Manipulating Tables with dplyr

Data Wrangling: Session 3

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Statistical Horizons, April 2022

Time to play with some data

Time to play with some **data**

woohoo!

Load our libraries

```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()
```

Tidyverse components, again

```
library(tidyverse)
Loading tidyverse: ggplot2
Loading tidyverse: tibble
Loading tidyverse: tidyr
Loading tidyverse: readr
Loading tidyverse: purrr
Loading tidyverse: dplyr
```

Tidyverse components, again

```r
library(tidyverse)
Loading tidyverse: ggplot2
Loading tidyverse: tibble
Loading tidyverse: tidyr
Loading tidyverse: readr
Loading tidyverse: purrr
Loading tidyverse: dplyr
```

Call the package and ...

< | **Draw graphs**
< | **Nicer data tables**
< | **Tidy your data**
< | **Get data into R**
< | **Fancy Iteration**
< | **Action verbs for tables**

Other tidyverse components

```
forcats
haven
lubridate
readxl
stringr
reprex
```

Other tidyverse components

`forcats    <|` Deal with factors
`haven      <|` Import Stata, SPSS, etc
`lubridate  <|` Dates, Durations, Times
`readxl     <|` Import from spreadsheets
`stringr    <|` Strings and Regular Expressions
`reprex     <|` Make reproducible examples

Other tidyverse components

`forcats    <|` **Deal with factors**
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`lubridate  <|` **Dates, Durations, Times**
`readxl     <|` **Import from spreadsheets**
`stringr    <|` **Strings and Regular Expressions**
`reprex     <|` **Make reproducible examples**

Not all of these are attached when we do `library(tidyverse)`

dplyr lets you work with tibbles

Remember, tibbles are tables of data where the columns can be of different types, such as numeric, logical, character, factor, etc.

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Remember, tibbles are tables of data where the columns can be of different types, such as numeric, logical, character, factor, etc.

We'll use dplyr to *transform* and *summarize* our data.

We'll use the pipe operator, **%>%**, to chain together sequences of actions on our tables.

`dplyr` draws on the logic and language of database queries, where the focus is on manipulating tables

Some **actions** to take on a single table

Some actions to take on a single table

Group the data at the level we want, such as "*Religion by Region*" or "*Children by School*".

Subset either the rows or columns of or table.

Mutate the data. That is, change something at the *current* level of grouping. Mutating adds new columns to the table, or changes the content of an existing column. It never changes the number of rows.

Summarize or aggregate the data. That is, make something new at a *higher* level of grouping. E.g., calculate means or counts by some grouping variable. This will generally result in a smaller, *summary* table.

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Group using `group_by()`.

Subset has one action for rows and one for columns. We `filter()` rows and `select()` columns.

Mutate tables (i.e. add new columns, or re-make existing ones) using `mutate()`.

Summarize tables (i.e. perform aggregating calculations) using `summarize()`.

General Social Survey data: `gss_sm`

```
## library(socviz) # if not loaded
gss_sm
```

```
## # A tibble: 2,867 × 32
##     year    id ballot       age childs sibs   degree race  sex   region income16
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct>   
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $170000…
##  2  2016     2 2             61      0 3      High … White Male  New E… $50000 …
##  3  2016     3 3             72      2 3      Bache… White Male  New E… $75000 …
##  4  2016     4 1             43      4 3      High … White Fema… New E… $170000…
##  5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170000…
##  6  2016     6 2             53      2 2      Junio… White Fema… New E… $60000 …
##  7  2016     7 1             50      2 2      High … White Male  New E… $170000…
##  8  2016     8 3             23      3 6      High … Other Fema… Middl… $30000 …
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## 10  2016    10 3             71      4 1      Junio… White Male  Middl… $60000 …
## # … with 2,857 more rows, and 21 more variables: relig <fct>, marital <fct>,
## #   padeg <fct>, madeg <fct>, partyid <fct>, polviews <fct>, happy <fct>,
## #   partners <fct>, grass <fct>, zodiac <fct>, pres12 <labelled>,
## #   wtssall <dbl>, income_rc <fct>, agegrp <fct>, ageq <fct>, siblings <fct>,
## #   kids <fct>, religion <fct>, bigregion <fct>, partners_rc <fct>, obama <dbl>
```

General Social Survey data: `gss_sm`

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```
## # A tibble: 2,867 × 32
##      year    id ballot       age childs sibs   degree race  sex   region income16
##     <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct>
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## #   wtssall <dbl>, income_rc <fct>, agegrp <fct>, ageq <fct>, siblings <fct>,
## #   kids <fct>, religion <fct>, bigregion <fct>, partners_rc <fct>, obama <dbl>
```

Notice how the tibble already tells us a lot.

Summarizing a Table

Here's what we're going to do:

1. Individual-Level GSS Data on Region and Religion

id	bigregion	religion
1014	Midwest	Protestant
1544	South	Protestant
665	Northeast	None
1618	South	None
2115	West	Catholic
417	South	Protestant
2045	West	Protestant
1863	Northeast	Other
1884	Midwest	Christian
1628	South	Protestant

2. Summary Count of Religious Preferences by Census Region

bigregion	religion	N
Northeast	Protestant	123
Northeast	Catholic	149
Northeast	Jewish	15
Northeast	None	97
Northeast	Christian	14
Northeast	Other	31

3. Percent Religious Preferences by Census Region

bigregion	religion	N	pct
Northeast	Protestant	123	28.3
Northeast	Catholic	149	34.3
Northeast	Jewish	15	3.4
Northeast	None	97	22.3
Northeast	Christian	14	3.2
Northeast	Other	31	7.1

Summarizing a Table

```r
## Just take a look at the columns we will work on
gss_sm %>%
  select(id, bigregion, religion)
```

```
## # A tibble: 2,867 × 3
##       id bigregion religion
##    <dbl> <fct>     <fct>
##  1     1 Northeast None
##  2     2 Northeast None
##  3     3 Northeast Catholic
##  4     4 Northeast Catholic
##  5     5 Northeast None
##  6     6 Northeast None
##  7     7 Northeast None
##  8     8 Northeast Catholic
##  9     9 Northeast Protestant
## 10    10 Northeast None
## # … with 2,857 more rows
```

We're just taking a look at the relevant columns here.

Group by *one* column or variable

```
gss_sm %>%
  group_by(bigregion)
```

```
## # A tibble: 2,867 × 32
## # Groups:   bigregion [4]
##     year    id ballot       age childs sibs   degree race  sex   region income16
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct>
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```

Grouping just changes the logical structure of the tibble.

Group and summarize by *one* column

```
gss_sm
```

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```

Group and summarize by *one* column

```r
gss_sm %>%
  group_by(bigregion) %>%
  summarize(total = n())
```

```
## # A tibble: 4 × 2
##   bigregion total
##   <fct>     <int>
## 1 Northeast   488
## 2 Midwest     695
## 3 South      1052
## 4 West        632
```

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The function `n()` counts up the rows within each group.

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All the other columns are dropped in the summary operation

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```

The function `n()` counts up the rows within each group.

All the other columns are dropped in the summary operation

Your original `gss_sm` table is untouched

Group and summarize by *two* columns

```
gss_sm
```

```
## # A tibble: 2,867 × 32
##     year    id ballot       age childs sibs   degree race  sex   region i
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $
##  2  2016     2 2             61      0 3      High … White Male  New E… $
##  3  2016     3 3             72      2 3      Bache… White Male  New E… $
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## #   partners <fct>, grass <fct>, zodiac <fct>, pres12 <labelled>,
## #   wtssall <dbl>, income_rc <fct>, agegrp <fct>, ageq <fct>, siblings <f
## #   kids <fct>, religion <fct>, bigregion <fct>, partners_rc <fct>, obama
```

Group and summarize by *two* columns

```
gss_sm %>%
  group_by(bigregion, religion)
```

```
## # A tibble: 2,867 × 32
## # Groups:   bigregion, religion [24]
##     year    id ballot      age childs sibs   degree race  sex   region i
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $
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## #   kids <fct>, religion <fct>, bigregion <fct>, partners_rc <fct>, obama
```

Group and summarize by *two* columns

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(total = n())
```

```
## # A tibble: 24 × 3
## # Groups:   bigregion [4]
##    bigregion religion   total
##    <fct>     <fct>      <int>
##  1 Northeast Protestant   158
##  2 Northeast Catholic     162
##  3 Northeast Jewish        27
##  4 Northeast None         112
##  5 Northeast Other         28
##  6 Northeast <NA>           1
##  7 Midwest   Protestant   325
##  8 Midwest   Catholic     172
##  9 Midwest   Jewish         3
## 10 Midwest   None         157
## # … with 14 more rows
```

Group and summarize by *two* columns

```r
gss_sm %>%
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  summarize(total = n())
```

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##  9 Midwest   Jewish         3
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## # … with 14 more rows
```

The function `n()` counts up the rows within the *innermost* (i.e. the rightmost) group.

