

# Data Visualization - 5.

# Dplyr and Geoms

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Code Horizons

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# Work with dplyr and ggplot

# Load our libraries

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

# Tidyverse components

```
library(tidyverse)
```

Load the package and ...

```
Loading tidyverse: ggplot2
```

◁ Draw graphs

```
Loading tidyverse: tibble
```

◁ Nicer data tables

```
Loading tidyverse: tidyr
```

◁ Tidy your data

```
Loading tidyverse: readr
```

◁ Get data into R

```
Loading tidyverse: purrr
```

◁ Fancy Iteration

```
Loading tidyverse: dplyr
```

◁ 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)`

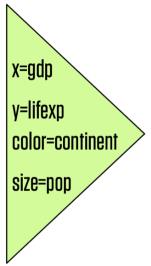
# ggplot's FLOW OF ACTION

## 1. Tidy Data

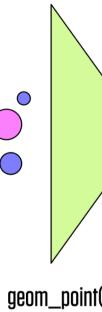
	gdp	lifexp	pop	continent
340	65	31	Euro	
227	51	200	Amer	
909	81	80	Euro	
126	40	20	Asia	

```
ggplot(data = gapminder, mapping = aes(x = gdp, y = lifespan, color = continent, size = pop))
```

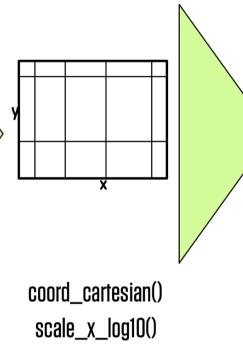
## 2. Mapping



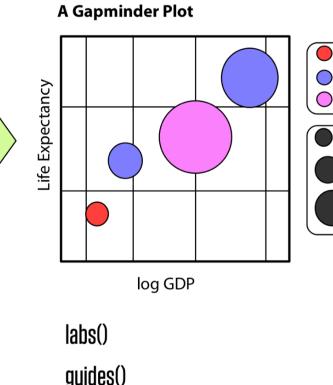
## 3. Geom



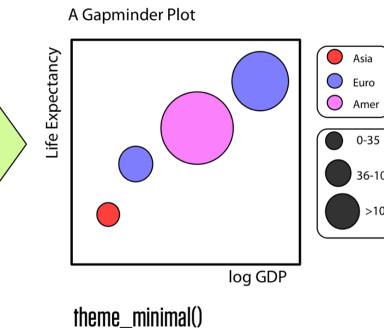
## 4. Co-ordinates, Scales



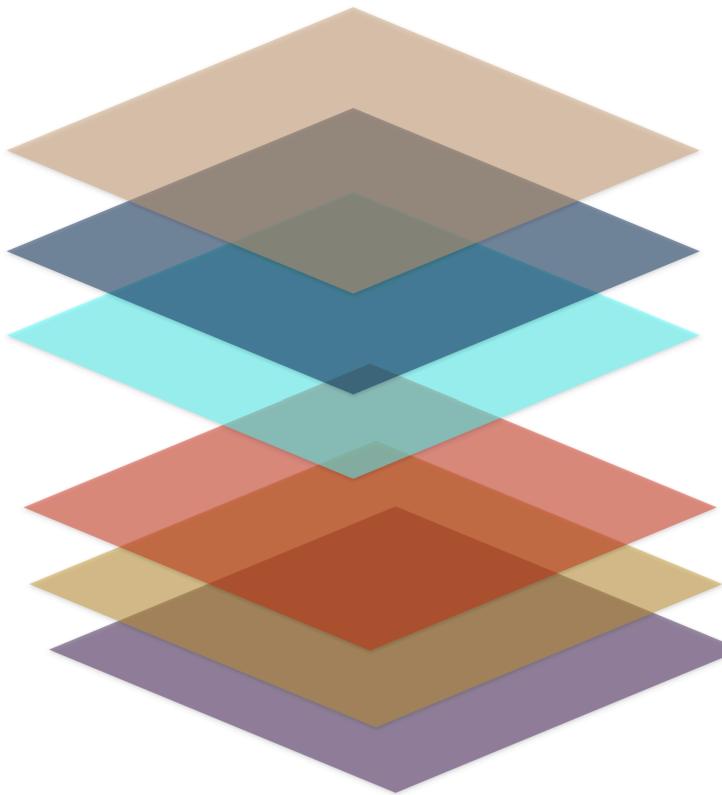
