Iterating on data with purrr and map

Data Wrangling: Session 7

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Load the packages, as always

```r
library(here)      # manage file paths
```

```
## here() starts at /Users/kjhealy/Documents/courses/data_wrangling
```

```r
library(socviz)    # data and some useful functions
```

```
##
## Attaching package: 'socviz'

## The following object is masked from 'package:kjhutils':
##
##     %nin%
```

```r
library(tidyverse) # your friend and mine
```

```
## ── Attaching packages ─────────────────────────────────────── tidyverse 1.3.1 ──

## ✓ ggplot2 3.3.5     ✓ purrr   0.3.4
## ✓ tibble  3.1.6     ✓ dplyr   1.0.8
## ✓ tidyr   1.2.0     ✓ stringr 1.4.0
## ✓ readr   2.1.2     ✓ forcats 0.5.1

## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## x readr::edition_get()   masks testthat::edition_get()
## x dplyr::filter()        masks stats::filter()
## x purrr::is_null()       masks testthat::is_null()
## x dplyr::lag()           masks stats::lag()
## x readr::local_edition() masks testthat::local_edition()
## x dplyr::matches()       masks tidyr::matches(), testthat::matches()
```

Moar Data

More than one data file

Inside the `data/` folder of the course packet is a folder named `congress/`

```
# A little trick from the fs package:
fs::dir_tree(here("data", "congress"))
```

```
## /Users/kjhealy/Documents/courses/data_wrangling/data/congress
## ├── 01_79_congress.csv
## ├── 02_80_congress.csv
## ├── 03_81_congress.csv
## ├── 04_82_congress.csv
## ├── 05_83_congress.csv
## ├── 06_84_congress.csv
## ├── 07_85_congress.csv
## ├── 08_86_congress.csv
## ├── 09_87_congress.csv
## ├── 10_88_congress.csv
## ├── 11_89_congress.csv
## ├── 12_90_congress.csv
## ├── 13_91_congress.csv
## ├── 14_92_congress.csv
## ├── 15_93_congress.csv
## ├── 16_94_congress.csv
## ├── 17_95_congress.csv
## ├── 18_96_congress.csv
## ├── 19_97_congress.csv
## ├── 20_98_congress.csv
## ├── 21_99_congress.csv
## ├── 22_100_congress.csv
## ├── 23_101_congress.csv
## ├── 24_102_congress.csv
## ├── 25_103_congress.csv
## ├── 26_104_congress.csv
## ├── 27_105_congress.csv
## ├── 28_106_congress.csv
## ├── 29_107_congress.csv
```

More than one data file

Let's look at one.

```
read_csv(here("data", "congress", "17_95_congress.csv")) %>%
  janitor::clean_names() %>%
  head()
```

```
## # A tibble: 6 × 25
##   last     first   middle suffix nickname born  death sex   position party state
##   <chr>    <chr>   <chr>  <chr>  <chr>    <chr> <chr> <chr> <chr>    <chr> <chr>
## 1 Abdnor   James   <NA>   <NA>   <NA>     02/1… 11/0… M     U.S. Re… Repu… SD
## 2 Abourezk James   George <NA>   <NA>     02/2… <NA>  M     U.S. Se… Demo… SD
## 3 Adams    Brockm… <NA>   <NA>   Brock    01/1… 09/1… M     U.S. Re… Demo… WA
## 4 Addabbo  Joseph  Patri… <NA>   <NA>     03/1… 04/1… M     U.S. Re… Demo… NY
## 5 Aiken    George  David  <NA>   <NA>     08/2… 11/1… M     U.S. Se… Repu… VT
## 6 Akaka    Daniel  Kahik… <NA>   <NA>     09/1… 04/0… M     U.S. Re… Demo… HI
## # … with 14 more variables: district <chr>, start <chr>, end <chr>,
## #   religion <chr>, race <chr>, educational_attainment <chr>, job_type1 <chr>,
## #   job_type2 <chr>, job_type3 <chr>, job_type4 <chr>, job_type5 <lgl>,
## #   mil1 <chr>, mil2 <chr>, mil3 <chr>
```

We often find ourselves in this situation. We know each file has the same structure, and we would like to use them all at once.

Loops?

How to read them all in?

One traditional way, which we could do in R, is to write an explicit *loop* that iterated over a vector of filenames, read each file, and then joined the results together in a tall rectangle.

```
# Pseudocode

filenames <- c("01_79_congress.csv", "02_80_congress.csv", "03_81_congress.csv",
                "04_82_congress.csv" [etc etc])

collected_files <- NULL

for(i in 1:length(filenames)) {
      new_file <- read_file(filenames[i])
      collected_files <- append_to(collected_files, new_files)
}
```

Loops?

You may have noticed we have not written any loops, however.

While loops are still lurking there underneath the surface, what we will do instead is to take advantage of the combination of vectors and functions and *map* one to the other in order to generate results.

Speaking loosely, think of **`map()`** as a way of iterating without writing loops. You start with a vector of things. You feed it one thing at a time to some function. The function does whatever it does. You get back output that is the same length as your input, and of a specific type.

Mapping is just a kind of iteration

The `purrr` package provides a big family of mapping functions. One reason there are a lot of them is that `purrr`, like the rest of the tidyverse, is picky about data types.

Mapping is just a kind of iteration

The `purrr` package provides a big family of mapping functions. One reason there are a lot of them is that `purrr`, like the rest of the tidyverse, is picky about data types.

So in addition to the basic `map()`, which always returns a *list*, we also have `map_chr()`, `map_int()`, `map_dbl()`, `map_lgl()` and others. They always return the data type indicated by their suffix, or die trying.

Vectorized arithmetic again

The simplest cases are not that different from the vectorized arithmetic we're already familiar with.

```r
a <- c(1:10)

b <- 1

# You know what R will do here
a + b
```

```
##  [1]  2  3  4  5  6  7  8  9 10 11
```

Vectorized arithmetic again

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```
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b <- 1

# You know what R will do here
a + b
```

```
##  [1]  2  3  4  5  6  7  8  9 10 11
```

R's vectorized rules add `b` to every element of `a`. In a sense, the **+** operation can be thought of as a function that takes each element of `a` and does something with it. In this case "add b".

Vectorized arithmetic again

We can make this explicit by writing a function:

```
add_b <- function(x) {
  b <- 1
  x + b # for any x
}
```

Now:

```
add_b(x = a)
```

```
##  [1]  2  3  4  5  6  7  8  9 10 11
```

Vectorized arithmetic again

Again, R's vectorized approach means it automatically adds b to every element of the x we give it.

```
add_b(x = 10)
```

```
## [1] 11
```

```
add_b(x = c(1, 99, 1000))
```

```
## [1]    2  100 1001
```

Iterating in a pipeline

Some operations can't directly be vectorized in this way, which is why we need to manually iterate, or will want to write loops.

```
library(gapminder)
gapminder %>%
  summarize(country_n = n_distinct(country),
            continent_n = n_distinct(continent),
            year_n = n_distinct(year),
            lifeExp_n = n_distinct(lifeExp),
            population_n = n_distinct(population))
```

```
## # A tibble: 1 × 5
##   country_n continent_n year_n lifeExp_n population_n
##       <int>       <int>  <int>     <int>        <int>
## 1       142           5     12      1626         4060
```

That's tedious to write! Computers are supposed to allow us to avoid that sort of thing.

Iterating in a pipeline

So how would we iterate this? What we want is to apply the `n_distinct()` function to each column of `gapminder`, but in a way that still allows us to use pipelines and so on.

```
library(gapminder)
gapminder %>%
  summarize(n_distinct(country),
            n_distinct(continent),
            n_distinct(year),
            n_distinct(lifeExp),
            n_distinct(population))
```

```
## # A tibble: 1 × 5
##   `n_distinct(country)` `n_distinct(continen…` `n_distinct(ye…` `n_distinct(li…`
##                   <int>                  <int>            <int>            <int>
## 1                   142                      5               12             1626
## # … with 1 more variable: `n_distinct(population)` <int>
```

Using `n_distinct()` in this context is an idea I got from Rebecca Barter's discussion of `purrr`.

Iterating in a pipeline

You'd use **across()**, like this:

```
gapminder %>%
  summarize(across(everything(), n_distinct))
```

```
## # A tibble: 1 × 6
##   country continent  year lifeExp   pop gdpPercap
##     <int>     <int> <int>   <int> <int>     <int>
## 1     142         5    12    1626  1704      1704
```

Iterating in a pipeline

But you could also do this ...

```
map(gapminder, n_distinct)
```

```
## $country
## [1] 142
##
## $continent
## [1] 5
##
## $year
## [1] 12
##
## $lifeExp
## [1] 1626
##
## $pop
## [1] 1704
##
## $gdpPercap
## [1] 1704
```

Read it as "Feed each column of `gapminder` to the **`n_distinct()`** function.

(This is pretty much what **`across()`** is doing more nicely.)

Iterating in a pipeline

Or, in pipeline form:

```
gapminder %>%
  map(n_distinct)
```

```
## $country
## [1] 142
##
## $continent
## [1] 5
##
## $year
## [1] 12
##
## $lifeExp
## [1] 1626
##
## $pop
## [1] 1704
##
## $gdpPercap
## [1] 1704
```

You can see we are getting a *list* back.

Iterating in a pipeline

Or, in pipeline form:

```r
result <- gapminder %>%
  map(n_distinct)

class(result)
```

```
## [1] "list"
```

```r
result$continent
```

```
## [1] 5
```

```r
result[[2]]
```

```
## [1] 5
```

Iterating in a pipeline

But we know `n_distinct()` should always return an integer. So we use `map_int()` instead of the generic `map()`.

```
gapminder %>%
  map_int(n_distinct)
```

```
##   country continent      year   lifeExp       pop gdpPercap
##       142         5        12      1626      1704      1704
```

The thing about the `map()` family is that they can deal with all kinds of input types and output types.

Get a vector of filenames

```r
filenames <- dir(path = here("data", "congress"),
                 pattern = "*.csv",
                 full.names = TRUE)

filenames[1:15] # Just displaying the first 15, to save slide space
```

```
##  [1] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/01_79_congress.csv"
##  [2] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/02_80_congress.csv"
##  [3] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/03_81_congress.csv"
##  [4] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/04_82_congress.csv"
##  [5] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/05_83_congress.csv"
##  [6] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/06_84_congress.csv"
##  [7] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/07_85_congress.csv"
##  [8] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/08_86_congress.csv"
##  [9] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/09_87_congress.csv"
## [10] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/10_88_congress.csv"
## [11] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/11_89_congress.csv"
## [12] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/12_90_congress.csv"
## [13] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/13_91_congress.csv"
## [14] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/14_92_congress.csv"
## [15] "/Users/kjhealy/Documents/courses/data_wrangling/data/congress/15_93_congress.csv"
```

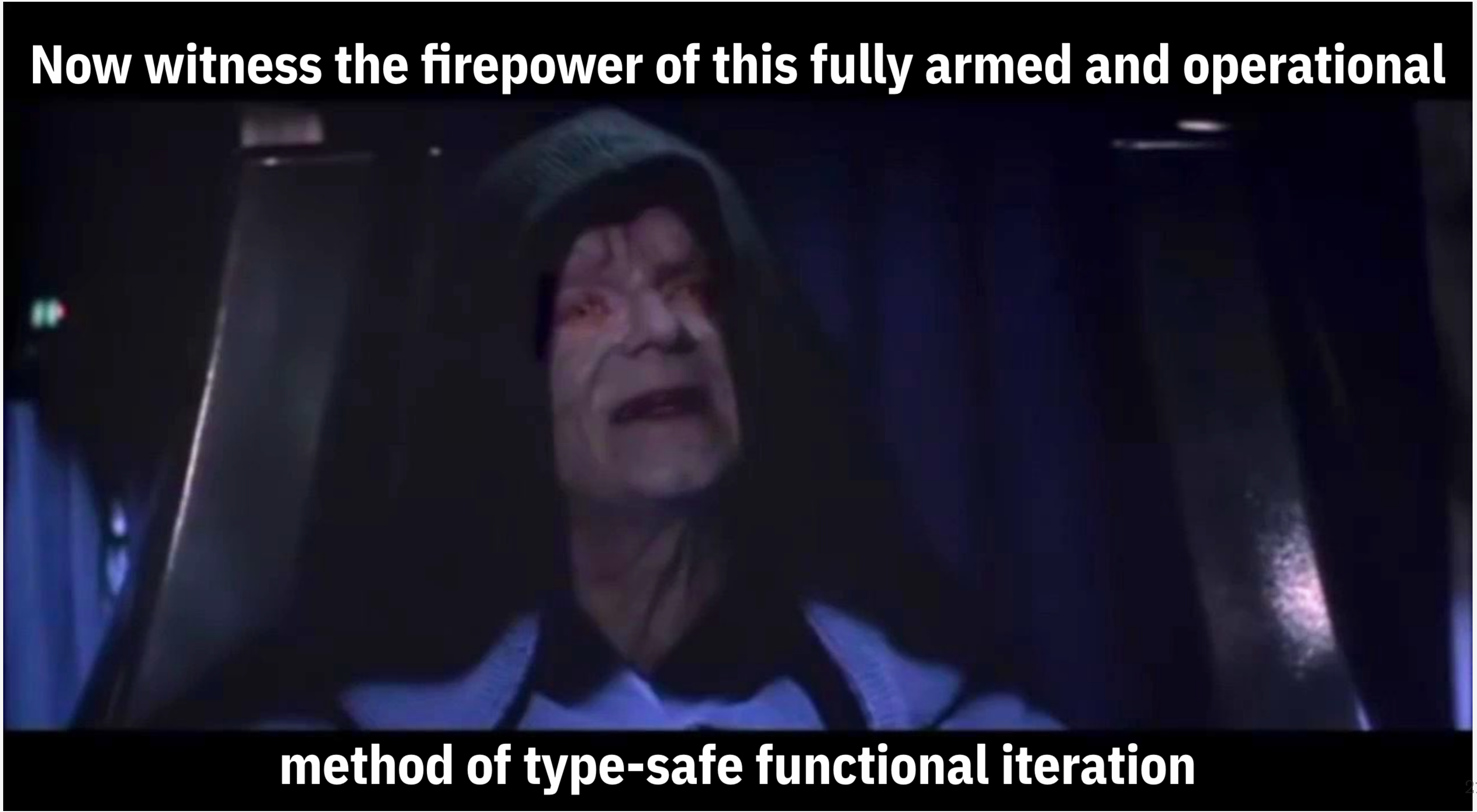
And feed it to `read_csv()`

… using the variant of **`map()`** that returns data frames and tibbles.