Calculate frequencies

```
gss_sm
```

```
## # A tibble: 2,867 × 32
##      year    id ballot       age childs sibs   degree race  sex   region inco
##     <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $170
##  2  2016     2 2             61      0 3      High … White Male  New E… $500
##  3  2016     3 3             72      2 3      Bache… White Male  New E… $750
##  4  2016     4 1             43      4 3      High … White Fema… New E… $170
##  5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170
##  6  2016     6 2             53      2 2      Junio… White Fema… New E… $600
##  7  2016     7 1             50      2 2      High … White Male  New E… $170
##  8  2016     8 3             23      3 6      High … Other Fema… Middl… $300
##  9  2016     9 1             45      3 5      High … Black Male  Middl… $600
## 10  2016    10 3             71      4 1      Junio… White Male  Middl… $600
## # … with 2,857 more rows, and 21 more variables: relig <fct>, marital <fct>,
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## #   partners <fct>, grass <fct>, zodiac <fct>, pres12 <labelled>,
## #   wtssall <dbl>, income_rc <fct>, agegrp <fct>, ageq <fct>, siblings <fct
## #   kids <fct>, religion <fct>, bigregion <fct>, partners_rc <fct>, obama <
```

Calculate frequencies

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gss_sm %>%
  group_by(bigregion, religion)
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##     year    id ballot       age childs sibs   degree race  sex   region inco
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $170
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##  4  2016     4 1             43      4 3      High … White Fema… New E… $170
##  5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170
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```

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gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(total = n())
```

```
## # A tibble: 24 × 3
## # Groups:   bigregion [4]
##    bigregion religion   total
##    <fct>     <fct>      <int>
##  1 Northeast Protestant   158
##  2 Northeast Catholic     162
##  3 Northeast Jewish        27
##  4 Northeast None         112
##  5 Northeast Other         28
##  6 Northeast <NA>           1
##  7 Midwest   Protestant   325
##  8 Midwest   Catholic     172
##  9 Midwest   Jewish         3
## 10 Midwest   None         157
## # … with 14 more rows
```

Calculate frequencies

```r
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(total = n()) %>%
  mutate(freq = total / sum(total),
           pct = round((freq*100), 1))
```

```
## # A tibble: 24 × 5
## # Groups:   bigregion [4]
##    bigregion religion   total    freq   pct
##    <fct>     <fct>      <int>   <dbl> <dbl>
##  1 Northeast Protestant   158 0.324    32.4
##  2 Northeast Catholic     162 0.332    33.2
##  3 Northeast Jewish        27 0.0553    5.5
##  4 Northeast None         112 0.230    23  
##  5 Northeast Other         28 0.0574    5.7
##  6 Northeast <NA>           1 0.00205   0.2
##  7 Midwest   Protestant   325 0.468    46.8
##  8 Midwest   Catholic     172 0.247    24.7
##  9 Midwest   Jewish         3 0.00432   0.4
## 10 Midwest   None         157 0.226    22.6
## # … with 14 more rows
```

Calculate frequencies

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(total = n()) %>%
  mutate(freq = total / sum(total),
           pct = round((freq*100), 1))
```

```
## # A tibble: 24 × 5
## # Groups:   bigregion [4]
##    bigregion religion   total    freq   pct
##    <fct>     <fct>      <int>   <dbl> <dbl>
##  1 Northeast Protestant   158 0.324    32.4
##  2 Northeast Catholic     162 0.332    33.2
##  3 Northeast Jewish        27 0.0553    5.5
##  4 Northeast None         112 0.230    23
##  5 Northeast Other         28 0.0574    5.7
##  6 Northeast <NA>           1 0.00205   0.2
##  7 Midwest   Protestant   325 0.468    46.8
##  8 Midwest   Catholic     172 0.247    24.7
##  9 Midwest   Jewish         3 0.00432   0.4
## 10 Midwest   None         157 0.226    22.6
## # … with 14 more rows
```

The function `n()` counts up the rows

Calculate frequencies

```r
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(total = n()) %>%
  mutate(freq = total / sum(total),
         pct = round((freq*100), 1))
```

```
## # A tibble: 24 × 5
## # Groups:   bigregion [4]
##    bigregion religion   total    freq   pct
##    <fct>     <fct>      <int>   <dbl> <dbl>
##  1 Northeast Protestant   158 0.324    32.4
##  2 Northeast Catholic     162 0.332    33.2
##  3 Northeast Jewish        27 0.0553    5.5
##  4 Northeast None         112 0.230    23  
##  5 Northeast Other         28 0.0574    5.7
##  6 Northeast <NA>           1 0.00205   0.2
##  7 Midwest   Protestant   325 0.468    46.8
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##  9 Midwest   Jewish         3 0.00432   0.4
## 10 Midwest   None         157 0.226    22.6
## # … with 14 more rows
```

The function `n()` counts up the rows

Which rows? The ones fed down the pipeline

Calculate frequencies

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(total = n()) %>%
  mutate(freq = total / sum(total),
         pct = round((freq*100), 1))
```

```
## # A tibble: 24 × 5
## # Groups:   bigregion [4]
##    bigregion religion   total    freq   pct
##    <fct>     <fct>      <int>   <dbl> <dbl>
##  1 Northeast Protestant   158 0.324    32.4
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## 10 Midwest   None         157 0.226    22.6
## # … with 14 more rows
```

The function `n()` counts up the rows

Which rows? The ones fed down the pipeline

The *innermost* (i.e. the rightmost) group.

Pipelines carry assumptions forward

```r
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(total = n()) %>%
  mutate(freq = total / sum(total),
         pct = round((freq*100), 1))
```

```
## # A tibble: 24 × 5
## # Groups:   bigregion [4]
##    bigregion religion   total    freq   pct
##    <fct>     <fct>      <int>   <dbl> <dbl>
##  1 Northeast Protestant   158 0.324    32.4
##  2 Northeast Catholic     162 0.332    33.2
##  3 Northeast Jewish        27 0.0553    5.5
##  4 Northeast None         112 0.230    23  
##  5 Northeast Other         28 0.0574    5.7
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##  7 Midwest   Protestant   325 0.468    46.8
##  8 Midwest   Catholic     172 0.247    24.7
##  9 Midwest   Jewish         3 0.00432   0.4
## 10 Midwest   None         157 0.226    22.6
## # … with 14 more rows
```

Groups are carried forward till summarized or explicitly ungrouped

Pipelines carry assumptions forward

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(total = n()) %>%
  mutate(freq = total / sum(total),
         pct = round((freq*100), 1))
```

```
## # A tibble: 24 × 5
## # Groups:   bigregion [4]
##    bigregion religion   total    freq   pct
##    <fct>     <fct>      <int>   <dbl> <dbl>
##  1 Northeast Protestant   158 0.324    32.4
##  2 Northeast Catholic     162 0.332    33.2
##  3 Northeast Jewish        27 0.0553    5.5
##  4 Northeast None         112 0.230    23  
##  5 Northeast Other         28 0.0574    5.7
##  6 Northeast <NA>           1 0.00205   0.2
##  7 Midwest   Protestant   325 0.468    46.8
##  8 Midwest   Catholic     172 0.247    24.7
##  9 Midwest   Jewish         3 0.00432   0.4
## 10 Midwest   None         157 0.226    22.6
## # … with 14 more rows
```

Groups are carried forward till summarized or explicitly ungrouped

Summary calculations are done on the innermost group, which then "disappears". (Notice how it's no longer a group in the output.)

Pipelines carry assumptions forward

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(total = n()) %>%
  mutate(freq = total / sum(total),
         pct = round((freq*100), 1))
```

```
## # A tibble: 24 × 5
## # Groups:   bigregion [4]
##    bigregion religion   total    freq   pct
##    <fct>     <fct>      <int>   <dbl> <dbl>
##  1 Northeast Protestant   158 0.324    32.4
##  2 Northeast Catholic     162 0.332    33.2
##  3 Northeast Jewish        27 0.0553    5.5
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##  6 Northeast <NA>           1 0.00205   0.2
##  7 Midwest   Protestant   325 0.468    46.8
##  8 Midwest   Catholic     172 0.247    24.7
##  9 Midwest   Jewish         3 0.00432   0.4
## 10 Midwest   None         157 0.226    22.6
## # … with 14 more rows
```

`mutate()` is quite clever. See how we can immediately use **`freq`**, even though we are creating it in the same **`mutate()`** expression.

Convenience functions

```r
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(total = n()) %>%
  mutate(freq = total / sum(total),
         pct = round((freq*100), 1))
```

```
## # A tibble: 24 × 5
## # Groups:   bigregion [4]
##    bigregion religion   total    freq   pct
##    <fct>     <fct>      <int>   <dbl> <dbl>
##  1 Northeast Protestant   158 0.324    32.4
##  2 Northeast Catholic     162 0.332    33.2
##  3 Northeast Jewish        27 0.0553    5.5
##  4 Northeast None         112 0.230    23  
##  5 Northeast Other         28 0.0574    5.7
##  6 Northeast <NA>           1 0.00205   0.2
##  7 Midwest   Protestant   325 0.468    46.8
##  8 Midwest   Catholic     172 0.247    24.7
##  9 Midwest   Jewish         3 0.00432   0.4
## 10 Midwest   None         157 0.226    22.6
## # … with 14 more rows
```

We're going to be doing this `group_by()` ... `n()` step a lot. Some shorthand for it would be useful.

Three options for counting up rows

Do it yourself with `n()`

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(n = n())
```

```
## # A tibble: 24 × 3
## # Groups:   bigregion [4]
##    bigregion religion        n
##    <fct>     <fct>       <int>
##  1 Northeast Protestant    158
##  2 Northeast Catholic      162
##  3 Northeast Jewish         27
##  4 Northeast None          112
##  5 Northeast Other          28
##  6 Northeast <NA>            1
##  7 Midwest   Protestant    325
##  8 Midwest   Catholic      172
##  9 Midwest   Jewish          3
## 10 Midwest   None          157
## # … with 14 more rows
```

Result is a grouped tibble.

