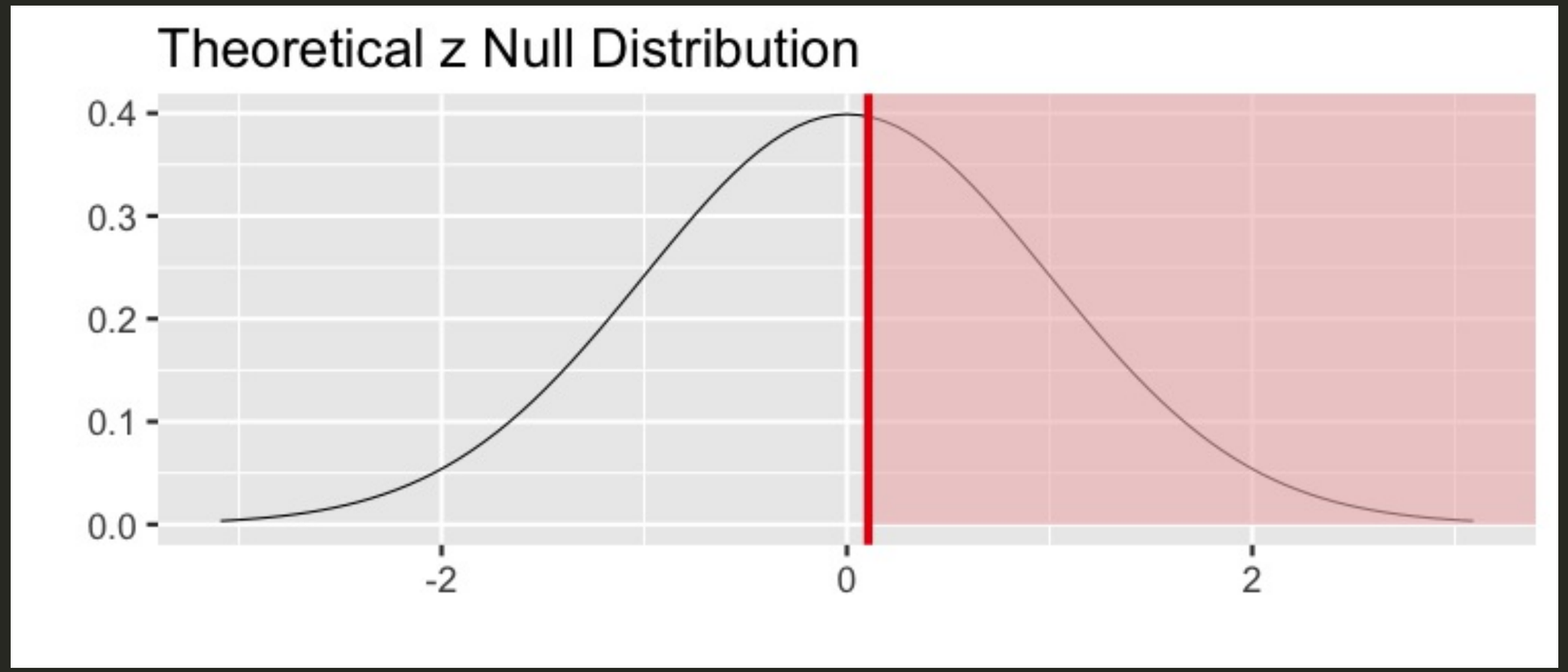
Rely on theory to tell us what the null distribution looks like.

```
yawn_myth %>%
  specify(yawn ~ group, success = "1") %>%
  hypothesize(null = "independence") %>%
  # generate() is not needed since we are not doing simulation
  calculate(stat = "z", order = c("seed", "control")) %>%
  visualize(method = "theoretical", obs_stat = obs_z,
            direction = "right")
```

Classical inference

Rely on theory to tell us what the null distribution looks like.

```
Warning: Check to make sure the conditions have been met for the
theoretical method. `infer` currently does not check these for you.
```