```
df <- filenames %>%
  map_dfr(read_csv, .id = "congress") %>%
  janitor::clean_names()

df
```

```
## # A tibble: 20,580 × 26
##    congress last   first middle suffix nickname born  death sex   position party
##    <chr>    <chr>  <chr> <chr>  <chr>  <chr>    <chr> <chr> <chr> <chr>    <chr>
##  1 1        Abern… Thom… Gerst… <NA>   <NA>     05/1… 01/2… M     U.S. Re… Demo…
##  2 1        Adams  Sher… <NA>   <NA>   <NA>     01/0… 10/2… M     U.S. Re… Repu…
##  3 1        Aiken  Geor… David  <NA>   <NA>     08/2… 11/1… M     U.S. Se… Repu…
##  4 1        Allen  Asa   Leona… <NA>   <NA>     01/0… 01/0… M     U.S. Re… Demo…
##  5 1        Allen  Leo   Elwood <NA>   <NA>     10/0… 01/1… M     U.S. Re… Repu…
##  6 1        Almond J.    Linds… Jr.    <NA>     06/1… 04/1… M     U.S. Re… Demo…
##  7 1        Ander… Herm… Carl   <NA>   <NA>     01/2… 07/2… M     U.S. Re… Repu…
##  8 1        Ander… Clin… Presba <NA>   <NA>     10/2… 11/1… M     U.S. Re… Demo…
##  9 1        Ander… John  Zuing… <NA>   <NA>     03/2… 02/0… M     U.S. Re… Repu…
## 10 1        Andre… Augu… Herman <NA>   <NA>     10/1… 01/1… M     U.S. Re… Repu…
## # … with 20,570 more rows, and 15 more variables: state <chr>, district <chr>,
## #   start <chr>, end <chr>, religion <chr>, race <chr>,
## #   educational_attainment <chr>, job_type1 <chr>, job_type2 <chr>,
## #   job_type3 <chr>, job_type4 <chr>, job_type5 <chr>, mil1 <chr>, mil2 <chr>,
## #   mil3 <chr>
```


Now witness the firepower of this fully armed and operational
method of type-safe functional iteration

`read_csv()` can do this directly now!

No `map_df()` required

```
tmp <- read_csv(filenames, id = "path",
                name_repair = janitor::make_clean_names)

tmp %>%
  mutate(congress = stringr::str_extract(path, "_\\d{2,3}_congress"),
         congress = stringr::str_extract(congress, "\\d{2,3}")) %>%
  relocate(congress)
```

```
## # A tibble: 20,580 × 27
##    congress path   last  first middle suffix nickname born  death sex   position
##    <chr>    <chr>  <chr> <chr> <chr>  <chr>  <chr>    <chr> <chr> <chr> <chr>
##  1 79       /User… Aber… Thom… Gerst… <NA>   <NA>     05/1… 01/2… M     U.S. Re…
##  2 79       /User… Adams Sher… <NA>   <NA>   <NA>     01/0… 10/2… M     U.S. Re…
##  3 79       /User… Aiken Geor… David  <NA>   <NA>     08/2… 11/1… M     U.S. Se…
##  4 79       /User… Allen Asa   Leona… <NA>   <NA>     01/0… 01/0… M     U.S. Re…
##  5 79       /User… Allen Leo   Elwood <NA>   <NA>     10/0… 01/1… M     U.S. Re…
##  6 79       /User… Almo… J.    Linds… Jr.    <NA>     06/1… 04/1… M     U.S. Re…
##  7 79       /User… Ande… Herm… Carl   <NA>   <NA>     01/2… 07/2… M     U.S. Re…
##  8 79       /User… Ande… Clin… Presba <NA>   <NA>     10/2… 11/1… M     U.S. Re…
##  9 79       /User… Ande… John  Zuing… <NA>   <NA>     03/2… 02/0… M     U.S. Re…
## 10 79       /User… Andr… Augu… Herman <NA>   <NA>     10/1… 01/1… M     U.S. Re…
## # … with 20,570 more rows, and 16 more variables: party <chr>, state <chr>,
## #   district <chr>, start <chr>, end <chr>, religion <chr>, race <chr>,
## #   educational_attainment <chr>, job_type1 <chr>, job_type2 <chr>,
## #   job_type3 <chr>, job_type4 <chr>, job_type5 <chr>, mil1 <chr>, mil2 <chr>,
## #   mil3 <chr>
```

Example: Iterating on the US Census

But mapped iteration is not just for local files!

```r
## Register for a free Census API key
library(tidycensus)
```

```r
out <- get_acs(geography = "county",
                    variables = "B19013_001",
                    state = "NY",
                    county = "New York",
                    survey = "acs1",
                    year = 2005)
```

```r
out
```

```
## # A tibble: 1 × 5
##   GEOID NAME                      variable   estimate   moe
##   <chr> <chr>                     <chr>         <dbl> <dbl>
## 1 36061 New York County, New York B19013_001    55973  1462
```

Example: Iterating on the US Census

All counties in New York State for a specific year

```
out <- get_acs(geography = "county",
                    variables = "B19013_001",
                    state = "NY",
                    survey = "acs1",
                    year = 2005)
```

```
out
```

```
## # A tibble: 38 × 5
##    GEOID NAME                        variable   estimate   moe
##    <chr> <chr>                       <chr>         <dbl> <dbl>
##  1 36001 Albany County, New York     B19013_001    50054  2030
##  2 36005 Bronx County, New York      B19013_001    29228   853
##  3 36007 Broome County, New York     B19013_001    36394  2340
##  4 36009 Cattaraugus County, New York B19013_001    37580  2282
##  5 36011 Cayuga County, New York     B19013_001    42057  2406
##  6 36013 Chautauqua County, New York  B19013_001    35495  2077
##  7 36015 Chemung County, New York    B19013_001    37418  3143
##  8 36019 Clinton County, New York    B19013_001    44757  3500
##  9 36027 Dutchess County, New York   B19013_001    61889  2431
## 10 36029 Erie County, New York       B19013_001    41967  1231
## # … with 28 more rows
```

Example: Iterating on the US Census

What if we want the results for *every* available year?

First, a handy function: `set_names()`

```
x <- c(1:10)

x
```

```
##  [1]  1  2  3  4  5  6  7  8  9 10
```

```
x <- set_names(x, nm = letters[1:10])

x
```

```
##  a  b  c  d  e  f  g  h  i  j
##  1  2  3  4  5  6  7  8  9 10
```

Example: Iterating on the US Census

By default, `set_names()` will label a vector with that vector's values:

```
c(1:10) %>%
  set_names()
```

```
##  1  2  3  4  5  6  7  8  9 10
##  1  2  3  4  5  6  7  8  9 10
```

Example: Iterating on the US Census

Meanwhile, `map_dfr()` has an `.id` argument that lets you add a row-identifier to whatever you are binding. Like this:

```
df <- 2005:2019 %>%
  map_dfr(~ get_acs(geography = "county",
                    variables = "B19013_001",
                    state = "NY",
                    county = "New York",
                    survey = "acs1",
                    year = .x),
        .id = "id")
```

```
df
```

```
## # A tibble: 15 × 6
##    id    GEOID NAME                       variable   estimate   moe
##    <chr> <chr> <chr>                      <chr>         <dbl> <dbl>
##  1 1     36061 New York County, New York B19013_001    55973  1462
##  2 2     36061 New York County, New York B19013_001    60017  1603
##  3 3     36061 New York County, New York B19013_001    64217  2002
##  4 4     36061 New York County, New York B19013_001    69017  1943
##  5 5     36061 New York County, New York B19013_001    68706  1471
##  6 6     36061 New York County, New York B19013_001    63832  2125
##  7 7     36061 New York County, New York B19013_001    66299  1783
##  8 8     36061 New York County, New York B19013_001    67099  1640
##  9 9     36061 New York County, New York B19013_001    72190  2200
## 10 10    36061 New York County, New York B19013_001    76089  2016
```

Example: Iterating on the US Census

Our `id` column tracks the year. But we'd like it to *be* the year. So, we use **`set_names()`**, and also name it `year` when we create it:

```
df <- 2005:2019 %>%
  set_names() %>%
  map_dfr(~ get_acs(geography = "county",
                    variables = "B19013_001",
                    state = "NY",
                    county = "New York",
                    survey = "acs1",
                    year = .x),
        .id = "year") %>%
  mutate(year = as.integer(year))
```

Example: Iterating on the US Census