Three options for counting up rows

Do it yourself with `n()`

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(n = n())
```

```
## # A tibble: 24 × 3
## # Groups:   bigregion [4]
##    bigregion religion       n
##    <fct>     <fct>      <int>
##  1 Northeast Protestant   158
##  2 Northeast Catholic     162
##  3 Northeast Jewish        27
##  4 Northeast None         112
##  5 Northeast Other         28
##  6 Northeast <NA>           1
##  7 Midwest   Protestant   325
##  8 Midwest   Catholic     172
##  9 Midwest   Jewish         3
## 10 Midwest   None         157
## # … with 14 more rows
```

Result is a grouped tibble.

use `tally()`

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  tally()
```

```
## # A tibble: 24 × 3
## # Groups:   bigregion [4]
##    bigregion religion       n
##    <fct>     <fct>      <int>
##  1 Northeast Protestant   158
##  2 Northeast Catholic     162
##  3 Northeast Jewish        27
##  4 Northeast None         112
##  5 Northeast Other         28
##  6 Northeast <NA>           1
##  7 Midwest   Protestant   325
##  8 Midwest   Catholic     172
##  9 Midwest   Jewish         3
## 10 Midwest   None         157
## # … with 14 more rows
```

Group it yourself; result is grouped.

Three options for counting up rows

Do it yourself with `n()`

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(n = n())
```

```
## # A tibble: 24 × 3
## # Groups:   bigregion [4]
##    bigregion religion       n
##    <fct>     <fct>      <int>
##  1 Northeast Protestant   158
##  2 Northeast Catholic     162
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##  6 Northeast <NA>           1
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##  9 Midwest   Jewish         3
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## # … with 14 more rows
```

Result is a grouped tibble.

use `tally()`

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  tally()
```

```
## # A tibble: 24 × 3
## # Groups:   bigregion [4]
##    bigregion religion       n
##    <fct>     <fct>      <int>
##  1 Northeast Protestant   158
##  2 Northeast Catholic     162
##  3 Northeast Jewish        27
##  4 Northeast None         112
##  5 Northeast Other         28
##  6 Northeast <NA>           1
##  7 Midwest   Protestant   325
##  8 Midwest   Catholic     172
##  9 Midwest   Jewish         3
## 10 Midwest   None         157
## # … with 14 more rows
```

Group it yourself; result is grouped.

use `count()`

```
gss_sm %>%
  count(bigregion, religion)
```

```
## # A tibble: 24 × 3
##    bigregion religion       n
##    <fct>     <fct>      <int>
##  1 Northeast Protestant   158
##  2 Northeast Catholic     162
##  3 Northeast Jewish        27
##  4 Northeast None         112
##  5 Northeast Other         28
##  6 Northeast <NA>           1
##  7 Midwest   Protestant   325
##  8 Midwest   Catholic     172
##  9 Midwest   Jewish         3
## 10 Midwest   None         157
## # … with 14 more rows
```

One step; result is not grouped.

Pass your pipeline on to ... a **table**

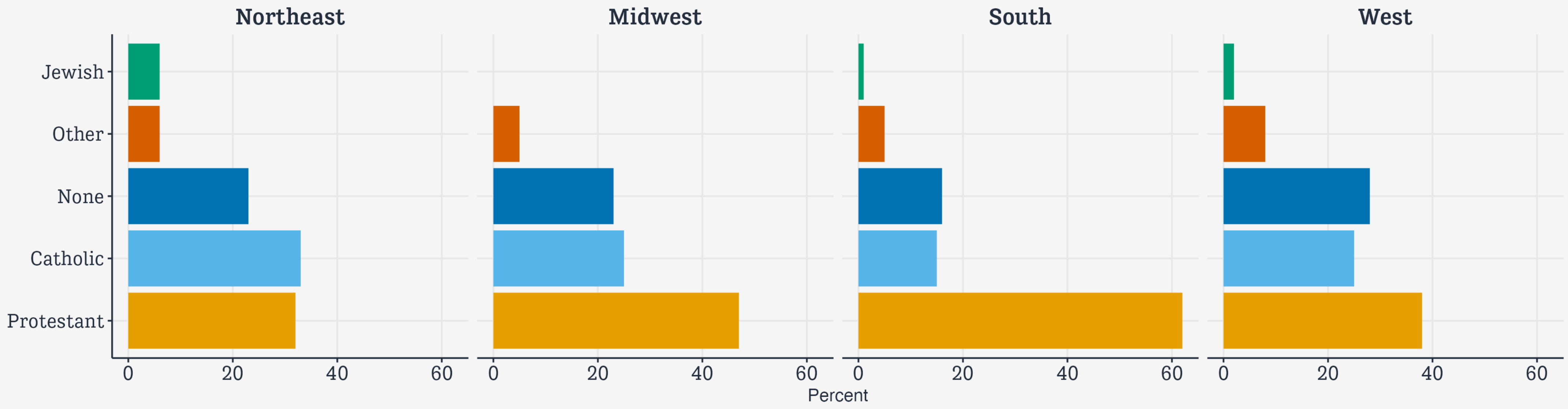
```
gss_sm %>%
  count(bigregion, religion) %>%
  pivot_wider(names_from = bigregion, values_from = n) %>%
  kable()
```

religion	Northeast	Midwest	South	West
Protestant	158	325	650	238
Catholic	162	172	160	155
Jewish	27	3	11	10
None	112	157	170	180
Other	28	33	50	48
NA	1	5	11	1

More on `pivot_wider()` and `kable()` soon ...

Pass your pipeline on to ... a graph

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  tally() %>%
  mutate(pct = round((n/sum(n))*100), 1) %>%
  drop_na() %>%
  ggplot(mapping = aes(x = pct, y = reorder(religion, -pct), fill = religion)) +
  geom_col() +
    labs(x = "Percent", y = NULL) +
    guides(fill = "none") +
    facet_wrap(~ bigregion, nrow = 1)
```



Pass your pipeline on to ... an object

You can do it like this ...

```
rel_by_region <- gss_sm %>%
  count(bigregion, religion) %>%
  mutate(pct = round((n/sum(n))*100, 1))

rel_by_region
```

```
## # A tibble: 24 × 4
##    bigregion religion       n   pct
##    <fct>     <fct>      <int> <dbl>
##  1 Northeast Protestant   158   5.5
##  2 Northeast Catholic     162   5.7
##  3 Northeast Jewish        27   0.9
##  4 Northeast None         112   3.9
##  5 Northeast Other         28   1
##  6 Northeast <NA>           1   0
##  7 Midwest   Protestant   325  11.3
##  8 Midwest   Catholic     172   6
##  9 Midwest   Jewish         3   0.1
## 10 Midwest   None         157   5.5
## # … with 14 more rows
```

Pass your pipeline on to ... an object

You can do it like this ...

```
rel_by_region <- gss_sm %>%
  count(bigregion, religion) %>%
  mutate(pct = round((n/sum(n))*100, 1))

rel_by_region
```

```
## # A tibble: 24 × 4
##    bigregion religion       n   pct
##    <fct>     <fct>      <int> <dbl>
##  1 Northeast Protestant   158   5.5
##  2 Northeast Catholic     162   5.7
##  3 Northeast Jewish        27   0.9
##  4 Northeast None         112   3.9
##  5 Northeast Other         28   1
##  6 Northeast <NA>           1   0
##  7 Midwest   Protestant   325  11.3
##  8 Midwest   Catholic     172   6
##  9 Midwest   Jewish         3   0.1
## 10 Midwest   None         157   5.5
## # … with 14 more rows
```

Or like this!

```
gss_sm %>%
  count(bigregion, religion) %>%
  mutate(pct = round((n/sum(n))*100, 1)) ->
rel_by_region

rel_by_region
```

```
## # A tibble: 24 × 4
##    bigregion religion       n   pct
##    <fct>     <fct>      <int> <dbl>
##  1 Northeast Protestant   158   5.5
##  2 Northeast Catholic     162   5.7
##  3 Northeast Jewish        27   0.9
##  4 Northeast None         112   3.9
##  5 Northeast Other         28   1
##  6 Northeast <NA>           1   0
##  7 Midwest   Protestant   325  11.3
##  8 Midwest   Catholic     172   6
##  9 Midwest   Jewish         3   0.1
## 10 Midwest   None         157   5.5
## # … with 14 more rows
```

Right assignmment is a thing, like Left

Left assignment is standard

```
gss_tab <- gss_sm %>%
  count(bigregion, religion)
```

This may feel awkward with a pipe: "`gss_tab` *gets* the output of the following pipeline."

Right assignmment is a thing, like Left

Left assignment is standard

```
gss_tab <- gss_sm %>%
  count(bigregion, religion)
```

This may feel awkward with a pipe: "`gss_tab` *gets* the output of the following pipeline."

Right assignment also works!

