

Manipulating tables with `dplyr`

Data Wrangling, Session 3

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Code Horizons

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dplyr is your toolkit for
tabular data

So let's
play with
some **data**

woohoo!

Load our libraries

```
library(here)      # manage file paths  
library(socviz)    # data and some useful functions  
library(tidyverse) # your friend and mine
```

Tidyverse components, again

```
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`

◀ 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

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.

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's core verbs

dp1yr draws on
the logic and
language of
database queries

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—i.e. remove them before doing anything.

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. Usually this will have the same number of *rows* as there are *groups* being summarized.

For each **action** there's a **function**

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()**.

Group and 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 ...
9  2016     9 1      45     3 5    High ... Black Male  Middl... $60000 ...
10 2016    10 3      71     4 1    Junio... White Male  Middl... $60000 ...

# i 2,857 more rows
# i 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>
```

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

```
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  
# i 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>  
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 ...  
9  2016     9 1      45      3 5  High ... Black Male  Middl... $60000 ...  
10 2016    10 3      71      4 1  Junio... White Male  Middl... $60000 ...  
# i 2,857 more rows  
# i 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>,
```

Grouping just changes the logical structure of the tibble.

Group and summarize by *one* column

```
gss_sm
```

```
# A tibble: 2,867 × 32
  year   id ballot age child 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 ...
9  2016     9 1      45     3 5  High ... Black Male Middl... $60000 ...
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# i 2,857 more rows
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# 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>
```

Group and summarize by *one* column

```
gss_sm ►  
  group_by(bigregion)
```

```
# A tibble: 2,867 × 32  
# Groups:   bigregion [4]  
   year   id ballot   age child 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 ...  
9  2016     9 1      45     3 5   High ... Black Male Middl... $60000 ...  
10 2016    10 3      71     4 1   Junio... White Male Middl... $60000 ...  
# i 2,857 more rows  
# i 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>
```

Group and summarize by *one* column

```
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
```

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 child 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 ...
9  2016     9 1      45    3 5   High ... Black Male Middl... $60000 ...
10 2016    10 3      71    4 1   Junio... White Male Middl... $60000 ...
# i 2,857 more rows
# i 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>
```

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 income16  
   <dbl> <dbl> <labelled> <dbl>   <dbl> <label> <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 ...  
9  2016     9  1         45     3  5  High ... Black Male  Middl... $60000 ...  
10 2016    10  3         71     4  1  Junio... White Male  Middl... $60000 ...  
# i 2,857 more rows  
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# 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>
```

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
# i 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 child 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 ...
9  2016     9 1      45     3 5 High ... Black Male Middl... $60000 ...
10 2016    10 3      71     4 1 Junio... White Male Middl... $60000 ...

# i 2,857 more rows
# i 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>
```

Calculate frequencies

```
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 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 ...  
9  2016     9  1      45     3  5  High ... Black Male  Middl... $60000 ...  
10 2016    10  3      71     4  1  Junio... White Male  Middl... $60000 ...  
# i 2,857 more rows  
# i 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>
```


Calculate frequencies

```
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
# i 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
# i 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

```
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
# i 14 more rows
```

Groups are carried forward till summarized or explicitly ungrouped

Summary calculations are done on the innermost group, which then

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
# i 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

```
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
# i 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

Use `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
# i 14 more rows
```

Group it yourself;
result is grouped.

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
# i 14 more rows
```

More compact;
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
# i 14 more rows
```

One step; result is
not grouped.