```
df
```

```
## # A tibble: 15 × 6
##     year GEOID NAME                         variable   estimate   moe
##    <int> <chr> <chr>                        <chr>         <dbl> <dbl>
##  1  2005 36061 New York County, New York B19013_001    55973  1462
##  2  2006 36061 New York County, New York B19013_001    60017  1603
##  3  2007 36061 New York County, New York B19013_001    64217  2002
##  4  2008 36061 New York County, New York B19013_001    69017  1943
##  5  2009 36061 New York County, New York B19013_001    68706  1471
##  6  2010 36061 New York County, New York B19013_001    63832  2125
##  7  2011 36061 New York County, New York B19013_001    66299  1783
##  8  2012 36061 New York County, New York B19013_001    67099  1640
##  9  2013 36061 New York County, New York B19013_001    72190  2200
## 10  2014 36061 New York County, New York B19013_001    76089  2016
## 11  2015 36061 New York County, New York B19013_001    75575  2566
## 12  2016 36061 New York County, New York B19013_001    77559  2469
## 13  2017 36061 New York County, New York B19013_001    85071  3520
## 14  2018 36061 New York County, New York B19013_001    85066  3480
## 15  2019 36061 New York County, New York B19013_001    93651  3322
```

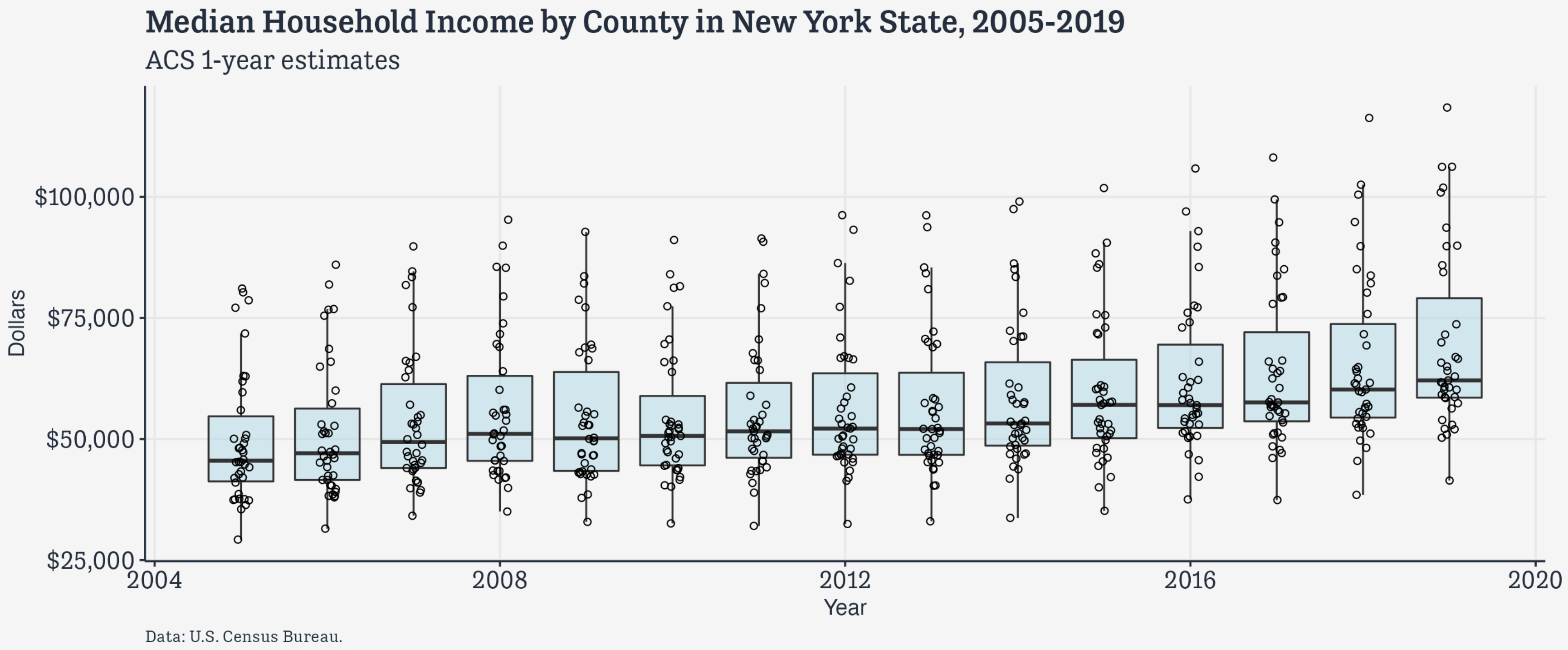
Now `year` is just the year. The `year` column will be created as a character vector, so we converted it back to an integer again at the end.

Example: Iterating on the US Census

```r
p_out <- 2005:2019 %>%
  set_names() %>%
  map_dfr(~ get_acs(geography = "county", variables = "B19013_001",
                    state = "NY", survey = "acs1", year = .x), .id = "year") %>%
  mutate(year = as.integer(year)) %>%
  ggplot(mapping = aes(x = year, y = estimate, group = year)) +
  geom_boxplot(fill = "lightblue", alpha = 0.5, outlier.alpha = 0) +
  geom_jitter(position = position_jitter(width = 0.1), shape = 1) +
  scale_y_continuous(labels = scales::label_dollar()) + labs(x = "Year", y = "Dollars",
  title = "Median Household Income by County in New York State, 2005-2019",
  subtitle = "ACS 1-year estimates", caption = "Data: U.S. Census Bureau.")
```

Example: Iterating on the US Census

```
print(p_out)
```



Cleaning up **congress**

```
df <- filenames %>%
  map_dfr(read_csv, .id = "congress") %>%
  janitor::clean_names()

df %>%
  select(born, death, start, end)
```

```
## # A tibble: 20,580 × 4
##    born       death      start      end
##    <chr>      <chr>      <chr>      <chr>
##  1 05/16/1903 01/23/1953 01/03/1945 01/03/1953
##  2 01/08/1899 10/27/1986 01/03/1945 01/03/1947
##  3 08/20/1892 11/19/1984 01/03/1945 01/03/1979
##  4 01/05/1891 01/05/1969 01/03/1945 01/03/1953
##  5 10/05/1898 01/19/1973 01/03/1945 01/02/1949
##  6 06/15/1898 04/14/1986 02/04/1946 04/17/1948
##  7 01/27/1897 07/26/1978 01/03/1945 01/03/1963
##  8 10/23/1895 11/11/1975 01/03/1941 06/30/1945
##  9 03/22/1904 02/09/1981 01/03/1945 01/03/1953
## 10 10/11/1890 01/14/1958 01/03/1945 01/14/1958
## # … with 20,570 more rows
```

We'll use the **lubridate** package to sort these out.

Lubridate has a wide range of functions to handle dates, times, and durations.

Cleaning up congress

```r
library(lubridate)

date_recodes <- c("born", "death", "start", "end")
df <- df %>%
    mutate(across(any_of(date_recodes), mdy),
           congress = as.double(congress) + 78)

df
```

```
## # A tibble: 20,580 × 26
##    congress last      first   middle suffix nickname born       death      sex  
##       <dbl> <chr>     <chr>   <chr>  <chr>  <chr>    <date>     <date>     <chr>
##  1       79 Abernethy Thomas  Gerst… <NA>   <NA>     1903-05-16 1953-01-23 M    
##  2       79 Adams     Sherman <NA>   <NA>   <NA>     1899-01-08 1986-10-27 M    
##  3       79 Aiken     George  David  <NA>   <NA>     1892-08-20 1984-11-19 M    
##  4       79 Allen     Asa     Leona… <NA>   <NA>     1891-01-05 1969-01-05 M    
##  5       79 Allen     Leo     Elwood <NA>   <NA>     1898-10-05 1973-01-19 M    
##  6       79 Almond    J.      Linds… Jr.    <NA>     1898-06-15 1986-04-14 M    
##  7       79 Andersen  Herman  Carl   <NA>   <NA>     1897-01-27 1978-07-26 M    
##  8       79 Anderson  Clinton Presba <NA>   <NA>     1895-10-23 1975-11-11 M    
##  9       79 Anderson  John    Zuing… <NA>   <NA>     1904-03-22 1981-02-09 M    
## 10       79 Andresen  August  Herman <NA>   <NA>     1890-10-11 1958-01-14 M    
## # … with 20,570 more rows, and 17 more variables: position <chr>, party <chr>,
## #   state <chr>, district <chr>, start <date>, end <date>, religion <chr>,
## #   race <chr>, educational_attainment <chr>, job_type1 <chr>, job_type2 <chr>,
## #   job_type3 <chr>, job_type4 <chr>, job_type5 <chr>, mil1 <chr>, mil2 <chr>,
## #   mil3 <chr>
```

Cleaning up **congress**

```r
sessions <- tibble(congress = 79:116,
                   start_year = seq(1945, 2019, by = 2),
                   end_year = seq(1947, 2021, by = 2)) %>%
  mutate(start_year = ymd(paste(start_year, "01", "03", sep = "-")),
         end_year = ymd(paste(end_year, "01", "03", sep = "-")))


sessions
```

```
## # A tibble: 38 × 3
##    congress start_year end_year
##       <int> <date>     <date>
##  1       79 1945-01-03 1947-01-03
##  2       80 1947-01-03 1949-01-03
##  3       81 1949-01-03 1951-01-03
##  4       82 1951-01-03 1953-01-03
##  5       83 1953-01-03 1955-01-03
##  6       84 1955-01-03 1957-01-03
##  7       85 1957-01-03 1959-01-03
##  8       86 1959-01-03 1961-01-03
##  9       87 1961-01-03 1963-01-03
## 10       88 1963-01-03 1965-01-03
## # … with 28 more rows
```

We're going to join these tables

The big table

```
df %>%
  select(congress, last, born)
```

```
## # A tibble: 20,580 × 3
##    congress last      born
##       <dbl> <chr>     <date>
##  1       79 Abernethy 1903-05-16
##  2       79 Adams     1899-01-08
##  3       79 Aiken     1892-08-20
##  4       79 Allen     1891-01-05
##  5       79 Allen     1898-10-05
##  6       79 Almond    1898-06-15
##  7       79 Andersen  1897-01-27
##  8       79 Anderson  1895-10-23
##  9       79 Anderson  1904-03-22
## 10       79 Andresen  1890-10-11
## # … with 20,570 more rows
```

The smaller table

```
sessions
```

```
## # A tibble: 38 × 3
##    congress start_year end_year
##       <int> <date>     <date>
##  1       79 1945-01-03 1947-01-03
##  2       80 1947-01-03 1949-01-03
##  3       81 1949-01-03 1951-01-03
##  4       82 1951-01-03 1953-01-03
##  5       83 1953-01-03 1955-01-03
##  6       84 1955-01-03 1957-01-03
##  7       85 1957-01-03 1959-01-03
##  8       86 1959-01-03 1961-01-03
##  9       87 1961-01-03 1963-01-03
## 10       88 1963-01-03 1965-01-03
## # … with 28 more rows
```

We're going to join these tables

We will use `left_join()` which is what you want most of the time when you are looking to merge a smaller table with additional information into a larger main one.

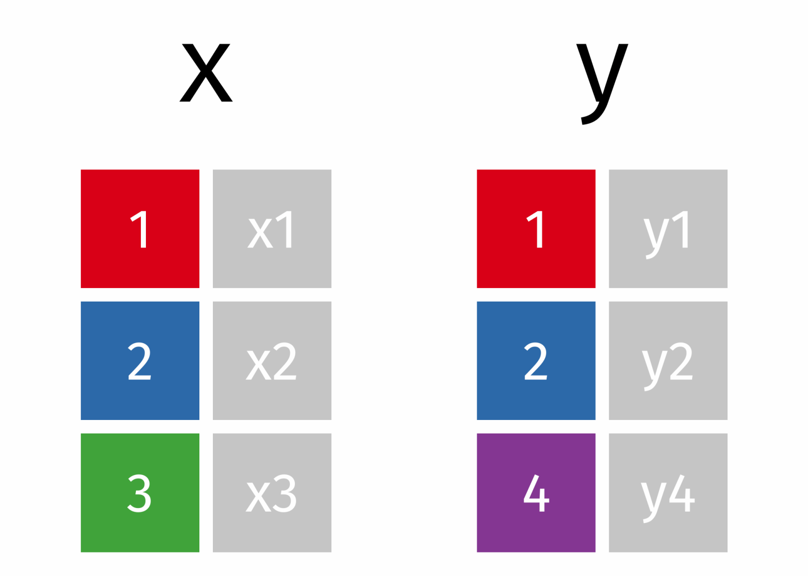
```
df <- left_join(df, sessions) %>%
  relocate(start_year:end_year, .after = congress)
```