```
gss_sm %>%
  count(bigregion, religion) -> gss_tab
```

Without any authority, I assert that right-assignment should be read as, e.g., "This pipeline *begets* `gss_tab`"

Pipelined tables can be quickly checked

```
rel_by_region <- gss_sm %>%
  count(bigregion, religion) %>%
  mutate(pct = round((n/sum(n))*100, 1))

rel_by_region
```

```
## # A tibble: 24 × 4
##    bigregion religion        n   pct
##    <fct>     <fct>       <int> <dbl>
##  1 Northeast Protestant    158   5.5
##  2 Northeast Catholic      162   5.7
##  3 Northeast Jewish         27   0.9
##  4 Northeast None          112   3.9
##  5 Northeast Other          28   1
##  6 Northeast <NA>            1   0
##  7 Midwest   Protestant    325  11.3
##  8 Midwest   Catholic      172   6
##  9 Midwest   Jewish          3   0.1
## 10 Midwest   None          157   5.5
## # … with 14 more rows
```

Hm, did I sum over right group?

Pipelined tables can be quickly checked

```r
rel_by_region <- gss_sm %>%
  count(bigregion, religion) %>%
  mutate(pct = round((n/sum(n))*100, 1))

rel_by_region
```

```
## # A tibble: 24 × 4
##    bigregion religion        n   pct
##    <fct>     <fct>       <int> <dbl>
##  1 Northeast Protestant    158   5.5
##  2 Northeast Catholic      162   5.7
##  3 Northeast Jewish         27   0.9
##  4 Northeast None          112   3.9
##  5 Northeast Other          28   1
##  6 Northeast <NA>            1   0
##  7 Midwest   Protestant    325  11.3
##  8 Midwest   Catholic      172   6
##  9 Midwest   Jewish          3   0.1
## 10 Midwest   None          157   5.5
## # … with 14 more rows
```

Hm, did I sum over right group?

```r
## Each region should sum to ~100
rel_by_region %>%
  group_by(bigregion) %>%
  summarize(total = sum(pct))
```

```
## # A tibble: 4 × 2
##   bigregion total
##   <fct>     <dbl>
## 1 Northeast  17
## 2 Midwest    24.3
## 3 South      36.7
## 4 West       22
```

No! What has gone wrong here?

Pipelined tables can be quickly checked

```
rel_by_region <- gss_sm %>%
  count(bigregion, religion) %>%
  mutate(pct = round((n/sum(n))*100, 1))
```

`count()` returns ungrouped results, so there are no groups carry forward to the `mutate()` step.

```
rel_by_region %>%
  summarize(total = sum(pct))
```

```
## # A tibble: 1 × 1
##   total
##   <dbl>
## 1   100
```

With `count()`, the `pct` values here are the marginals for the whole table.

Pipelined tables can be quickly checked

```
rel_by_region <- gss_sm %>%
  count(bigregion, religion) %>%
  mutate(pct = round((n/sum(n))*100, 1))
```

`count()` returns ungrouped results, so there are no groups carry forward to the `mutate()` step.

```
rel_by_region %>%
  summarize(total = sum(pct))
```

```
## # A tibble: 1 × 1
##   total
##   <dbl>
## 1   100
```

With `count()`, the `pct` values here are the marginals for the whole table.

```
rel_by_region <- gss_sm %>%
  group_by(bigregion, religion) %>%
  tally() %>%
  mutate(pct = round((n/sum(n))*100, 1))
```

```
# Check
rel_by_region %>%
  group_by(bigregion) %>%
  summarize(total = sum(pct))
```

```
## # A tibble: 4 × 2
##   bigregion total
##   <fct>     <dbl>
## 1 Northeast 100
## 2 Midwest    99.9
## 3 South     100
## 4 West      100.
```

We get some rounding error because we used `round()` after summing originally.

Two lessons

Check your tables!

Pipelines feed their content forward, so you need to make sure your results are not incorrect.

Two lessons

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Often, complex tables and graphs can be disturbingly plausible even when wrong.

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Often, complex tables and graphs can be disturbingly plausible even when wrong.

So, figure out what the result should be and test it!

Two lessons

Check your tables!

Pipelines feed their content forward, so you need to make sure your results are not incorrect.

Often, complex tables and graphs can be disturbingly plausible even when wrong.

So, figure out what the result should be and test it!

Starting with simple or toy cases can help with this process.

Two lessons

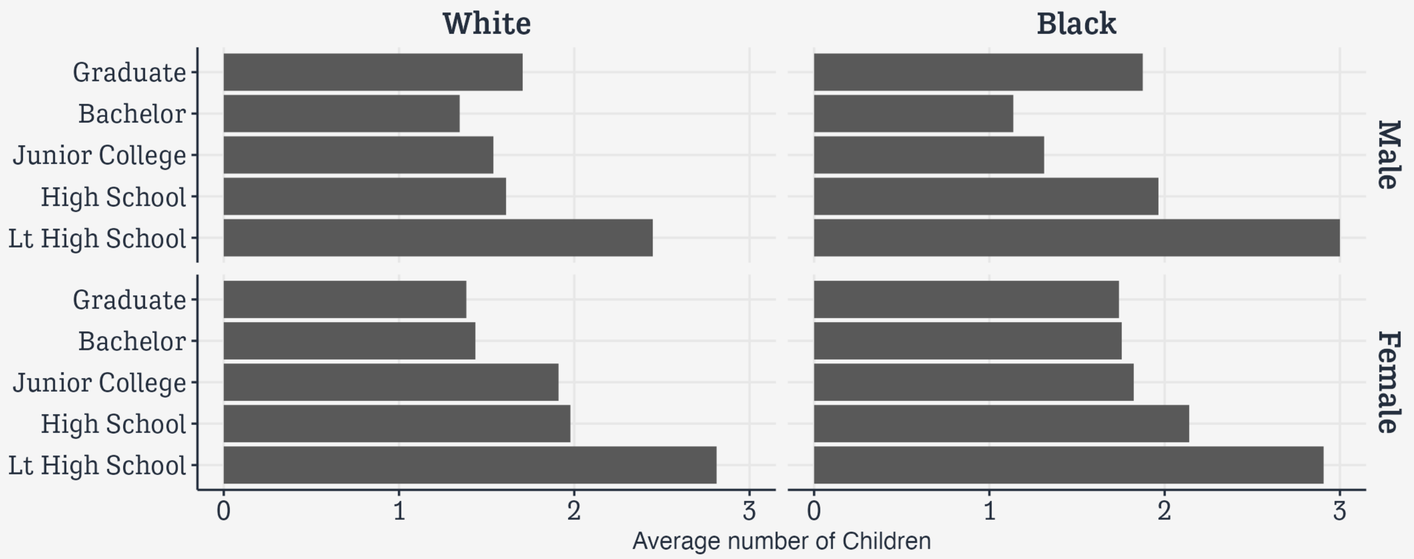
Inspect your pipes!

Understand pipelines by running them forward or peeling them back a step at a time.

This is a *very* effective way to understand your own and other people's code.

Following a pipeline

```
gss_sm %>%
  group_by(race, sex, degree) %>%
  summarize(n = n(),
            mean_age = mean(age, na.rm = TRUE),
            mean_kids = mean(childs, na.rm = TRUE)) %>%
  mutate(pct = n/sum(n)*100) %>%
  filter(race !="Other") %>%
  drop_na() %>%
  ggplot(mapping = aes(x = mean_kids, y = degree)) + # I'm sorry I can't talk more about the graphs
  geom_col() + facet_grid(sex ~ race) +
  labs(x = "Average number of Children", y = NULL)
```



Following a pipeline

```
gss_sm
```

```
## # A tibble: 2,867 × 32
##     year    id ballot       age childs sibs   degree race  sex   region inco
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $170
##  2  2016     2 2             61      0 3      High … White Male  New E… $500
##  3  2016     3 3             72      2 3      Bache… White Male  New E… $750
##  4  2016     4 1             43      4 3      High … White Fema… New E… $170
##  5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170
##  6  2016     6 2             53      2 2      Junio… White Fema… New E… $600
##  7  2016     7 1             50      2 2      High … White Male  New E… $170
##  8  2016     8 3             23      3 6      High … Other Fema… Middl… $300
##  9  2016     9 1             45      3 5      High … Black Male  Middl… $600
## 10  2016    10 3             71      4 1      Junio… White Male  Middl… $600
## # … with 2,857 more rows, and 21 more variables: relig <fct>, marital <fct>,
## #   padeg <fct>, madeg <fct>, partyid <fct>, polviews <fct>, happy <fct>,
## #   partners <fct>, grass <fct>, zodiac <fct>, pres12 <labelled>,
## #   wtssall <dbl>, income_rc <fct>, agegrp <fct>, ageq <fct>, siblings <fct
## #   kids <fct>, religion <fct>, bigregion <fct>, partners_rc <fct>, obama <
```

Following a pipeline