## 5. Labels & Guides



## 6. Themes



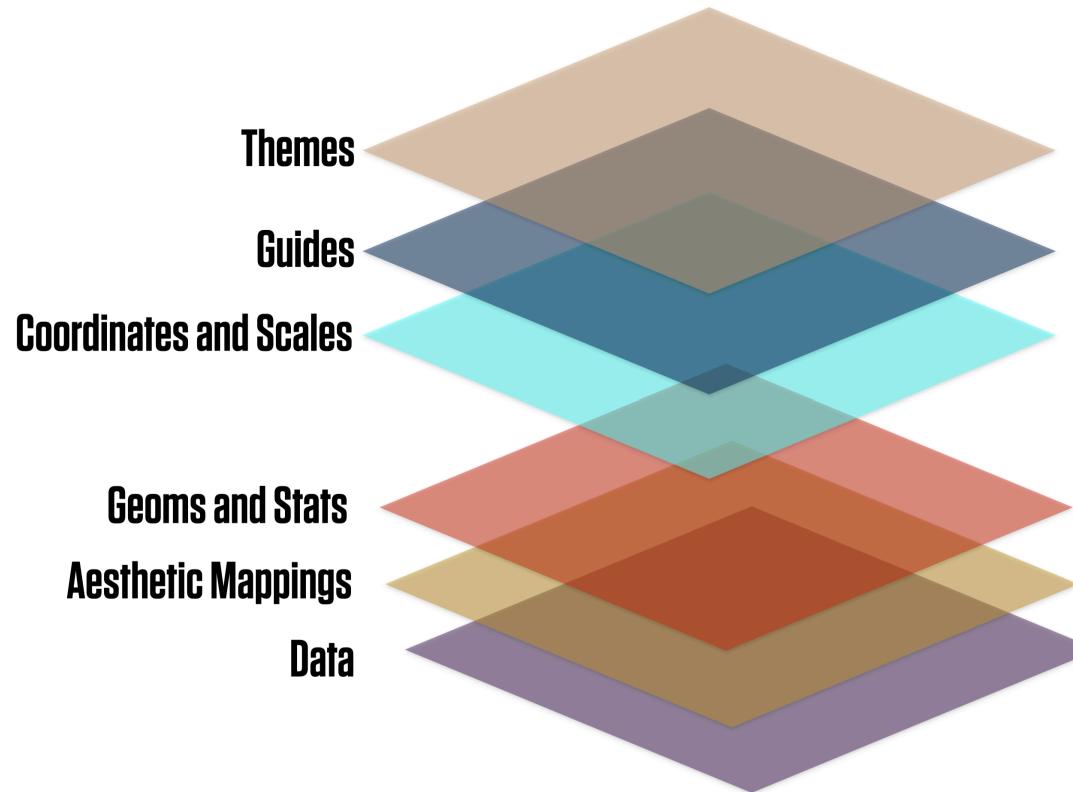
ggplot's flow of action



Thinking in terms of layers



Thinking in terms of layers



Thinking in terms of layers

# Feeding data to ggplot

**Transform and  
summarize first.**

**Then send your  
clean tables to  
ggplot.**

# Crosstabulation and beyond

# U.S. General Social Survey data:

## gss\_sm

```
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  Bach... 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  Bach... 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>
```

We often want summary tables or graphs of data like this.

# Two-way tables: Row percents

bigregion	Protestant	Catholic	Jewish	None	Other	Total
Northeast	32.4	33.3	5.5	23.0	5.7	100.0
Midwest	47.1	24.9	0.4	22.8	4.8	100.0
South	62.4	15.4	1.1	16.3	4.8	100.0
West	37.7	24.6	1.6	28.5	7.6	100.0

# Two-way tables: Column percents

bigregion	Protestant	Catholic	Jewish	None	Other
Northeast	11.5	25.0	52.9	18.1	17.6
Midwest	23.7	26.5	5.9	25.4	20.8
South	47.4	24.7	21.6	27.5	31.4
West	17.4	23.9	19.6	29.1	30.2
Total	100.0	100.0	100.0	100.0	100.0

# Two-way tables: Full marginals

bigregion	Protestant	Catholic	Jewish	None	Other
Northeast	5.5	5.7	0.9	3.9	1.0
Midwest	11.4	6.0	0.1	5.5	1.2
South	22.8	5.6	0.4	6.0	1.8
West	8.4	5.4	0.4	6.3	1.7