```
## Joining, by = "congress"
```

```
df
```

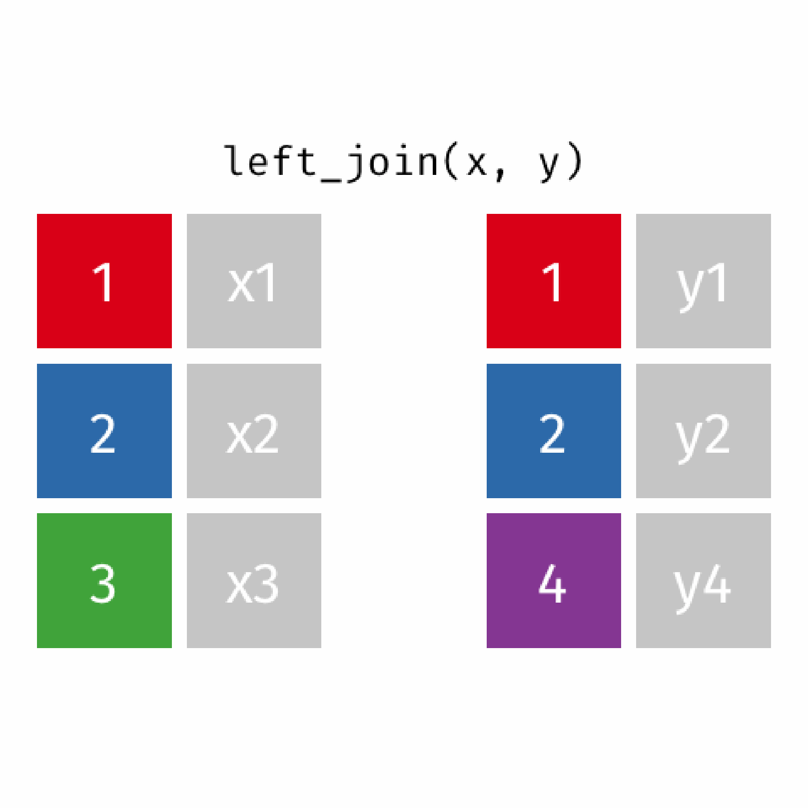
```
## # A tibble: 20,580 × 28
##    congress start_year end_year   last   first middle suffix nickname born
##       <dbl> <date>     <date>     <chr>  <chr> <chr>  <chr>  <chr>    <date>
##  1       79 1945-01-03 1947-01-03 Abern… Thom… Gerst… <NA>   <NA>     1903-05-16
##  2       79 1945-01-03 1947-01-03 Adams  Sher… <NA>   <NA>   <NA>     1899-01-08
##  3       79 1945-01-03 1947-01-03 Aiken  Geor… David  <NA>   <NA>     1892-08-20
##  4       79 1945-01-03 1947-01-03 Allen  Asa   Leona… <NA>   <NA>     1891-01-05
##  5       79 1945-01-03 1947-01-03 Allen  Leo   Elwood <NA>   <NA>     1898-10-05
##  6       79 1945-01-03 1947-01-03 Almond J.    Linds… Jr.    <NA>     1898-06-15
##  7       79 1945-01-03 1947-01-03 Ander… Herm… Carl   <NA>   <NA>     1897-01-27
##  8       79 1945-01-03 1947-01-03 Ander… Clin… Presba <NA>   <NA>     1895-10-23
##  9       79 1945-01-03 1947-01-03 Ander… John  Zuing… <NA>   <NA>     1904-03-22
## 10       79 1945-01-03 1947-01-03 Andre… Augu… Herman <NA>   <NA>     1890-10-11
## # … with 20,570 more rows, and 19 more variables: death <date>, sex <chr>,
## #   position <chr>, party <chr>, state <chr>, district <chr>, start <date>,
## #   end <date>, religion <chr>, race <chr>, educational_attainment <chr>,
## #   job_type1 <chr>, job_type2 <chr>, job_type3 <chr>, job_type4 <chr>,
## #   job_type5 <chr>, mil1 <chr>, mil2 <chr>, mil3 <chr>
```

Table joins



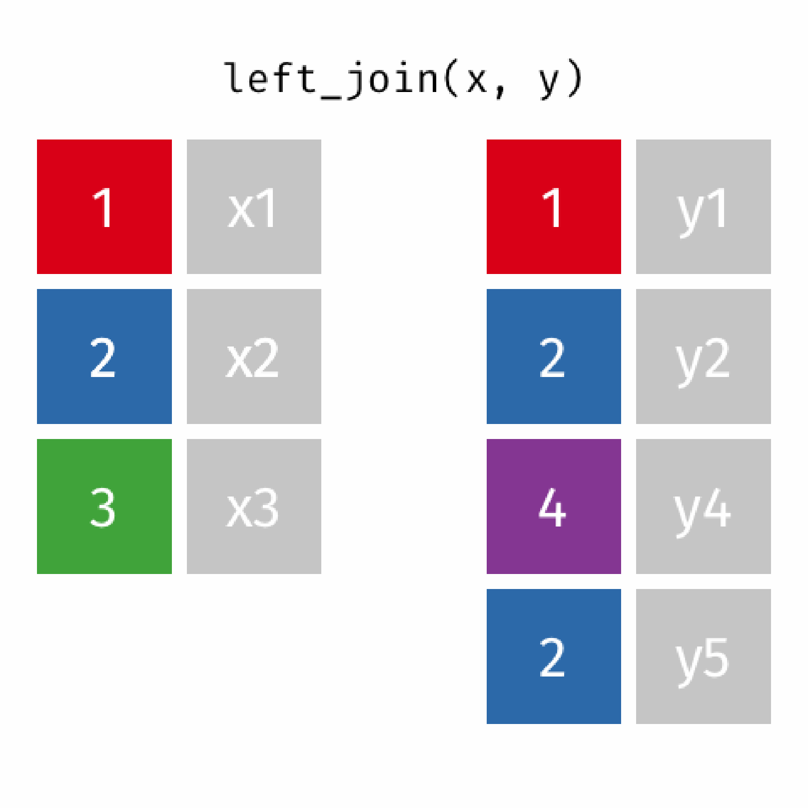
*Spiffy Join Animatations courtesy Garrick Aden-Buie

Left join, left_join()



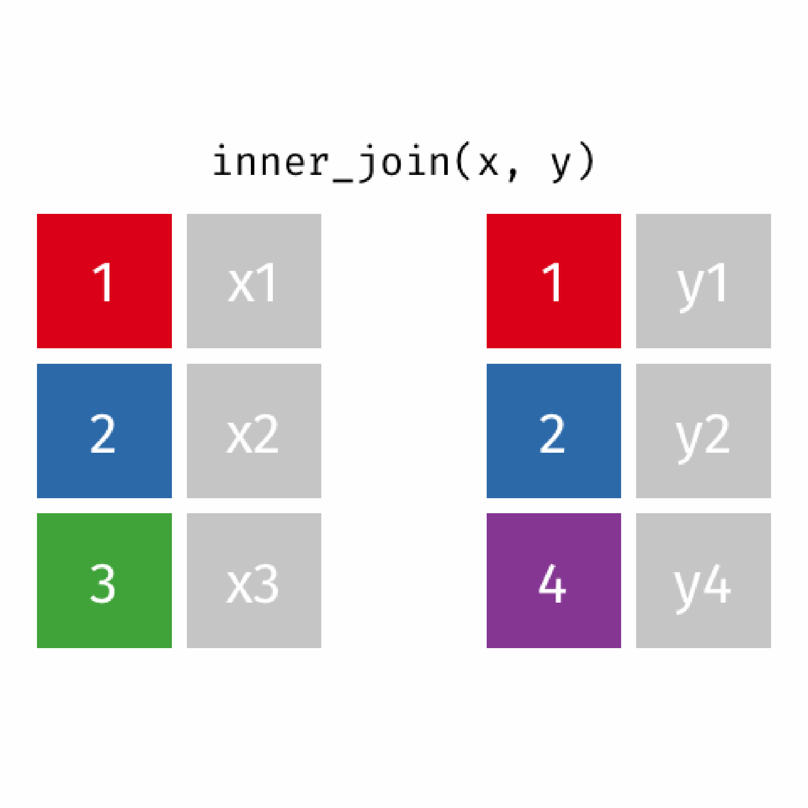
All rows from x, and all columns from x and y. Rows in x with no match in y will have NA values in the new columns.

Left join (contd), left_join()



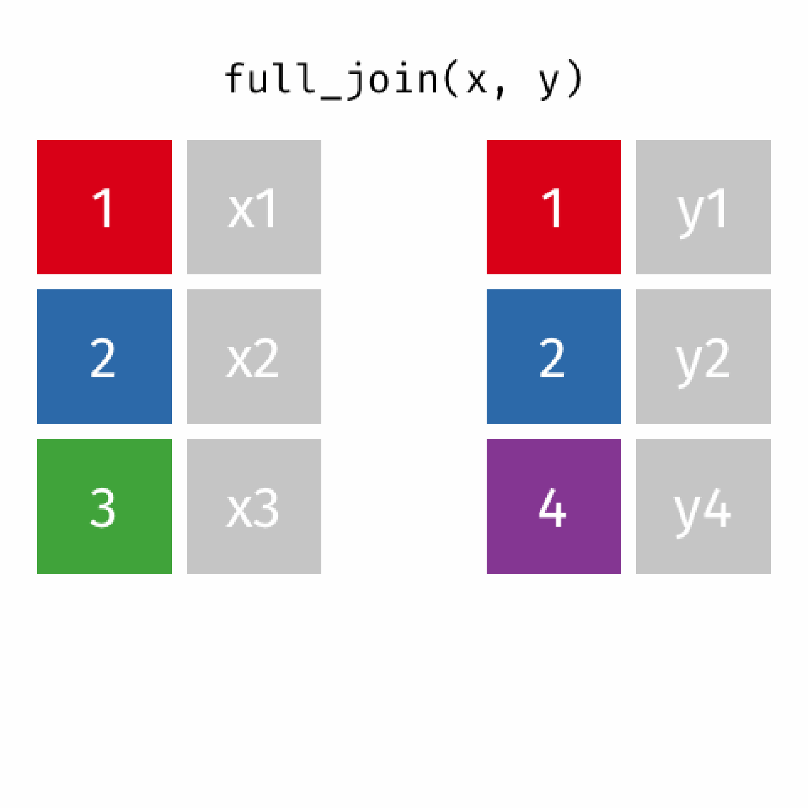
If there are multiple matches between x and y, all combinations of the matches are returned.

Inner join, inner_join()



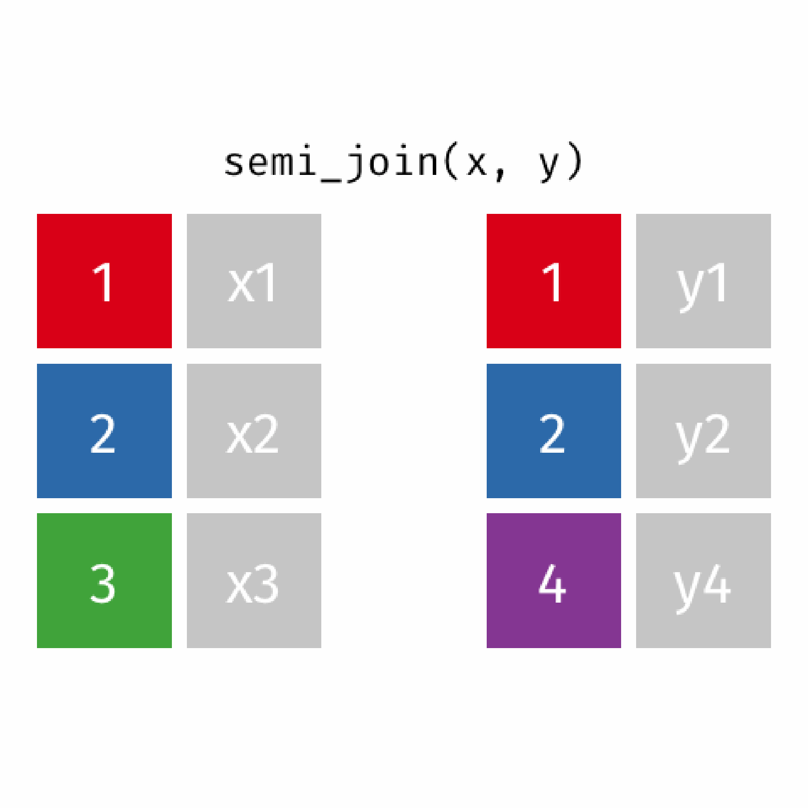
All rows from x where there are matching values in y, and all columns from x and y.

Full join, full_join()



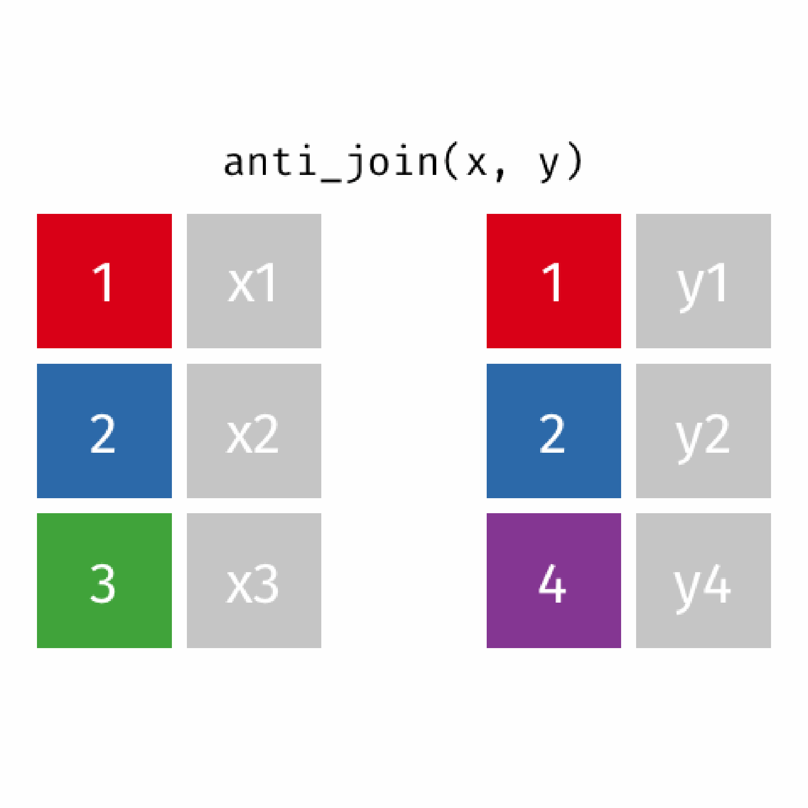
All rows and all columns from both x and y. Where there are not matching values, returns NA for the one missing.

Semi join, semi_join()



All rows from x where there are matching values in y, keeping just columns from x.

Anti join, anti_join()



All rows from x where there are not matching values in y, keeping just columns from x.

Left join, `left_join()`

Most of the time you will be looking to make a `left_join()`

Missing Data

Never test for missingness with ==

The result of almost any operation involving a missing/unknown value will be missing/unknown.