Slides available at http://bit.ly/ness-infer

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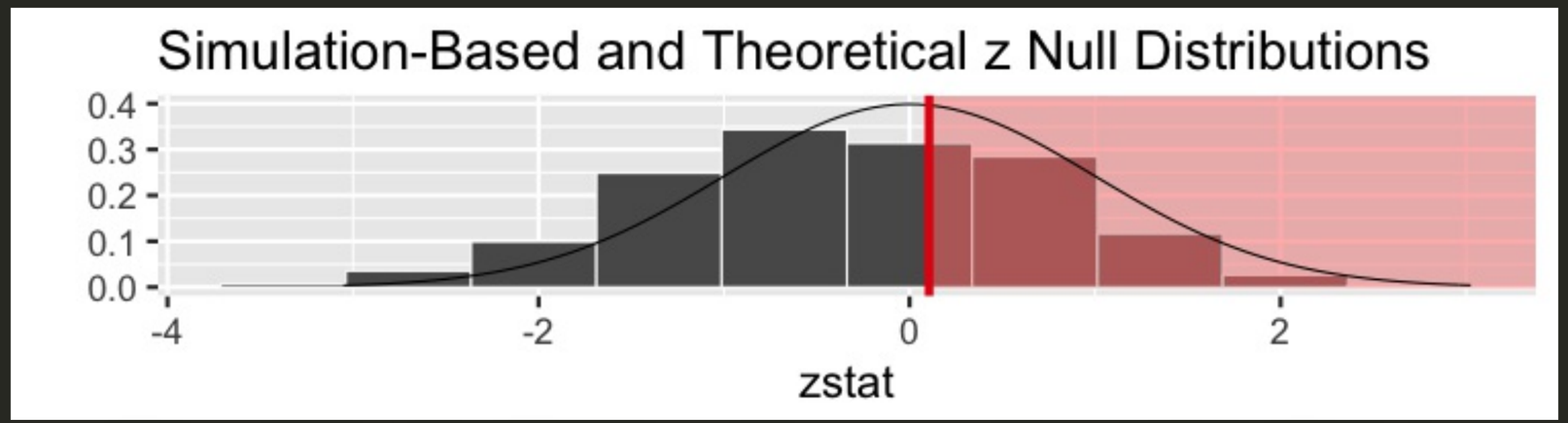
Resampling vs Classical (`stat = "z"`)

```
yawn_myth %>%
  specify(yawn ~ group, success = "1") %>%
  hypothesize(null = "independence") %>%
  generate(reps = 1000, type = "permute") %>%
  calculate(stat = "z", order = c("seed", "control")) %>%
  visualize(method = "both", bins = 10, obs_stat = obs_z,
            direction = "right")
```

```
Warning: Check to make sure the conditions have been met for the
theoretical method. `infer` currently does not check these for you.
```



Slides available at http://bit.ly/ness-infer

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Practice

- Read in/prep the `mazes` data

```
library(readr)
mazes <- read_csv("http://bit.ly/mazes-gist") %>%
  janitor::clean_names() %>% filter(dx %in% c("ASD", "TD"))
```

- Use `infer` to compare a numerical variable between the two groups using:
    - A permutation test and
    - A classical theoretical test.

About the data: Quantitative analysis of disfluency in children with autism spectrum disorder or language impairment

More practice (time permitting)

- Find a data set / use your own and perform statistical inference on one or two of the variables there using the `infer` package

More info and resources

- https://infer.netlify.com (https://infer-dev.netlify.com for development)
  - Many examples under Articles with more to come
  - To be discussed in www.ModernDive.com
    - Sign up to the mailing list for updates
- DataCamp courses that use `infer`
  - Inference for Numerical Data
  - Inference for Regression
  - Two more DataCamp courses to launch soon
- Learn the Tidyverse

Future plans

- Generalize `calculate()`'s `stat` argument
- Improve speed and memory used by shifting to list-columns
- Rewrite the inference part of the ModernDive book
- Lead more workshops on using the `infer` package to extend knowledge of the `tidyverse`, R, and statistics

DataCamp

ModernDive

Thanks for attending! Contact me: Email or Twitter

- Special thanks to
  - Albert Y. Kim
  - Andrew Bray
  - Alison Hill
- Slides created via the R package xaringan by Yihui Xie
- Slides' source code at https://github.com/ismayc/talks/