Pass results on to ... a **table**

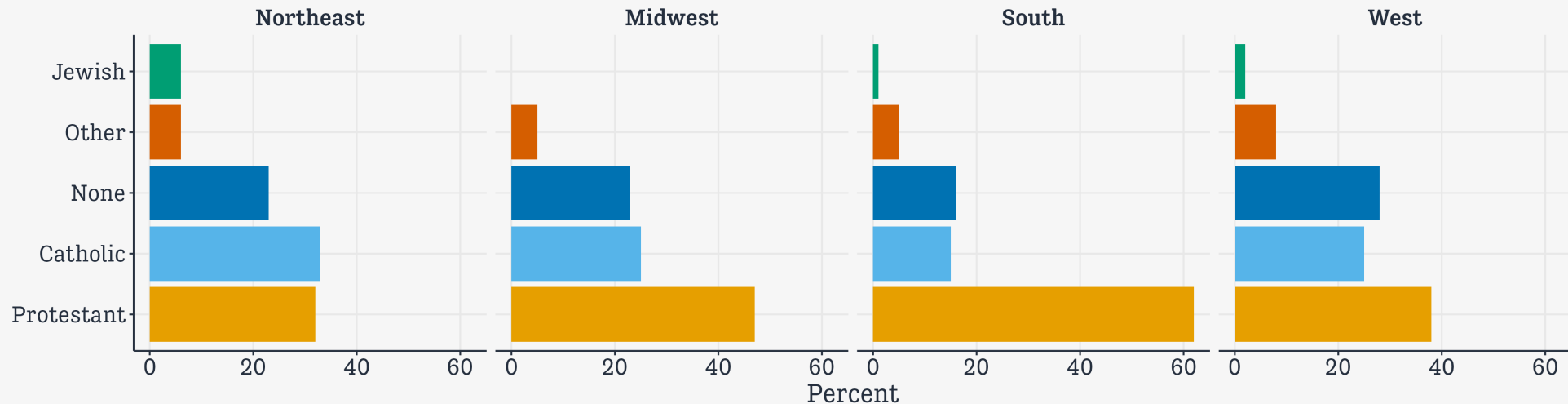
```
gss_sm >
  count(bigregion, religion) >
  pivot_wider(names_from = bigregion, values_from = n) >
  knitr::kable()
```

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 results 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 results 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  
# i 14 more rows
```

Pass results 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  
# i 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  
# i 14 more rows
```

Right assignment 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**”

Check by summarizing

```
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
# i 14 more rows
```

Hm, did I sum over right group?

Check by summarizing

```
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

```
# i 14 more rows
```

```
## 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?

Hm, did I sum over right group?

Check by summarizing

```
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.

Check by summarizing

```
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.

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!

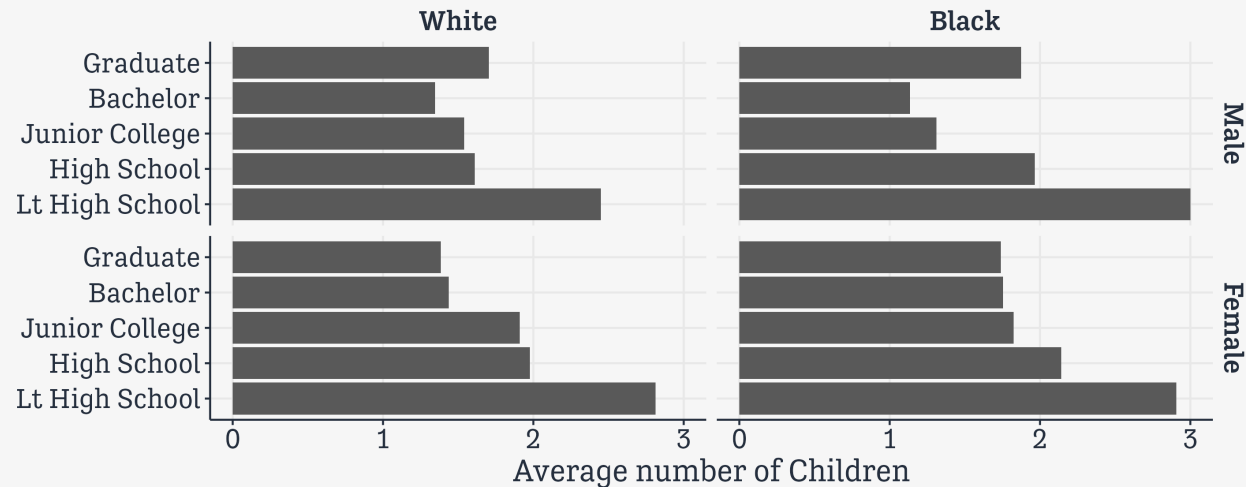
Understand pipelines by running them forward or peeling them back a step at a time.