```
df <- tribble(
  ~subject, ~age,
  "A", 20,
  "B", 25,
  "C", NA,
  "D", 34
)

df
```

```
## # A tibble: 4 × 2
##   subject   age
##   <chr>   <dbl>
## 1 A          20
## 2 B          25
## 3 C          NA
## 4 D          34
```

Never test for missingness with ==

The result of almost any operation involving a missing/unknown value will be missing/unknown.

```r
# OK
df %>%
  filter(age == 25)
```

```
## # A tibble: 1 × 2
##   subject   age
##   <chr>   <dbl>
## 1 B          25
```

Never test for missingness with ==

The result of almost any operation involving a missing/unknown value will be missing/unknown.

```r
# OK
df %>%
  filter(age == 25)
```

```
## # A tibble: 1 × 2
##   subject   age
##   <chr>   <dbl>
## 1 B          25
```

```r
# Nope
df %>%
  filter(age == NA)
```

```
## # A tibble: 0 × 2
## # … with 2 variables: subject <chr>, age <dbl>
```

```r
# E.g.
23 == NA
```

```
## [1] NA
```

Never test for missingness with `==`

Always use `is.na()` instead

```
# Yes
df %>%
  filter(is.na(age))
```

```
## # A tibble: 1 × 2
##   subject   age
##   <chr>   <dbl>
## 1 C          NA
```

A quick plug for naniar and visdat

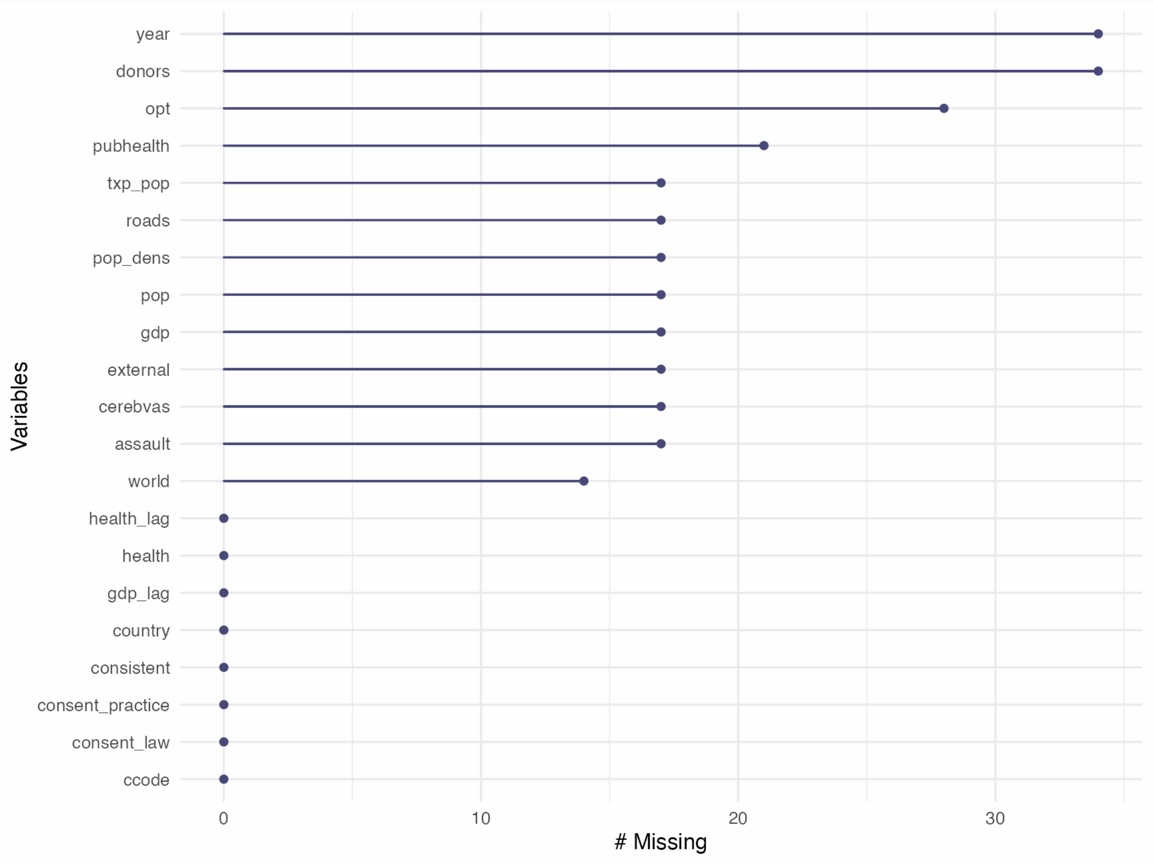
```r
library(naniar)
library(visdat)

organdata
```

```
## # A tibble: 238 × 21
##    country   year       donors   pop pop_dens   gdp gdp_lag health health_lag
##    <chr>     <date>      <dbl> <int>    <dbl> <int>   <int>  <dbl>      <dbl>
##  1 Australia NA          NA    17065    0.220 16774   16591   1300       1224
##  2 Australia 1991-01-01  12.1  17284    0.223 17171   16774   1379       1300
##  3 Australia 1992-01-01  12.4  17495    0.226 17914   17171   1455       1379
##  4 Australia 1993-01-01  12.5  17667    0.228 18883   17914   1540       1455
##  5 Australia 1994-01-01  10.2  17855    0.231 19849   18883   1626       1540
##  6 Australia 1995-01-01  10.2  18072    0.233 21079   19849   1737       1626
##  7 Australia 1996-01-01  10.6  18311    0.237 21923   21079   1846       1737
##  8 Australia 1997-01-01  10.3  18518    0.239 22961   21923   1948       1846
##  9 Australia 1998-01-01  10.5  18711    0.242 24148   22961   2077       1948
## 10 Australia 1999-01-01   8.67 18926    0.244 25445   24148   2231       2077
## # … with 228 more rows, and 12 more variables: pubhealth <dbl>, roads <dbl>,
## #   cerebvas <int>, assault <int>, external <int>, txp_pop <dbl>, world <chr>,
## #   opt <chr>, consent_law <chr>, consent_practice <chr>, consistent <chr>,
## #   ccode <chr>
```

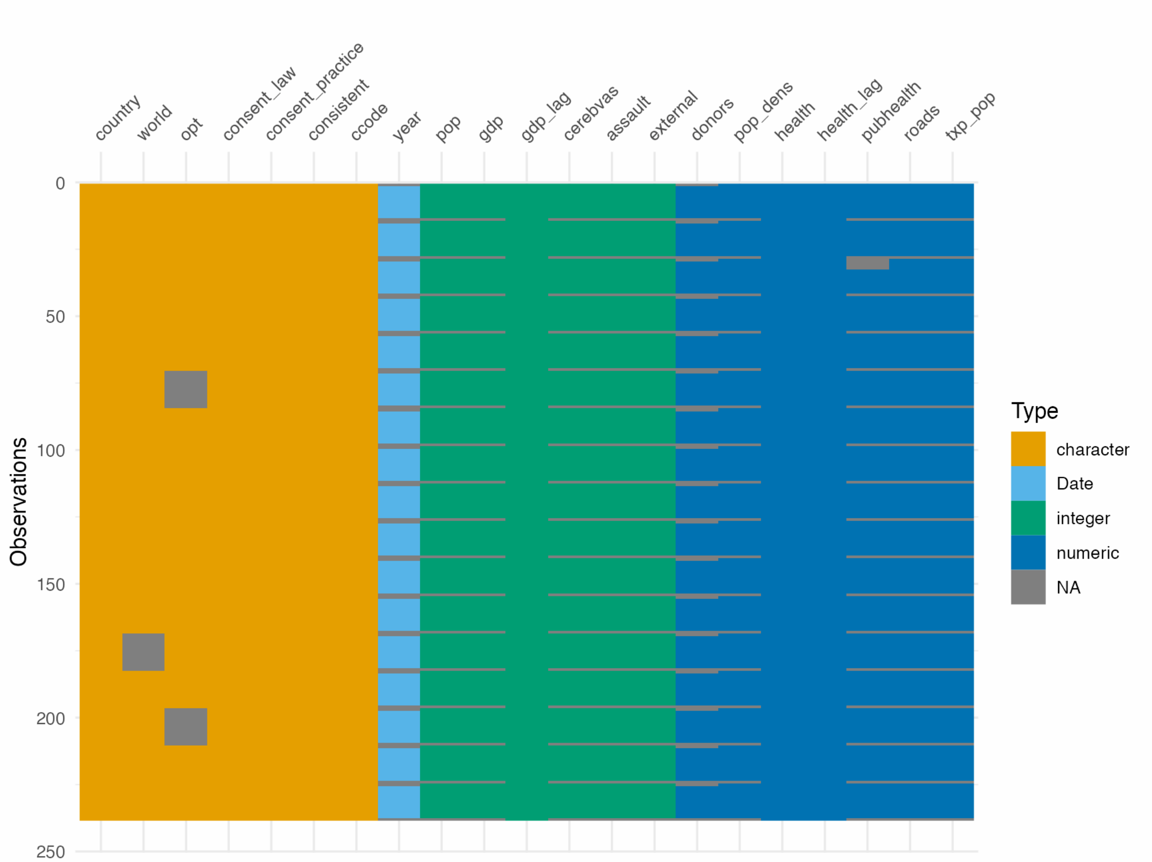
A quick plug for naniar and visdat

```r
gg_miss_var(organdata)
```



A quick plug for **naniar** and **visdat**

```
vis_dat(organdata)
```



A quick plug for naniar and visdat

```r
miss_var_summary(organdata)
```

```
## # A tibble: 21 × 3
##    variable  n_miss pct_miss
##    <chr>      <int>    <dbl>
##  1 year          34    14.3 
##  2 donors        34    14.3 
##  3 opt           28    11.8 
##  4 pubhealth     21     8.82
##  5 pop           17     7.14
##  6 pop_dens      17     7.14
##  7 gdp           17     7.14
##  8 roads         17     7.14
##  9 cerebvas      17     7.14
## 10 assault       17     7.14
## # … with 11 more rows
```

A quick plug for naniar and visdat