```
gss_sm %>%
  group_by(race, sex, degree)
```

```
## # A tibble: 2,867 × 32
## # Groups:   race, sex, degree [34]
##     year    id ballot       age childs sibs   degree race  sex   region inco
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $170
##  2  2016     2 2             61      0 3      High … White Male  New E… $500
##  3  2016     3 3             72      2 3      Bache… White Male  New E… $750
##  4  2016     4 1             43      4 3      High … White Fema… New E… $170
##  5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170
##  6  2016     6 2             53      2 2      Junio… White Fema… New E… $600
##  7  2016     7 1             50      2 2      High … White Male  New E… $170
##  8  2016     8 3             23      3 6      High … Other Fema… Middl… $300
##  9  2016     9 1             45      3 5      High … Black Male  Middl… $600
## 10  2016    10 3             71      4 1      Junio… White Male  Middl… $600
## # … with 2,857 more rows, and 21 more variables: relig <fct>, marital <fct>,
## #   padeg <fct>, madeg <fct>, partyid <fct>, polviews <fct>, happy <fct>,
## #   partners <fct>, grass <fct>, zodiac <fct>, pres12 <labelled>,
## #   wtssall <dbl>, income_rc <fct>, agegrp <fct>, ageq <fct>, siblings <fct
## #   kids <fct>, religion <fct>, bigregion <fct>, partners_rc <fct>, obama <d
```

Following a pipeline

```r
gss_sm %>%
  group_by(race, sex, degree) %>%
  summarize(n = n(),
            mean_age = mean(age, na.rm = TRUE),
            mean_kids = mean(childs, na.rm = TRUE)
```

```
## # A tibble: 34 × 6
## # Groups:   race, sex [6]
##    race  sex    degree             n mean_age mean_kids
##    <fct> <fct>  <fct>          <int>    <dbl>     <dbl>
##  1 White Male   Lt High School    96     52.9      2.45
##  2 White Male   High School      470     48.8      1.61
##  3 White Male   Junior College    65     47.1      1.54
##  4 White Male   Bachelor         208     48.6      1.35
##  5 White Male   Graduate         112     56.0      1.71
##  6 White Female Lt High School   101     55.4      2.81
##  7 White Female High School      587     51.9      1.98
##  8 White Female Junior College   101     48.2      1.91
##  9 White Female Bachelor         218     49.2      1.44
## 10 White Female Graduate         138     53.6      1.38
## # … with 24 more rows
```

Following a pipeline

```r
gss_sm %>%
  group_by(race, sex, degree) %>%
  summarize(n = n(),
            mean_age = mean(age, na.rm = TRUE),
            mean_kids = mean(childs, na.rm = TRUE)
  mutate(pct = n/sum(n)*100)
```

```
## # A tibble: 34 × 7
## # Groups:   race, sex [6]
##    race  sex    degree             n mean_age mean_kids   pct
##    <fct> <fct>  <fct>          <int>    <dbl>     <dbl> <dbl>
##  1 White Male   Lt High School    96     52.9      2.45 10.1
##  2 White Male   High School      470     48.8      1.61 49.4
##  3 White Male   Junior College    65     47.1      1.54  6.83
##  4 White Male   Bachelor         208     48.6      1.35 21.9
##  5 White Male   Graduate         112     56.0      1.71 11.8
##  6 White Female Lt High School   101     55.4      2.81  8.79
##  7 White Female High School      587     51.9      1.98 51.1
##  8 White Female Junior College   101     48.2      1.91  8.79
##  9 White Female Bachelor         218     49.2      1.44 19.0
## 10 White Female Graduate         138     53.6      1.38 12.0
## # … with 24 more rows
```

Following a pipeline

```
gss_sm %>%
  group_by(race, sex, degree) %>%
  summarize(n = n(),
            mean_age = mean(age, na.rm = TRUE),
            mean_kids = mean(childs, na.rm = TRUE)
  mutate(pct = n/sum(n)*100) %>%
  filter(race !="Other")
```

```
## # A tibble: 23 × 7
## # Groups:   race, sex [4]
##    race  sex    degree             n mean_age mean_kids   pct
##    <fct> <fct>  <fct>          <int>    <dbl>     <dbl> <dbl>
##  1 White Male   Lt High School    96     52.9      2.45 10.1
##  2 White Male   High School      470     48.8      1.61 49.4
##  3 White Male   Junior College    65     47.1      1.54  6.83
##  4 White Male   Bachelor         208     48.6      1.35 21.9
##  5 White Male   Graduate         112     56.0      1.71 11.8
##  6 White Female Lt High School   101     55.4      2.81  8.79
##  7 White Female High School      587     51.9      1.98 51.1
##  8 White Female Junior College   101     48.2      1.91  8.79
##  9 White Female Bachelor         218     49.2      1.44 19.0
## 10 White Female Graduate         138     53.6      1.38 12.0
## # … with 13 more rows
```

Following a pipeline

```r
gss_sm %>%
  group_by(race, sex, degree) %>%
  summarize(n = n(),
            mean_age = mean(age, na.rm = TRUE),
            mean_kids = mean(childs, na.rm = TRUE)
  mutate(pct = n/sum(n)*100) %>%
  filter(race !="Other") %>%
  drop_na()
```

```
## # A tibble: 20 × 7
## # Groups:   race, sex [4]
##    race  sex    degree             n mean_age mean_kids   pct
##    <fct> <fct>  <fct>          <int>    <dbl>     <dbl> <dbl>
##  1 White Male   Lt High School    96     52.9      2.45 10.1
##  2 White Male   High School      470     48.8      1.61 49.4
##  3 White Male   Junior College    65     47.1      1.54  6.83
##  4 White Male   Bachelor         208     48.6      1.35 21.9
##  5 White Male   Graduate         112     56.0      1.71 11.8
##  6 White Female Lt High School   101     55.4      2.81  8.79
##  7 White Female High School      587     51.9      1.98 51.1
##  8 White Female Junior College   101     48.2      1.91  8.79
##  9 White Female Bachelor         218     49.2      1.44 19.0
## 10 White Female Graduate         138     53.6      1.38 12.0
## 11 Black Male   Lt High School    17     56.1      3     8.21
## 12 Black Male   High School      142     43.6      1.96 68.6
## 13 Black Male   Junior College    16     47.1      1.31  7.73
## 14 Black Male   Bachelor          22     41.6      1.14 10.6
## 15 Black Male   Graduate           8     53.1      1.88  3.86
## 16 Black Female Lt High School    43     51.0      2.91 15.2
## 17 Black Female High School      150     43.1      2.14 53.0
## 18 Black Female Junior College    17     45.8      1.82  6.01
## 19 Black Female Bachelor          49     47.0      1.76 17.3
## 20 Black Female Graduate          23     51.2      1.74  8.13
```

Following a pipeline

```r
gss_sm %>%
  group_by(race, sex, degree) %>%
  summarize(n = n(),
            mean_age = mean(age, na.rm = TRUE),
            mean_kids = mean(childs, na.rm = TRUE)
  mutate(pct = n/sum(n)*100) %>%
  filter(race !="Other") %>%
  drop_na() %>%
  summarize(grp_totpct = sum(pct))
```

```
## # A tibble: 4 × 3
## # Groups:   race [2]
##   race  sex    grp_totpct
##   <fct> <fct>       <dbl>
## 1 White Male        100
## 2 White Female       99.7
## 3 Black Male         99.0
## 4 Black Female       99.6
```

Conditionals in `select()` and `filter()`

Some new data, this time on national rates of cadaveric organ donation:

```
# library(socviz)
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>
```

Conditionals in `select()` and `filter()`

```
organdata %>%
  filter(consent_law == "Informed" & donors > 15)
```

```
## # A tibble: 30 × 21
##    country year       donors   pop pop_dens   gdp gdp_lag health health_lag
##    <chr>   <date>      <dbl> <int>    <dbl> <int>   <int>  <dbl>      <dbl>
##  1 Canada  2000-01-01   15.3 30770    0.309 28472   26658   2541       2400
##  2 Denmark 1992-01-01   16.1  5171   12.0   19644   19126   1660       1603
##  3 Ireland 1991-01-01   19    3534    5.03  13495   12917    884        791
##  4 Ireland 1992-01-01   19.5  3558    5.06  14241   13495   1005        884
##  5 Ireland 1993-01-01   17.1  3576    5.09  14927   14241   1041       1005
##  6 Ireland 1994-01-01   20.3  3590    5.11  15990   14927   1119       1041
##  7 Ireland 1995-01-01   24.6  3609    5.14  17789   15990   1208       1119
##  8 Ireland 1996-01-01   16.8  3636    5.17  19245   17789   1269       1208
##  9 Ireland 1997-01-01   20.9  3673    5.23  22017   19245   1417       1269
## 10 Ireland 1998-01-01   23.8  3715    5.29  23995   22017   1487       1417
## # … with 20 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>
```

Conditionals in `select()` and `filter()`

```
organdata %>%
  select(country, year, where(is.integer))
```

```
## # A tibble: 238 × 8
##    country   year         pop   gdp gdp_lag cerebvas assault external
##    <chr>     <date>     <int> <int>   <int>    <int>   <int>    <int>
##  1 Australia NA         17065 16774   16591      682      21      444
##  2 Australia 1991-01-01 17284 17171   16774      647      19      425
##  3 Australia 1992-01-01 17495 17914   17171      630      17      406
##  4 Australia 1993-01-01 17667 18883   17914      611      18      376
##  5 Australia 1994-01-01 17855 19849   18883      631      17      387
##  6 Australia 1995-01-01 18072 21079   19849      592      16      371
##  7 Australia 1996-01-01 18311 21923   21079      576      17      395
##  8 Australia 1997-01-01 18518 22961   21923      525      17      385
##  9 Australia 1998-01-01 18711 24148   22961      516      16      410
## 10 Australia 1999-01-01 18926 25445   24148      493      15      409
## # … with 228 more rows
```

Use **`where()`** to test columns.

Conditionals in `select()` and `filter()`

When telling `where()` use `is.integer()` to test each column, we don't put parentheses at the end of its name. If we did, R would try to evaluate `is.integer()` right then, and fail:

```
> organdata %>%
+   select(country, year, where(is.integer()))
Error: 0 arguments passed to 'is.integer' which requires 1
Run `rlang::last_error()` to see where the error occurred.
```

This is true in similar situations elsewhere as well.

Conditionals in `select()` and `filter()`

```
organdata %>%
  select(country, year, where(is.character))
```

```
## # A tibble: 238 × 8
##    country  year       world opt   consent_law consent_practice consistent ccode
##    <chr>    <date>     <chr> <chr> <chr>       <chr>            <chr>      <chr>
##  1 Austral… NA         Libe… In    Informed    Informed         Yes        Oz
##  2 Austral… 1991-01-01 Libe… In    Informed    Informed         Yes        Oz
##  3 Austral… 1992-01-01 Libe… In    Informed    Informed         Yes        Oz
##  4 Austral… 1993-01-01 Libe… In    Informed    Informed         Yes        Oz
##  5 Austral… 1994-01-01 Libe… In    Informed    Informed         Yes        Oz
##  6 Austral… 1995-01-01 Libe… In    Informed    Informed         Yes        Oz
##  7 Austral… 1996-01-01 Libe… In    Informed    Informed         Yes        Oz
##  8 Austral… 1997-01-01 Libe… In    Informed    Informed         Yes        Oz
##  9 Austral… 1998-01-01 Libe… In    Informed    Informed         Yes        Oz
## 10 Austral… 1999-01-01 Libe… In    Informed    Informed         Yes        Oz
## # … with 228 more rows
```

We have functions like e.g. **`is.character()`**, **`is.numeric()`**, **`is.logical()`**, **`is.factor()`**, etc. All return either `TRUE` or `FALSE`.

Conditionals in `select()` and `filter()`

Sometimes we don't pass a function, but do want to use the result of one:

```
organdata %>%
  select(country, year, starts_with("gdp"))
```

```
## # A tibble: 238 × 4
##    country   year          gdp gdp_lag
##    <chr>     <date>      <int>   <int>
##  1 Australia NA          16774   16591
##  2 Australia 1991-01-01 17171   16774
##  3 Australia 1992-01-01 17914   17171
##  4 Australia 1993-01-01 18883   17914
##  5 Australia 1994-01-01 19849   18883
##  6 Australia 1995-01-01 21079   19849
##  7 Australia 1996-01-01 21923   21079
##  8 Australia 1997-01-01 22961   21923
##  9 Australia 1998-01-01 24148   22961
## 10 Australia 1999-01-01 25445   24148
## # … with 228 more rows
```

We have **`starts_with()`**, **`ends_with()`**, **`contains()`**, **`matches()`**, and **`num_range()`**. Collectively these are "tidy selectors".

Conditionals in `select()` and `filter()`

```r
organdata %>%
  filter(country == "Australia" | country == "Canada")
```

```
## # A tibble: 28 × 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 18 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>
```

This could get cumbersome fast.

Use %in% for multiple selections

```
my_countries <- c("Australia", "Canada", "United States", "Ireland")

organdata %>%
  filter(country %in% my_countries)
```

```
## # A tibble: 56 × 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 46 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>
```

Negating `%in%`

```r
my_countries <- c("Australia", "Canada", "United States", "Ireland")

organdata %>%
  filter(!(country %in% my_countries))
```

```
## # A tibble: 182 × 21
##    country year       donors   pop pop_dens   gdp gdp_lag health health_lag
##    <chr>   <date>      <dbl> <int>    <dbl> <int>   <int>  <dbl>      <dbl>
##  1 Austria NA           NA    7678     9.16 18914   17425   1344       1255
##  2 Austria 1991-01-01   27.6  7755     9.25 19860   18914   1419       1344
##  3 Austria 1992-01-01   23.1  7841     9.35 20601   19860   1551       1419
##  4 Austria 1993-01-01   26.2  7906     9.43 21119   20601   1674       1551
##  5 Austria 1994-01-01   21.4  7936     9.46 21940   21119   1739       1674
##  6 Austria 1995-01-01   21.5  7948     9.48 22817   21940   1865       1739
##  7 Austria 1996-01-01   24.7  7959     9.49 23798   22817   1986       1865
##  8 Austria 1997-01-01   19.5  7968     9.50 24364   23798   1848       1986
##  9 Austria 1998-01-01   20.7  7977     9.51 25423   24364   1953       1848
## 10 Austria 1999-01-01   25.9  7992     9.53 26513   25423   2069       1953
## # … with 172 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>
```

Also a bit awkward. There's no built-in "Not in" operator.

Negating %in%

We can make one!

```
`%nin%` <- Negate(`%in%`) # this operator is included in the socviz package
```

(The backticks are special here because we need to name an operator.)

Negating `%in%`

We can make one!

```
`%nin%` <- Negate(`%in%`) # this operator is included in the socviz package
```

(The backticks are special here because we need to name an operator.)

```
organdata %>%
  filter(country %nin% my_countries)
```

```
## # A tibble: 182 × 21
##    country year       donors   pop pop_dens   gdp gdp_lag health health_lag
##    <chr>   <date>      <dbl> <int>    <dbl> <int>   <int>  <dbl>      <dbl>
##  1 Austria NA           NA    7678     9.16 18914   17425   1344       1255
##  2 Austria 1991-01-01   27.6  7755     9.25 19860   18914   1419       1344
##  3 Austria 1992-01-01   23.1  7841     9.35 20601   19860   1551       1419
##  4 Austria 1993-01-01   26.2  7906     9.43 21119   20601   1674       1551
##  5 Austria 1994-01-01   21.4  7936     9.46 21940   21119   1739       1674
##  6 Austria 1995-01-01   21.5  7948     9.48 22817   21940   1865       1739
##  7 Austria 1996-01-01   24.7  7959     9.49 23798   22817   1986       1865
##  8 Austria 1997-01-01   19.5  7968     9.50 24364   23798   1848       1986
##  9 Austria 1998-01-01   20.7  7977     9.51 25423   24364   1953       1848
## 10 Austria 1999-01-01   25.9  7992     9.53 26513   25423   2069       1953
## # … with 172 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>
```

Do more than one thing

Earlier we saw this:

```
gss_sm %>%
  group_by(race, sex, degree) %>%
  summarize(n = n(),
            mean_age = mean(age, na.rm = TRUE),
            mean_kids = mean(childs, na.rm = TRUE))
```

```
## # A tibble: 34 × 6
## # Groups:   race, sex [6]
##    race  sex    degree             n mean_age mean_kids
##    <fct> <fct>  <fct>          <int>    <dbl>     <dbl>
##  1 White Male   Lt High School    96     52.9      2.45
##  2 White Male   High School      470     48.8      1.61
##  3 White Male   Junior College    65     47.1      1.54
##  4 White Male   Bachelor         208     48.6      1.35
##  5 White Male   Graduate         112     56.0      1.71
##  6 White Female Lt High School   101     55.4      2.81
##  7 White Female High School      587     51.9      1.98
##  8 White Female Junior College   101     48.2      1.91
##  9 White Female Bachelor         218     49.2      1.44
## 10 White Female Graduate         138     53.6      1.38
## # … with 24 more rows
```

Do more than one thing

Similarly for `organdata` we might want to do:

```
organdata %>%
  group_by(consent_law, country) %>%
  summarize(donors_mean = mean(donors, na.rm = TRUE),
            donors_sd = sd(donors, na.rm = TRUE),
            gdp_mean = mean(gdp, na.rm = TRUE),
            health_mean = mean(health, na.rm = TRUE),
            roads_mean = mean(roads, na.rm = TRUE))
```

```
## # A tibble: 17 × 7
## # Groups:   consent_law [2]
##    consent_law country     donors_mean donors_sd gdp_mean health_mean roads_mean
##    <chr>       <chr>             <dbl>     <dbl>    <dbl>       <dbl>      <dbl>
##  1 Informed    Australia          10.6     1.14    22179.       1958.      105.
##  2 Informed    Canada             14.0     0.751   23711.       2272.      109.
##  3 Informed    Denmark            13.1     1.47    23722.       2054.      102.
##  4 Informed    Germany            13.0     0.611   22163.       2349.      113.
##  5 Informed    Ireland            19.8     2.48    20824.       1480.      118.
##  6 Informed    Netherlands        13.7     1.55    23013.       1993.       76.1
##  7 Informed    United Kin…        13.5     0.775   21359.       1561.       67.9
##  8 Informed    United Sta…        20.0     1.33    29212.       3988.      155.
##  9 Presumed    Austria            23.5     2.42    23876.       1875.      150.
## 10 Presumed    Belgium            21.9     1.94    22500.       1958.      155.
## 11 Presumed    Finland            18.4     1.53    21019.       1615.       93.6
## 12 Presumed    France             16.8     1.60    22603.       2160.      156.
## 13 Presumed    Italy              11.1     4.28    21554.       1757       122.
## 14 Presumed    Norway             15.4     1.11    26448.       2217.       70.0
## 15 Presumed    Spain              28.1     4.96    16933        1289.      161.
## 16 Presumed    Sweden             13.1     1.75    22415.       1951.       72.3
```

Do more than one thing with `across()`

Instead, use `across()` to apply a function to more than one column.