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

Another example

Following a pipeline

```
gss_sm >
  group_by(race, sex, degree) >
  summarize(n = n(),
            mean_age = mean(age, na.rm = TRUE),
            mean_kids = mean(children, na.rm = TRUE)) >
  mutate(pct = n/sum(n)*100) >
  filter(race != "Other") >
  drop_na() >
  ggplot(mapping = aes(x = mean_kids, y = degree)) + # Some ggplot ...
  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 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 ...
9  2016     9 1      45     3 5  High ... Black Male Middl... $60000 ...
10 2016    10 3      71     4 1  Junio... White Male Middl... $60000 ...
# i 2,857 more rows
# i 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>
```

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 income16  
   <dbl> <dbl> <labelled> <dbl>   <dbl> <label> <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 ...  
9  2016     9  1         45     3  5    High ... Black Male  Middl... $60000 ...  
10 2016    10  3         71     4  1    Junio... White Male  Middl... $60000 ...  
# i 2,857 more rows  
# i 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>
```

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))
```

```
# 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
# i 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)
```

```
# 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
# i 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
# i 13 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(children, 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

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

Conditional selection

Conditionals in `select()` & `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

```
# i 228 more rows
```

```
# i 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()` & `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

```
# i 20 more rows
```

```
# i 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()` & `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  
# i 228 more rows
```

Use `where()` to test columns.

Conditionals in `select()` & `filter()`

When telling `where()` to 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()` & `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     0z  
2 Austral... 1991-01-01 Libe... In    Informed    Informed         Yes     0z  
3 Austral... 1992-01-01 Libe... In    Informed    Informed         Yes     0z  
4 Austral... 1993-01-01 Libe... In    Informed    Informed         Yes     0z  
5 Austral... 1994-01-01 Libe... In    Informed    Informed         Yes     0z  
6 Austral... 1995-01-01 Libe... In    Informed    Informed         Yes     0z  
7 Austral... 1996-01-01 Libe... In    Informed    Informed         Yes     0z  
8 Austral... 1997-01-01 Libe... In    Informed    Informed         Yes     0z  
9 Austral... 1998-01-01 Libe... In    Informed    Informed         Yes     0z  
10 Austral... 1999-01-01 Libe... In    Informed    Informed         Yes     0z  
# i 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()` & `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  
# i 228 more rows
```

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

Conditionals in `select()` & `filter()`

```
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

```
# i 18 more rows
```

```
# i 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

```
# i 46 more rows
```

```
# i 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%

```
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

```
# i 172 more rows
```

```
# i 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.

A custom operator

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

```
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
# i 172 more rows
# i 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>
```

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

Using `across()`

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(children, 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
# i 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.

Use `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(all_of(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.
```

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_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  
# i 228 more rows  
# i 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

```
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_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
# i 228 more rows
# i 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

```
my_vars ← c("gdp", "donors", "roads")

## nested parens again, but it's worth it
organdata >
  group_by(consent_law, country) >
  summarize(across(all_of(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()`**

We use **`all_of()`** or **`any_of()`** to be explicit

`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

It's OK to use the function names

```
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
```

Selection with `across(where())`

```
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.
# i 14 more rows
# i 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>, ...
```


Name new columns with `.names`

```
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.
# i 14 more rows
# i 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>, ...
```

Name new columns with `.names`

```
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.
# i 14 more rows
# i 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>, ...
```

Name new columns with `.names`

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  
# i 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
# i 12 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
# i 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
# i 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()**.