```r
miss_case_summary(organdata)
```

```
## # A tibble: 238 × 3
##     case n_miss pct_miss
##    <int>  <int>    <dbl>
##  1    84     12     57.1
##  2   182     12     57.1
##  3   210     12     57.1
##  4    14     11     52.4
##  5    28     11     52.4
##  6    42     11     52.4
##  7    56     11     52.4
##  8    70     11     52.4
##  9    98     11     52.4
## 10   112     11     52.4
## # … with 228 more rows
```

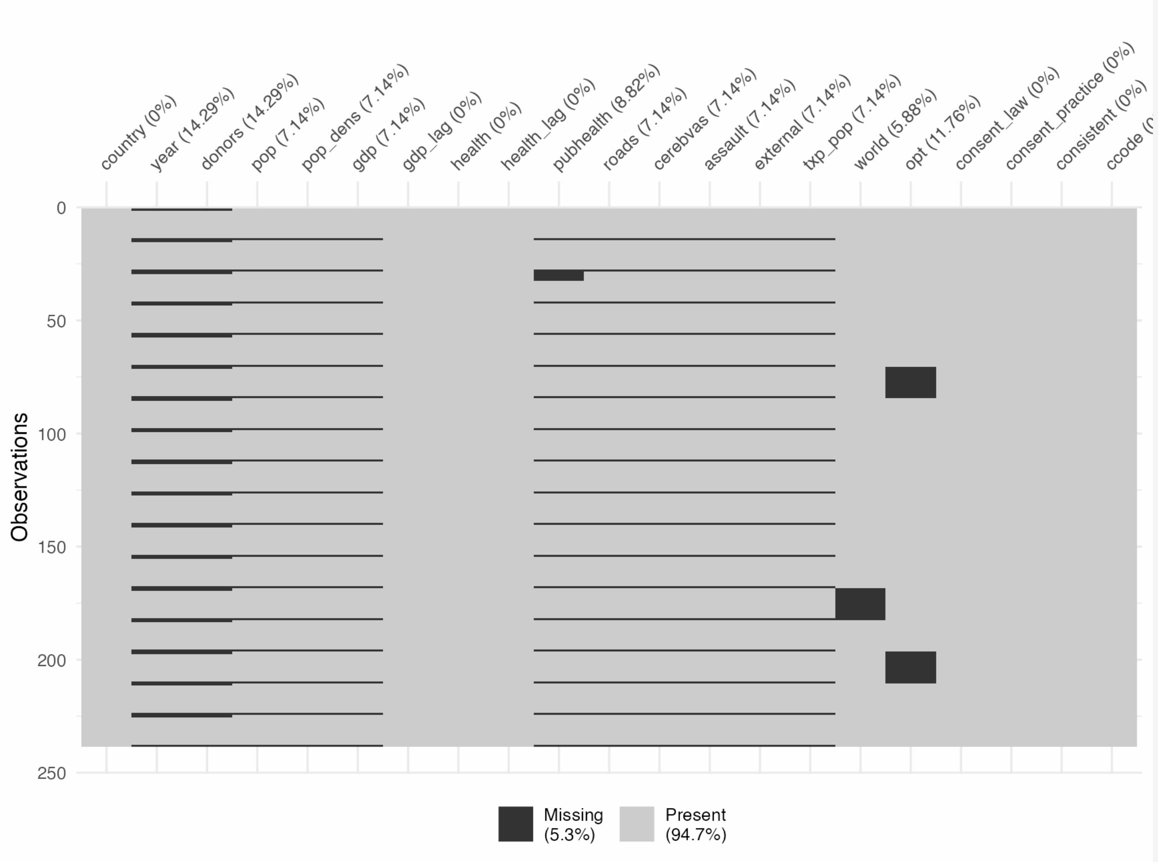
A quick plug for naniar and visdat

```
organdata %>%
  select(consent_law, year, pubhealth, roads) %>%
  group_by(consent_law) %>%
  miss_var_summary()
```

```
## # A tibble: 6 × 4
## # Groups:   consent_law [2]
##   consent_law variable  n_miss pct_miss
##   <chr>       <chr>      <int>    <dbl>
## 1 Informed    year          16    14.3
## 2 Informed    pubhealth      8     7.14
## 3 Informed    roads          8     7.14
## 4 Presumed    year          18    14.3
## 5 Presumed    pubhealth     13    10.3
## 6 Presumed    roads          9     7.14
```

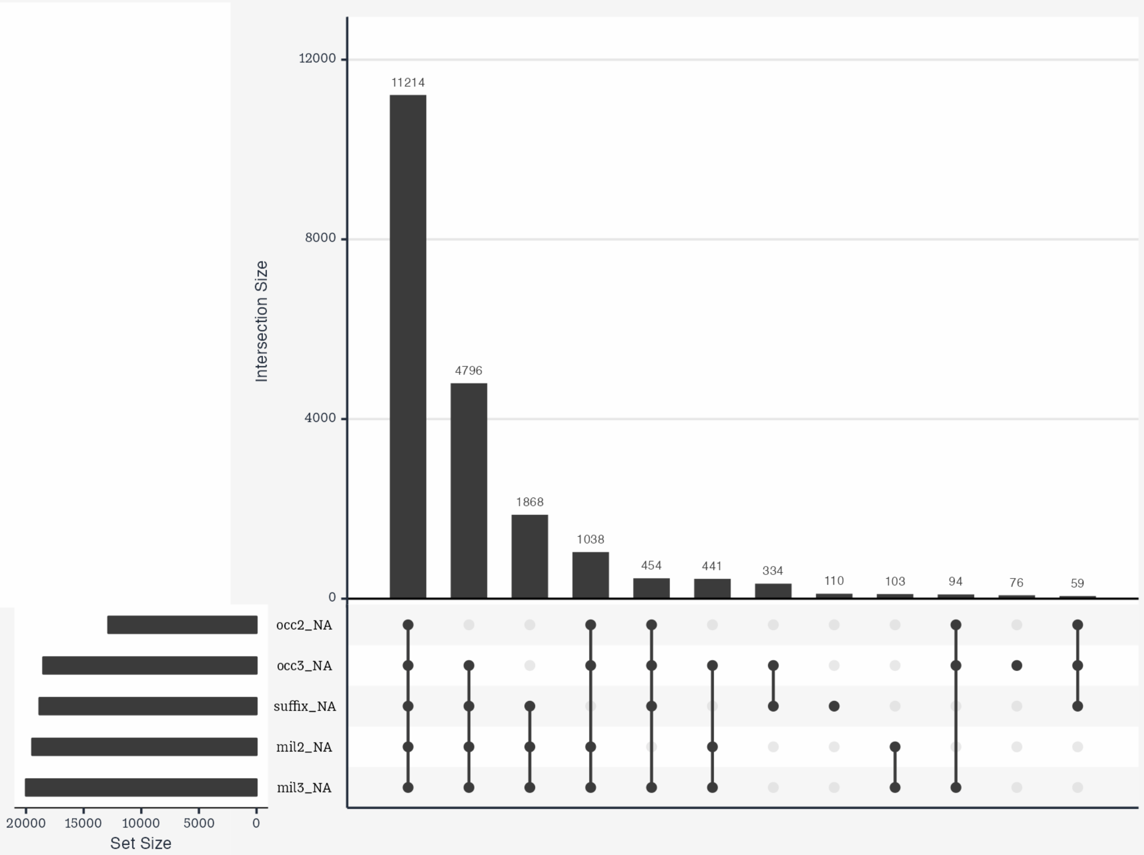
A quick plug for naniar and visdat

```
vis_miss(organdata)
```



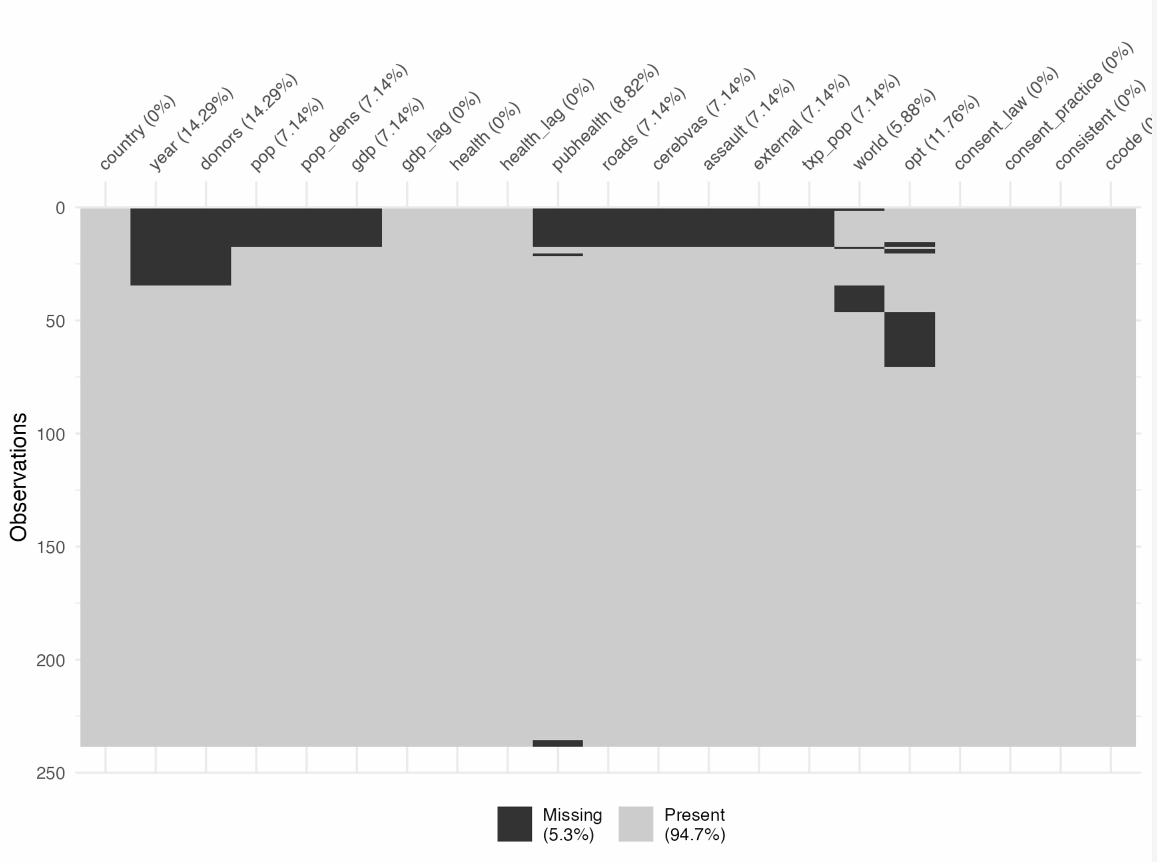
A quick plug for naniar and visdat

```r
library(congress)
gg_miss_upset(congress)
```



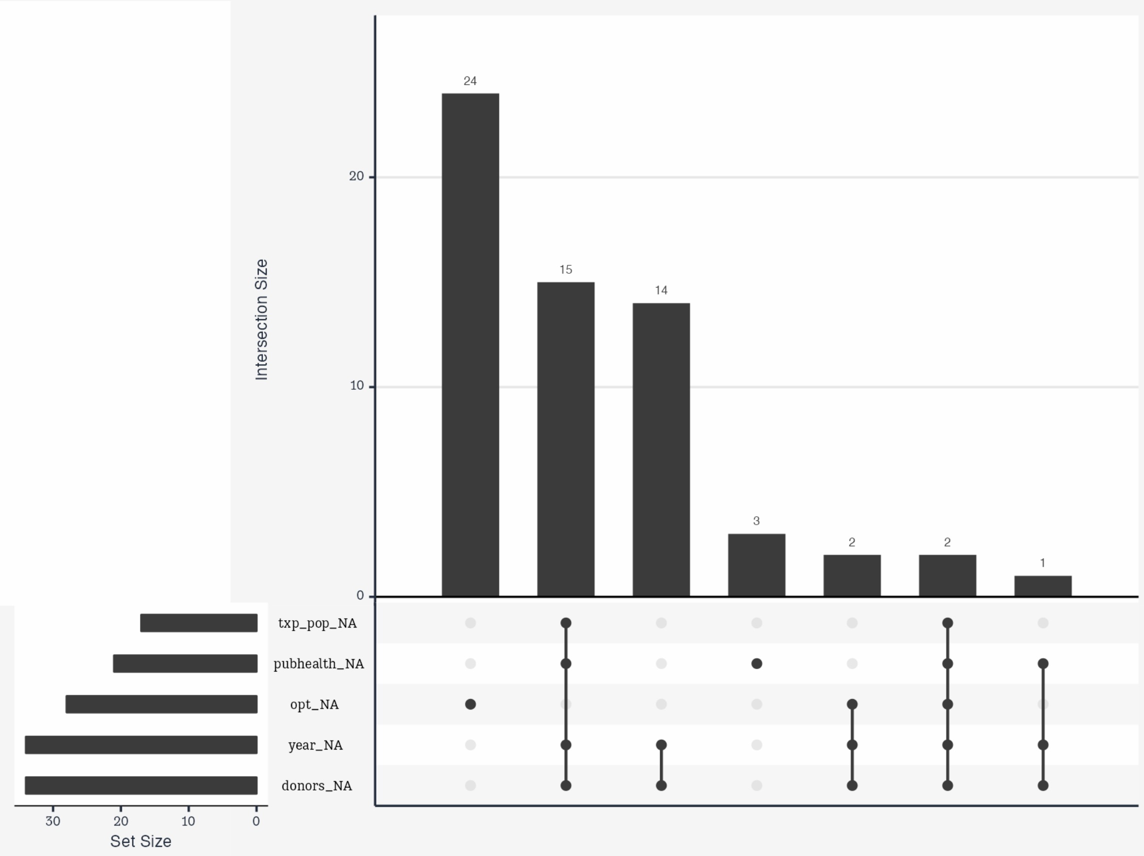
A quick plug for naniar and visdat