```
my_vars <- c("gdp", "donors", "roads")

## nested parens again, but it's worth it
organdata %>%
  group_by(consent_law, country) %>%
  summarize(across(my_vars,
                   list(avg = mean),
                   na.rm = TRUE))
```

```
## # A tibble: 17 × 5
## # Groups:   consent_law [2]
##    consent_law country        gdp_avg donors_avg roads_avg
##    <chr>       <chr>            <dbl>      <dbl>     <dbl>
##  1 Informed    Australia       22179.       10.6     105.
##  2 Informed    Canada          23711.       14.0     109.
##  3 Informed    Denmark         23722.       13.1     102.
##  4 Informed    Germany         22163.       13.0     113.
##  5 Informed    Ireland         20824.       19.8     118.
##  6 Informed    Netherlands     23013.       13.7      76.1
##  7 Informed    United Kingdom  21359.       13.5      67.9
##  8 Informed    United States   29212.       20.0     155.
##  9 Presumed    Austria         23876.       23.5     150.
## 10 Presumed    Belgium         22500.       21.9     155.
## 11 Presumed    Finland         21019.       18.4      93.6
## 12 Presumed    France          22603.       16.8     156.
## 13 Presumed    Italy           21554.       11.1     122.
## 14 Presumed    Norway          26448.       15.4      70.0
## 15 Presumed    Spain           16933        28.1     161.
```

Let's look at that again

```
my_vars <- c("gdp", "donors", "roads")
```

Let's look at that again

```
my_vars <- c("gdp", "donors", "roads")

## nested parens again, but it's worth it
organdata
```

```
## # A tibble: 238 × 21
##    country   year       donors   pop pop_dens   gdp gdp_lag health health_la
##    <chr>     <date>      <dbl> <int>    <dbl> <int>   <int>  <dbl>      <dbl
##  1 Australia NA          NA    17065    0.220 16774   16591   1300        122
##  2 Australia 1991-01-01  12.1  17284    0.223 17171   16774   1379        130
##  3 Australia 1992-01-01  12.4  17495    0.226 17914   17171   1455        137
##  4 Australia 1993-01-01  12.5  17667    0.228 18883   17914   1540        145
##  5 Australia 1994-01-01  10.2  17855    0.231 19849   18883   1626        154
##  6 Australia 1995-01-01  10.2  18072    0.233 21079   19849   1737        162
##  7 Australia 1996-01-01  10.6  18311    0.237 21923   21079   1846        173
##  8 Australia 1997-01-01  10.3  18518    0.239 22961   21923   1948        184
##  9 Australia 1998-01-01  10.5  18711    0.242 24148   22961   2077        194
## 10 Australia 1999-01-01   8.67 18926    0.244 25445   24148   2231        207
## # … 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>
```

Let's look at that again

```r
my_vars <- c("gdp", "donors", "roads")

## nested parens again, but it's worth it
organdata %>%
  group_by(consent_law, country)
```

```
## # A tibble: 238 × 21
## # Groups:   consent_law, country [17]
##    country   year       donors   pop pop_dens   gdp gdp_lag health health_la
##    <chr>     <date>      <dbl> <int>    <dbl> <int>   <int>  <dbl>      <dbl
##  1 Australia NA          NA    17065    0.220 16774   16591   1300       122
##  2 Australia 1991-01-01  12.1  17284    0.223 17171   16774   1379       130
##  3 Australia 1992-01-01  12.4  17495    0.226 17914   17171   1455       137
##  4 Australia 1993-01-01  12.5  17667    0.228 18883   17914   1540       145
##  5 Australia 1994-01-01  10.2  17855    0.231 19849   18883   1626       154
##  6 Australia 1995-01-01  10.2  18072    0.233 21079   19849   1737       162
##  7 Australia 1996-01-01  10.6  18311    0.237 21923   21079   1846       173
##  8 Australia 1997-01-01  10.3  18518    0.239 22961   21923   1948       184
##  9 Australia 1998-01-01  10.5  18711    0.242 24148   22961   2077       194
## 10 Australia 1999-01-01   8.67 18926    0.244 25445   24148   2231       207
## # … 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>
```

Let's look at that again

```r
my_vars <- c("gdp", "donors", "roads")

## nested parens again, but it's worth it
organdata %>%
  group_by(consent_law, country) %>%
  summarize(across(my_vars,
                   list(avg = mean),
                   na.rm = TRUE))
```

```
## # A tibble: 17 × 5
## # Groups:   consent_law [2]
##    consent_law country        gdp_avg donors_avg roads_avg
##    <chr>       <chr>            <dbl>      <dbl>     <dbl>
##  1 Informed    Australia       22179.       10.6     105. 
##  2 Informed    Canada          23711.       14.0     109. 
##  3 Informed    Denmark         23722.       13.1     102. 
##  4 Informed    Germany         22163.       13.0     113. 
##  5 Informed    Ireland         20824.       19.8     118. 
##  6 Informed    Netherlands     23013.       13.7      76.1
##  7 Informed    United Kingdom  21359.       13.5      67.9
##  8 Informed    United States   29212.       20.0     155. 
##  9 Presumed    Austria         23876.       23.5     150. 
## 10 Presumed    Belgium         22500.       21.9     155. 
## 11 Presumed    Finland         21019.       18.4      93.6
## 12 Presumed    France          22603.       16.8     156. 
## 13 Presumed    Italy           21554.       11.1     122. 
## 14 Presumed    Norway          26448.       15.4      70.0
## 15 Presumed    Spain           16933        28.1     161. 
## 16 Presumed    Sweden          22415.       13.1      72.3
## 17 Presumed    Switzerland     27233        14.2      96.4
```

`my_vars` are selected by `across()`

Let's look at that again

```r
my_vars <- c("gdp", "donors", "roads")

## nested parens again, but it's worth it
organdata %>%
  group_by(consent_law, country) %>%
  summarize(across(my_vars,
                   list(avg = mean),
                   na.rm = TRUE))
```

```
## # A tibble: 17 × 5
## # Groups:   consent_law [2]
##    consent_law country        gdp_avg donors_avg roads_avg
##    <chr>       <chr>            <dbl>      <dbl>     <dbl>
##  1 Informed    Australia       22179.       10.6     105.
##  2 Informed    Canada          23711.       14.0     109.
##  3 Informed    Denmark         23722.       13.1     102.
##  4 Informed    Germany         22163.       13.0     113.
##  5 Informed    Ireland         20824.       19.8     118.
##  6 Informed    Netherlands     23013.       13.7      76.1
##  7 Informed    United Kingdom  21359.       13.5      67.9
##  8 Informed    United States   29212.       20.0     155.
##  9 Presumed    Austria         23876.       23.5     150.
## 10 Presumed    Belgium         22500.       21.9     155.
## 11 Presumed    Finland         21019.       18.4      93.6
## 12 Presumed    France          22603.       16.8     156.
## 13 Presumed    Italy           21554.       11.1     122.
## 14 Presumed    Norway          26448.       15.4      70.0
## 15 Presumed    Spain           16933        28.1     161.
## 16 Presumed    Sweden          22415.       13.1      72.3
## 17 Presumed    Switzerland     27233        14.2      96.4
```

`my_vars` are selected by **`across()`**

`list()` of the form `result = function` gives the new columns that will be calculated.
`na.rm = TRUE` is passed through to the functions inside the `list()`

We can calculate more than one thing

```
my_vars <- c("gdp", "donors", "roads")

organdata %>%
  group_by(consent_law, country) %>%
  summarize(across(my_vars,
                   list(avg = mean,
                        sd = var,
                        md = median),
                   na.rm = TRUE))
```

```
## # A tibble: 17 × 11
## # Groups:   consent_law [2]
##    consent_law country      gdp_avg gdp_sd gdp_md donors_avg donors_sd donors_md
##    <chr>       <chr>          <dbl>  <dbl>  <int>      <dbl>     <dbl>     <dbl>
##  1 Informed    Australia     22179. 1.57e7  21923       10.6     1.31       10.4
##  2 Informed    Canada        23711. 1.57e7  22764       14.0     0.564      14.0
##  3 Informed    Denmark       23722. 1.52e7  23548       13.1     2.16       12.9
##  4 Informed    Germany       22163. 6.26e6  22164       13.0     0.374      13
##  5 Informed    Ireland       20824. 4.45e7  19245       19.8     6.14       19.2
##  6 Informed    Netherlands   23013. 1.42e7  22541       13.7     2.41       13.8
##  7 Informed    United King…  21359. 1.54e7  20839       13.5     0.601      13.5
##  8 Informed    United Stat…  29212. 2.09e7  28772       20.0     1.76       20.1
##  9 Presumed    Austria       23876. 1.12e7  23798       23.5     5.84       23.8
## 10 Presumed    Belgium       22500. 1.01e7  22152       21.9     3.75       21.4
## 11 Presumed    Finland       21019. 1.35e7  19842       18.4     2.33       19.4
## 12 Presumed    France        22603. 1.06e7  21990       16.8     2.55       16.6
## 13 Presumed    Italy         21554. 7.74e6  21396       11.1    18.3        11.3
## 14 Presumed    Norway        26448. 4.21e7  26218       15.4     1.23       15.4
## 15 Presumed    Spain         16933  8.34e6  16416       28.1    24.6        28
## 16 Presumed    Sweden        22415. 1.03e7  22029       13.1     3.07       12.7
```

It's OK to use the function names