```r
vis_miss(organdata, cluster = TRUE)
```

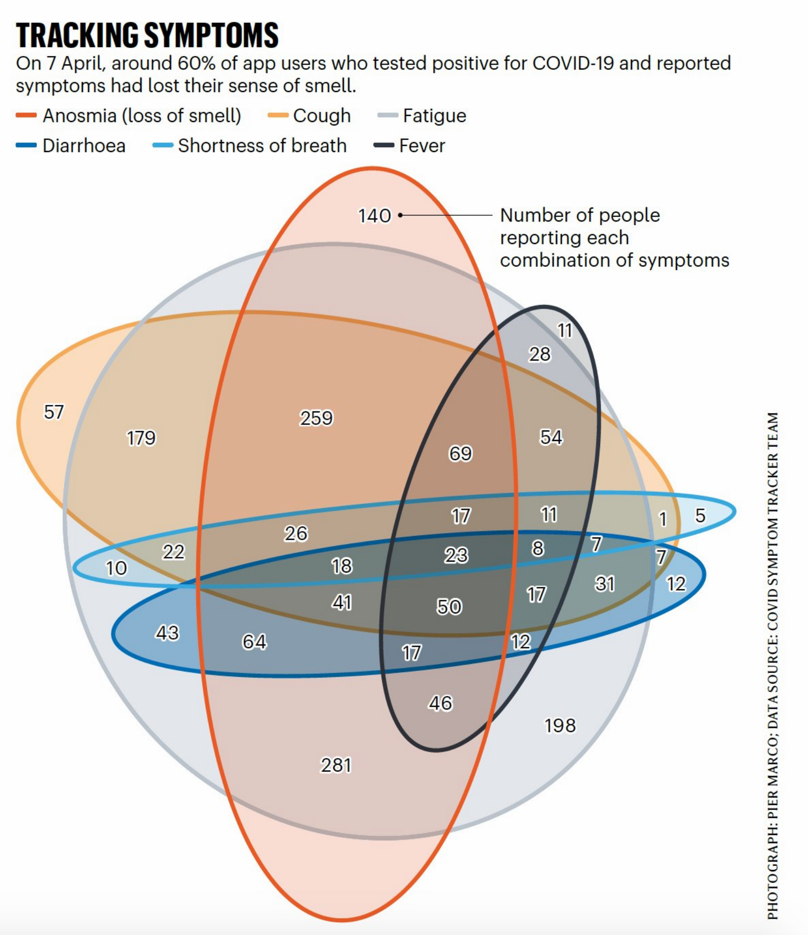


A quick plug for naniar and visdat

```
gg_miss_upset(organdata)
```



Upset plots and a bit of wrangling



Upset plots and a bit of wrangling

```r
symptoms <- c("Anosmia", "Cough", "Fatigue",
              "Diarrhea", "Breath", "Fever")
names(symptoms) <- symptoms
symptoms
```

```
##    Anosmia      Cough    Fatigue   Diarrhea     Breath      Fever
##  "Anosmia"    "Cough"  "Fatigue" "Diarrhea"   "Breath"    "Fever"
```

Upset plots and a bit of wrangling

```r
# An Excel file!
dat <- readxl::read_xlsx(here("data", "symptoms.xlsx"))
dat %>% print(n = nrow(dat))
```

```
## # A tibble: 32 × 2
##    combination                                  count
##    <chr>                                        <dbl>
##  1 Anosmia                                        140
##  2 Cough                                           57
##  3 Fatigue                                        198
##  4 Diarrhea                                        12
##  5 Breath                                           5
##  6 Fever                                           11
##  7 Cough&Fatigue                                  179
##  8 Fatigue&Fever                                   28
##  9 Breath&Fatigue                                  10
## 10 Diarrhea&Fatigue                                43
## 11 Anosmia&Fatigue                                281
## 12 Breath&Cough                                     1
## 13 Anosmia&Diarrhea&Fatigue                        64
## 14 Breath&Cough&Fatigue                            22
## 15 Anosmia&Cough&Fatigue                          259
## 16 Anosmia&Fever&Fatigue                           46
## 17 Cough&Fever&Fatigue                             54
## 18 Cough&Diarrhea                                   7
## 19 Cough&Diarrhea&Fatigue                          31
## 20 Anosmia&Breath&Cough&Fatigue                    26
## 21 Anosmia&Cough&Fatigue&Fever                     69
## 22 Anosmia&Breath&Cough&Diarrhea&Fatigue           18
## 23 Anosmia&Breath&Cough&Fatigue&Fever              17
```

Upset plots and a bit of wrangling

```
subsets <- dat %>%
  pull(combination)

## Check if each subset mentions each symptom or not
symptom_mat <- map_dfc(subsets, str_detect, symptoms) %>%
    data.frame() %>%
    t() %>% # transpose the result, this is a little gross, sorry
    as_tibble(.name_repair = "unique")

colnames(symptom_mat) <- symptoms
symptom_mat$count <- dat$count
```

Upset plots and a bit of wrangling

Now we have a table we can do something with.

```
symptom_mat %>% print(n = nrow(symptom_mat))
```

```
## # A tibble: 32 × 7
##    Anosmia Cough Fatigue Diarrhea Breath Fever count
##    <lgl>   <lgl> <lgl>   <lgl>    <lgl>  <lgl> <dbl>
##  1 TRUE    FALSE FALSE   FALSE    FALSE  FALSE   140
##  2 FALSE   TRUE  FALSE   FALSE    FALSE  FALSE    57
##  3 FALSE   FALSE TRUE    FALSE    FALSE  FALSE   198
##  4 FALSE   FALSE FALSE   TRUE     FALSE  FALSE    12
##  5 FALSE   FALSE FALSE   FALSE    TRUE   FALSE     5
##  6 FALSE   FALSE FALSE   FALSE    FALSE  TRUE     11
##  7 FALSE   TRUE  TRUE    FALSE    FALSE  FALSE   179
##  8 FALSE   FALSE TRUE    FALSE    FALSE  TRUE     28
##  9 FALSE   FALSE TRUE    FALSE    TRUE   FALSE    10
## 10 FALSE   FALSE TRUE    TRUE     FALSE  FALSE    43
## 11 TRUE    FALSE TRUE    FALSE    FALSE  FALSE   281
## 12 FALSE   TRUE  FALSE   FALSE    TRUE   FALSE     1
## 13 TRUE    FALSE TRUE    TRUE     FALSE  FALSE    64
## 14 FALSE   TRUE  TRUE    FALSE    TRUE   FALSE    22
## 15 TRUE    TRUE  TRUE    FALSE    FALSE  FALSE   259
## 16 TRUE    FALSE TRUE    FALSE    FALSE  TRUE     46
## 17 FALSE   TRUE  TRUE    FALSE    FALSE  TRUE     54
## 18 FALSE   TRUE  FALSE   TRUE     FALSE  FALSE     7
## 19 FALSE   TRUE  TRUE    TRUE     FALSE  FALSE    31
## 20 TRUE    TRUE  TRUE    FALSE    TRUE   FALSE    26
## 21 TRUE    TRUE  TRUE    FALSE    FALSE  TRUE     69
## 22 TRUE    TRUE  TRUE    TRUE     TRUE   FALSE    18
```

Upset plots and a bit of wrangling

Uncounting tables

```r
indvs <- symptom_mat %>%
    uncount(count)

indvs
```

```
## # A tibble: 1,764 × 6
##    Anosmia Cough Fatigue Diarrhea Breath Fever
##    <lgl>   <lgl> <lgl>   <lgl>    <lgl>  <lgl>
##  1 TRUE    FALSE FALSE   FALSE    FALSE  FALSE
##  2 TRUE    FALSE FALSE   FALSE    FALSE  FALSE
##  3 TRUE    FALSE FALSE   FALSE    FALSE  FALSE
##  4 TRUE    FALSE FALSE   FALSE    FALSE  FALSE
##  5 TRUE    FALSE FALSE   FALSE    FALSE  FALSE
##  6 TRUE    FALSE FALSE   FALSE    FALSE  FALSE
##  7 TRUE    FALSE FALSE   FALSE    FALSE  FALSE
##  8 TRUE    FALSE FALSE   FALSE    FALSE  FALSE
##  9 TRUE    FALSE FALSE   FALSE    FALSE  FALSE
## 10 TRUE    FALSE FALSE   FALSE    FALSE  FALSE
## # … with 1,754 more rows
```

Now we've reconstructed the individual-level observations.

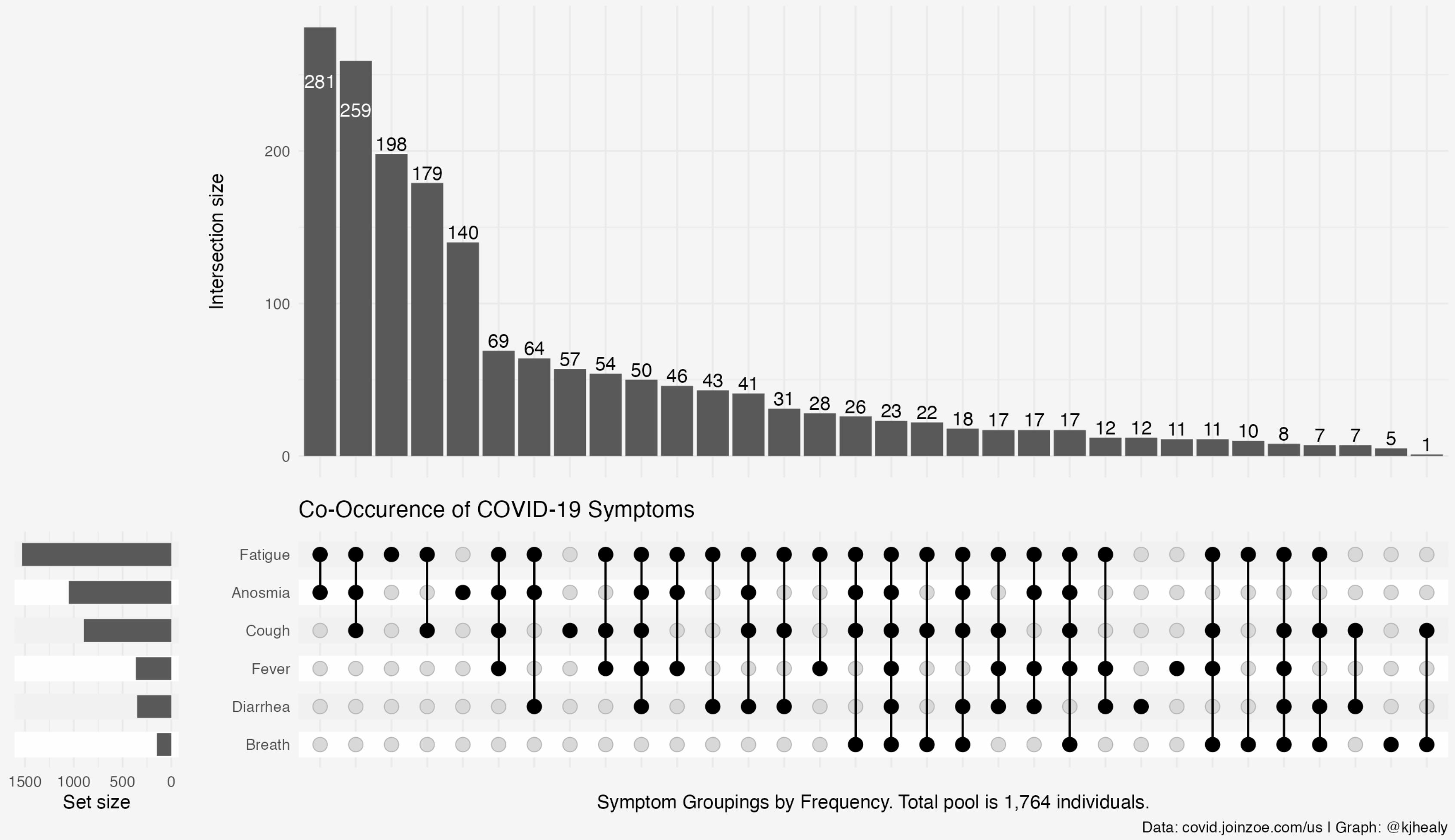
Upset plots and a bit of wrangling

```r
# devtools::install_github("krassowski/complex-upset")

library(ComplexUpset)

upset(data = indvs, intersect = symptoms,
      name="Symptom Groupings by Frequency. Total pool is 1,764 individuals.",
      min_size = 0,
      width_ratio = 0.125) +
    labs(title = "Co-Occurence of COVID-19 Symptoms",
         caption = "Data: covid.joinzoe.com/us | Graph: @kjhealy")
```

Upset plots and a bit of wrangling



Models

This is not a statistics seminar!

I'll just give you an example of the sort of thing that many other modeling packages implement for all kinds of modeling techniques.

Again, the principle is tidy incorporation of models and their output.

Tidy regression output with broom

```r
library(broom)
library(gapminder)
```

```r
out <- lm(formula = lifeExp ~ gdpPercap + pop + continent,
          data = gapminder)
```

Tidy regression output with broom

We can't *do* anything with this, programatically.