```r
my_vars <- c("gdp", "donors", "roads")

organdata %>%
  group_by(consent_law, country) %>%
  summarize(across(my_vars,
                   list(mean = mean,
                        var = var,
                        median = median),
                   na.rm = TRUE))
```

```
## # A tibble: 17 × 11
## # Groups:   consent_law [2]
##    consent_law country        gdp_mean gdp_var gdp_median donors_mean donors_var
##    <chr>       <chr>             <dbl>   <dbl>      <int>       <dbl>      <dbl>
##  1 Informed    Australia        22179.  1.57e7      21923        10.6      1.31
##  2 Informed    Canada           23711.  1.57e7      22764        14.0      0.564
##  3 Informed    Denmark          23722.  1.52e7      23548        13.1      2.16
##  4 Informed    Germany          22163.  6.26e6      22164        13.0      0.374
##  5 Informed    Ireland          20824.  4.45e7      19245        19.8      6.14
##  6 Informed    Netherlands      23013.  1.42e7      22541        13.7      2.41
##  7 Informed    United Kingdom   21359.  1.54e7      20839        13.5      0.601
##  8 Informed    United States    29212.  2.09e7      28772        20.0      1.76
##  9 Presumed    Austria          23876.  1.12e7      23798        23.5      5.84
## 10 Presumed    Belgium          22500.  1.01e7      22152        21.9      3.75
## 11 Presumed    Finland          21019.  1.35e7      19842        18.4      2.33
## 12 Presumed    France           22603.  1.06e7      21990        16.8      2.55
## 13 Presumed    Italy            21554.  7.74e6      21396        11.1     18.3
## 14 Presumed    Norway           26448.  4.21e7      26218        15.4      1.23
## 15 Presumed    Spain            16933   8.34e6      16416        28.1     24.6
## 16 Presumed    Sweden           22415.  1.03e7      22029        13.1      3.07
```

Selection with `across(where())`

```r
organdata %>%
  group_by(consent_law, country) %>%
  summarize(across(where(is.numeric),
                   list(mean = mean,
                        var = var,
                        median = median),
                   na.rm = TRUE)) %>%
    print(n = 3) # just to save slide space
```

```
## # A tibble: 17 × 41
## # Groups:   consent_law [2]
##   consent_law country   donors_mean donors_var donors_median pop_mean  pop_var
##   <chr>       <chr>           <dbl>      <dbl>         <dbl>    <dbl>    <dbl>
## 1 Informed    Australia        10.6      1.31           10.4   18318.  690385.
## 2 Informed    Canada           14.0      0.564          14.0   29608. 1422648.
## 3 Informed    Denmark          13.1      2.16           12.9    5257.    6497.
## # … with 14 more rows, and 34 more variables: pop_median <int>,
## #   pop_dens_mean <dbl>, pop_dens_var <dbl>, pop_dens_median <dbl>,
## #   gdp_mean <dbl>, gdp_var <dbl>, gdp_median <int>, gdp_lag_mean <dbl>,
## #   gdp_lag_var <dbl>, gdp_lag_median <dbl>, health_mean <dbl>,
## #   health_var <dbl>, health_median <dbl>, health_lag_mean <dbl>,
## #   health_lag_var <dbl>, health_lag_median <dbl>, pubhealth_mean <dbl>,
## #   pubhealth_var <dbl>, pubhealth_median <dbl>, roads_mean <dbl>, …
```

Name new columns with `.names`

```r
organdata %>%
  group_by(consent_law, country) %>%
  summarize(across(where(is.numeric),
                   list(mean = mean,
                        var = var,
                        median = median),
                   na.rm = TRUE,
                   .names = "{fn}_{col}")) %>%
  print(n = 3)
```

```
## # A tibble: 17 × 41
## # Groups:   consent_law [2]
##   consent_law country   mean_donors var_donors median_donors mean_pop  var_pop
##   <chr>       <chr>           <dbl>      <dbl>         <dbl>    <dbl>    <dbl>
## 1 Informed    Australia        10.6      1.31           10.4   18318.  690385.
## 2 Informed    Canada           14.0      0.564          14.0   29608. 1422648.
## 3 Informed    Denmark          13.1      2.16           12.9    5257.    6497.
## # … with 14 more rows, and 34 more variables: median_pop <int>,
## #   mean_pop_dens <dbl>, var_pop_dens <dbl>, median_pop_dens <dbl>,
## #   mean_gdp <dbl>, var_gdp <dbl>, median_gdp <int>, mean_gdp_lag <dbl>,
## #   var_gdp_lag <dbl>, median_gdp_lag <dbl>, mean_health <dbl>,
## #   var_health <dbl>, median_health <dbl>, mean_health_lag <dbl>,
## #   var_health_lag <dbl>, median_health_lag <dbl>, mean_pubhealth <dbl>,
## #   var_pubhealth <dbl>, median_pubhealth <dbl>, mean_roads <dbl>, …
```

In tidyverse functions, arguments that begin with a "." generally have it in order to avoid confusion with existing items, or are "pronouns" referring to e.g. "the name of the thing we're currently talking about as we evaluate this function".

This all works with `mutate()`, too

```
organdata %>%
  mutate(across(where(is.character), toupper)) %>%
  select(where(is.character))
```

```
## # A tibble: 238 × 7
##    country   world   opt   consent_law consent_practice consistent ccode
##    <chr>     <chr>   <chr> <chr>       <chr>            <chr>      <chr>
##  1 AUSTRALIA LIBERAL IN    INFORMED    INFORMED         YES        OZ
##  2 AUSTRALIA LIBERAL IN    INFORMED    INFORMED         YES        OZ
##  3 AUSTRALIA LIBERAL IN    INFORMED    INFORMED         YES        OZ
##  4 AUSTRALIA LIBERAL IN    INFORMED    INFORMED         YES        OZ
##  5 AUSTRALIA LIBERAL IN    INFORMED    INFORMED         YES        OZ
##  6 AUSTRALIA LIBERAL IN    INFORMED    INFORMED         YES        OZ
##  7 AUSTRALIA LIBERAL IN    INFORMED    INFORMED         YES        OZ
##  8 AUSTRALIA LIBERAL IN    INFORMED    INFORMED         YES        OZ
##  9 AUSTRALIA LIBERAL IN    INFORMED    INFORMED         YES        OZ
## 10 AUSTRALIA LIBERAL IN    INFORMED    INFORMED         YES        OZ
## # … with 228 more rows
```

Arrange rows and columns

Sort rows with `arrange()`

```
organdata %>%
  group_by(consent_law, country) %>%
  summarize(donors = mean(donors, na.rm = TRUE)) %>%
  arrange(donors) %>% ##<
  print(n = 5)
```

```
## # A tibble: 17 × 3
## # Groups:   consent_law [2]
##   consent_law country   donors
##   <chr>       <chr>      <dbl>
## 1 Informed    Australia   10.6
## 2 Presumed    Italy       11.1
## 3 Informed    Germany     13.0
## 4 Informed    Denmark     13.1
## 5 Presumed    Sweden      13.1
## # … with 12 more rows
```

```
organdata %>%
  group_by(consent_law, country) %>%
  summarize(donors = mean(donors, na.rm = TRUE)) %>%
  arrange(desc(donors)) %>%  ##<
  print(n = 5)
```

```
## # A tibble: 17 × 3
## # Groups:   consent_law [2]
##   consent_law country       donors
##   <chr>       <chr>          <dbl>
## 1 Presumed    Spain           28.1
## 2 Presumed    Austria         23.5
## 3 Presumed    Belgium         21.9
## 4 Informed    United States   20.0
## 5 Informed    Ireland         19.8
## # … with 12 more rows
```

Using `arrange()` to order rows in this way won't respect groupings.

More generally ...

```
organdata %>%
  group_by(consent_law, country) %>%
  summarize(donors = mean(donors, na.rm = TRUE)) %>%
  slice_max(donors, n = 5)
```

```
## # A tibble: 10 × 3
## # Groups:   consent_law [2]
##    consent_law country        donors
##    <chr>       <chr>           <dbl>
##  1 Informed    United States    20.0
##  2 Informed    Ireland          19.8
##  3 Informed    Canada           14.0
##  4 Informed    Netherlands      13.7
##  5 Informed    United Kingdom   13.5
##  6 Presumed    Spain            28.1
##  7 Presumed    Austria          23.5
##  8 Presumed    Belgium          21.9
##  9 Presumed    Finland          18.4
## 10 Presumed    France           16.8
```

You can see that `slice_max()` respects grouping.

There's `slice_min()`, `slice_head()`, `slice_tail()`, `slice_sample()`, and the most general one, `slice()`.