```
summary(out)
```

```
##
## Call:
## lm(formula = lifeExp ~ gdpPercap + pop + continent, data = gapminder)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -49.161  -4.486   0.297   5.110  25.175
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       4.781e+01  3.395e-01 140.819  < 2e-16 ***
## gdpPercap         4.495e-04  2.346e-05  19.158  < 2e-16 ***
## pop               6.570e-09  1.975e-09   3.326 0.000901 ***
## continentAmericas 1.348e+01  6.000e-01  22.458  < 2e-16 ***
## continentAsia     8.193e+00  5.712e-01  14.342  < 2e-16 ***
## continentEurope   1.747e+01  6.246e-01  27.973  < 2e-16 ***
## continentOceania  1.808e+01  1.782e+00  10.146  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.365 on 1697 degrees of freedom
## Multiple R-squared:  0.5821,	Adjusted R-squared:  0.5806
## F-statistic: 393.9 on 6 and 1697 DF,  p-value: < 2.2e-16
```

Tidy regression output with broom

```
library(broom)
```

```
tidy(out)
```

```
## # A tibble: 7 × 5
##   term               estimate     std.error statistic   p.value
##   <chr>                 <dbl>         <dbl>     <dbl>     <dbl>
## 1 (Intercept)         4.78e+1 0.340             141.   0       
## 2 gdpPercap           4.50e-4 0.0000235          19.2  3.24e- 74
## 3 pop                 6.57e-9 0.00000000198       3.33 9.01e-  4
## 4 continentAmericas   1.35e+1 0.600              22.5  5.19e- 98
## 5 continentAsia       8.19e+0 0.571              14.3  4.06e- 44
## 6 continentEurope     1.75e+1 0.625              28.0  6.34e-142
## 7 continentOceania    1.81e+1 1.78               10.1  1.59e- 23
```

That's a *lot* nicer. Now it's just a tibble. We know those.

Tidy regression output with broom

```r
out_conf <- tidy(out, conf.int = TRUE)
out_conf
```

```
## # A tibble: 7 × 7
##   term              estimate    std.error statistic   p.value conf.low conf.high
##   <chr>                <dbl>        <dbl>     <dbl>     <dbl>    <dbl>     <dbl>
## 1 (Intercept)        4.78e+1      3.40e-1    141.   0          4.71e+1   4.85e+1
## 2 gdpPercap          4.50e-4      2.35e-5     19.2  3.24e- 74  4.03e-4   4.96e-4
## 3 pop                6.57e-9      1.98e-9      3.33 9.01e-  4  2.70e-9   1.04e-8
## 4 continentAmericas  1.35e+1      6.00e-1     22.5  5.19e- 98  1.23e+1   1.47e+1
## 5 continentAsia      8.19e+0      5.71e-1     14.3  4.06e- 44  7.07e+0   9.31e+0
## 6 continentEurope    1.75e+1      6.25e-1     28.0  6.34e-142  1.62e+1   1.87e+1
## 7 continentOceania   1.81e+1      1.78e+0     10.1  1.59e- 23  1.46e+1   2.16e+1
```

Tidy regression output with broom

```r
out_conf %>%
    filter(term %nin% "(Intercept)") %>%
    mutate(nicelabs = prefix_strip(term, "continent")) %>%
    select(nicelabs, everything())
```

```
## # A tibble: 6 × 8
##   nicelabs  term       estimate std.error statistic   p.value conf.low conf.high
##   <chr>     <chr>         <dbl>     <dbl>     <dbl>     <dbl>    <dbl>     <dbl>
## 1 gdpPercap gdpPercap   4.50e-4   2.35e-5     19.2  3.24e- 74  4.03e-4   4.96e-4
## 2 Pop       pop         6.57e-9   1.98e-9      3.33 9.01e-  4  2.70e-9   1.04e-8
## 3 Americas  continent…  1.35e+1   6.00e-1     22.5  5.19e- 98  1.23e+1   1.47e+1
## 4 Asia      continent…  8.19e+0   5.71e-1     14.3  4.06e- 44  7.07e+0   9.31e+0
## 5 Europe    continent…  1.75e+1   6.25e-1     28.0  6.34e-142  1.62e+1   1.87e+1
## 6 Oceania   continent…  1.81e+1   1.78e+0     10.1  1.59e- 23  1.46e+1   2.16e+1
```

Grouped analysis and list columns

```
eu77 <- gapminder %>% filter(continent == "Europe", year == 1977)
fit <- lm(lifeExp ~ log(gdpPercap), data = eu77)
```

```
summary(fit)
```

```
##
## Call:
## lm(formula = lifeExp ~ log(gdpPercap), data = eu77)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.4956 -1.0306  0.0935  1.1755  3.7125
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)      29.489      7.161   4.118 0.000306 ***
## log(gdpPercap)    4.488      0.756   5.936 2.17e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.114 on 28 degrees of freedom
## Multiple R-squared:  0.5572,    Adjusted R-squared:  0.5414
## F-statistic: 35.24 on 1 and 28 DF,  p-value: 2.173e-06
```

Grouped analysis and list columns

```r
out_le <- gapminder %>%
    group_by(continent, year) %>%
    nest()

out_le
```

```
## # A tibble: 60 × 3
## # Groups:   continent, year [60]
##    continent  year data
##    <fct>     <int> <list>
##  1 Asia       1952 <tibble [33 × 4]>
##  2 Asia       1957 <tibble [33 × 4]>
##  3 Asia       1962 <tibble [33 × 4]>
##  4 Asia       1967 <tibble [33 × 4]>
##  5 Asia       1972 <tibble [33 × 4]>
##  6 Asia       1977 <tibble [33 × 4]>
##  7 Asia       1982 <tibble [33 × 4]>
##  8 Asia       1987 <tibble [33 × 4]>
##  9 Asia       1992 <tibble [33 × 4]>
## 10 Asia       1997 <tibble [33 × 4]>
## # … with 50 more rows
```

Think of nesting as a kind of "super-grouping". Look in the object inspector.

Grouped analysis and list columns

It's still in there.

```r
out_le %>% filter(continent == "Europe" & year == 1977) %>%
    unnest(cols = c(data))
```

```
## # A tibble: 30 × 6
## # Groups:   continent, year [1]
##    continent  year country                lifeExp      pop gdpPercap
##    <fct>     <int> <fct>                    <dbl>    <int>     <dbl>
##  1 Europe     1977 Albania                   68.9  2509048     3533.
##  2 Europe     1977 Austria                   72.2  7568430    19749.
##  3 Europe     1977 Belgium                   72.8  9821800    19118.
##  4 Europe     1977 Bosnia and Herzegovina    69.9  4086000     3528.
##  5 Europe     1977 Bulgaria                  70.8  8797022     7612.
##  6 Europe     1977 Croatia                   70.6  4318673    11305.
##  7 Europe     1977 Czech Republic            70.7 10161915    14800.
##  8 Europe     1977 Denmark                   74.7  5088419    20423.
##  9 Europe     1977 Finland                   72.5  4738902    15605.
## 10 Europe     1977 France                    73.8 53165019    18293.
## # … with 20 more rows
```

Grouped analysis and list columns

Here we `map()` a custom function to every row in the `data` column.

```
fit_ols <- function(df) {
    lm(lifeExp ~ log(gdpPercap), data = df)
}

out_le <- gapminder %>%
    group_by(continent, year) %>%
    nest() %>%
    mutate(model = map(data, fit_ols))
```

Grouped analysis and list columns

```r
out_le
```

```
## # A tibble: 60 × 4
## # Groups:   continent, year [60]
##    continent  year data              model
##    <fct>     <int> <list>            <list>
##  1 Asia       1952 <tibble [33 × 4]> <lm>
##  2 Asia       1957 <tibble [33 × 4]> <lm>
##  3 Asia       1962 <tibble [33 × 4]> <lm>
##  4 Asia       1967 <tibble [33 × 4]> <lm>
##  5 Asia       1972 <tibble [33 × 4]> <lm>
##  6 Asia       1977 <tibble [33 × 4]> <lm>
##  7 Asia       1982 <tibble [33 × 4]> <lm>
##  8 Asia       1987 <tibble [33 × 4]> <lm>
##  9 Asia       1992 <tibble [33 × 4]> <lm>
## 10 Asia       1997 <tibble [33 × 4]> <lm>
## # … with 50 more rows
```

Grouped analysis and list columns

We can tidy the nested models, too.

```
fit_ols <- function(df) {
    lm(lifeExp ~ log(gdpPercap), data = df)
}

out_tidy <- gapminder %>%
    group_by(continent, year) %>%
    nest() %>%
    mutate(model = map(data, fit_ols),
           tidied = map(model, tidy)) %>%
    unnest(cols = c(tidied)) %>%
    filter(term %nin% "(Intercept)" &
           continent %nin% "Oceania")
```

Grouped analysis and list columns

```
out_tidy
```

```
## # A tibble: 48 × 9
## # Groups:   continent, year [48]
##    continent  year data     model  term     estimate std.error statistic p.value
##    <fct>     <int> <list>   <list> <chr>       <dbl>     <dbl>     <dbl>   <dbl>
##  1 Asia       1952 <tibble> <lm>   log(gdp…     4.16     1.25       3.33 2.28e-3
##  2 Asia       1957 <tibble> <lm>   log(gdp…     4.17     1.28       3.26 2.71e-3
##  3 Asia       1962 <tibble> <lm>   log(gdp…     4.59     1.24       3.72 7.94e-4
##  4 Asia       1967 <tibble> <lm>   log(gdp…     4.50     1.15       3.90 4.77e-4
##  5 Asia       1972 <tibble> <lm>   log(gdp…     4.44     1.01       4.41 1.16e-4
##  6 Asia       1977 <tibble> <lm>   log(gdp…     4.87     1.03       4.75 4.42e-5
##  7 Asia       1982 <tibble> <lm>   log(gdp…     4.78     0.852      5.61 3.77e-6
##  8 Asia       1987 <tibble> <lm>   log(gdp…     5.17     0.727      7.12 5.31e-8
##  9 Asia       1992 <tibble> <lm>   log(gdp…     5.09     0.649      7.84 7.60e-9
## 10 Asia       1997 <tibble> <lm>   log(gdp…     5.11     0.628      8.15 3.35e-9
## # … with 38 more rows
```

Grouped analysis and list columns

```r
out_tidy %>%
    ungroup() %>%
    sample_n(5)
```

```
## # A tibble: 5 × 9
##   continent  year data      model  term      estimate std.error statistic p.value
##   <fct>     <int> <list>    <list> <chr>        <dbl>     <dbl>     <dbl>   <dbl>
## 1 Europe     2002 <tibble> <lm>   log(gdpP…     3.74     0.445      8.40 3.91e-9
## 2 Europe     1992 <tibble> <lm>   log(gdpP…     3.48     0.545      6.39 6.44e-7
## 3 Africa     1977 <tibble> <lm>   log(gdpP…     4.51     0.920      4.90 1.04e-5
## 4 Africa     2007 <tibble> <lm>   log(gdpP…     4.26     1.19       3.58 7.79e-4
## 5 Americas   1952 <tibble> <lm>   log(gdpP…    10.4      2.72       3.84 8.27e-4
```