# 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.

# 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

**dplyr** 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 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   Bach... 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   Bach... 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

<b>id</b>	<b>bigregion</b>	<b>religion</b>
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

<b>bigregion</b>	<b>religion</b>	<b>N</b>
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

<b>bigregion</b>	<b>religion</b>	<b>N</b>	<b>pct</b>
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 child� sibs degree race   sex   region income16
  <dbl> <dbl> <labelled> <dbl> <dbl> <labe> <fct> <fct> <fct> <fct>
1 2016     1 1           47     3 2  Bach... 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  Bach... 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  Bach... 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  Bach... 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 *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> <dbl> <labelling> <fct> <fct> <fct> <fct>  
1 2016     1 1           47     3 2   Bach... 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   Bach... White Male New E... $75000 ...  
4 2016     4 1           43     4 3   High ... White Fema... New E... $170000...  
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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...  
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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) %>  
  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  Bach... 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  Bach... 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> <dbl> <labbe> <fct> <fct> <fct> <fct>  
1 2016     1 1           47     3 2   Bach... 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   Bach... 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) %>  
  summarize(total = n())
```

```
# A tibble: 24 x 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>
1 2016     1 1           47     3 2  Bach... 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  Bach... 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> <dbl> <labelled> <dbl> <dbl> <dbl> <dbl> <fct> <fct> <fct> <fct>  
1 2016     1 1          47     3 2    Bach... 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    Bach... White Male New E... $75000 ...  
4 2016     4 1          43     4 3    High ... White Fema... New E... $170000...  
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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 x 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 x 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

# 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           12  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           12  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  
# 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
```

One step; result is  
not grouped.

# Pass results on to ... a table

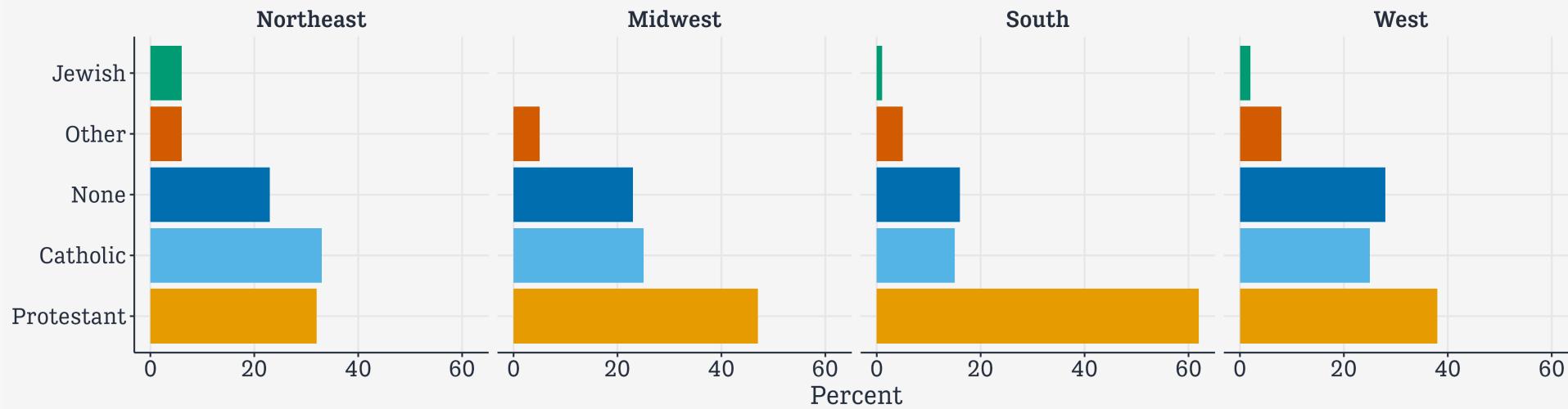
```
gss_sm %>  
  count(bigregion, religion) %>  
  pivot_wider(names_from = bigregion, values_from = n) %>  
  knitr::kable()
```

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)
```



# 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.

Use dplyr to  
make summary  
tables. Then send  
your clean tables  
to ggplot.

Facets are often  
better than Guides

# Let's put that table in an object

```
rel_by_region ← gss_sm ▷  
  group_by(bigregion, religion) ▷  
  tally() ▷  
  mutate(pct = round((n/sum(n))*100, 1)) ▷  
  drop_na()
```

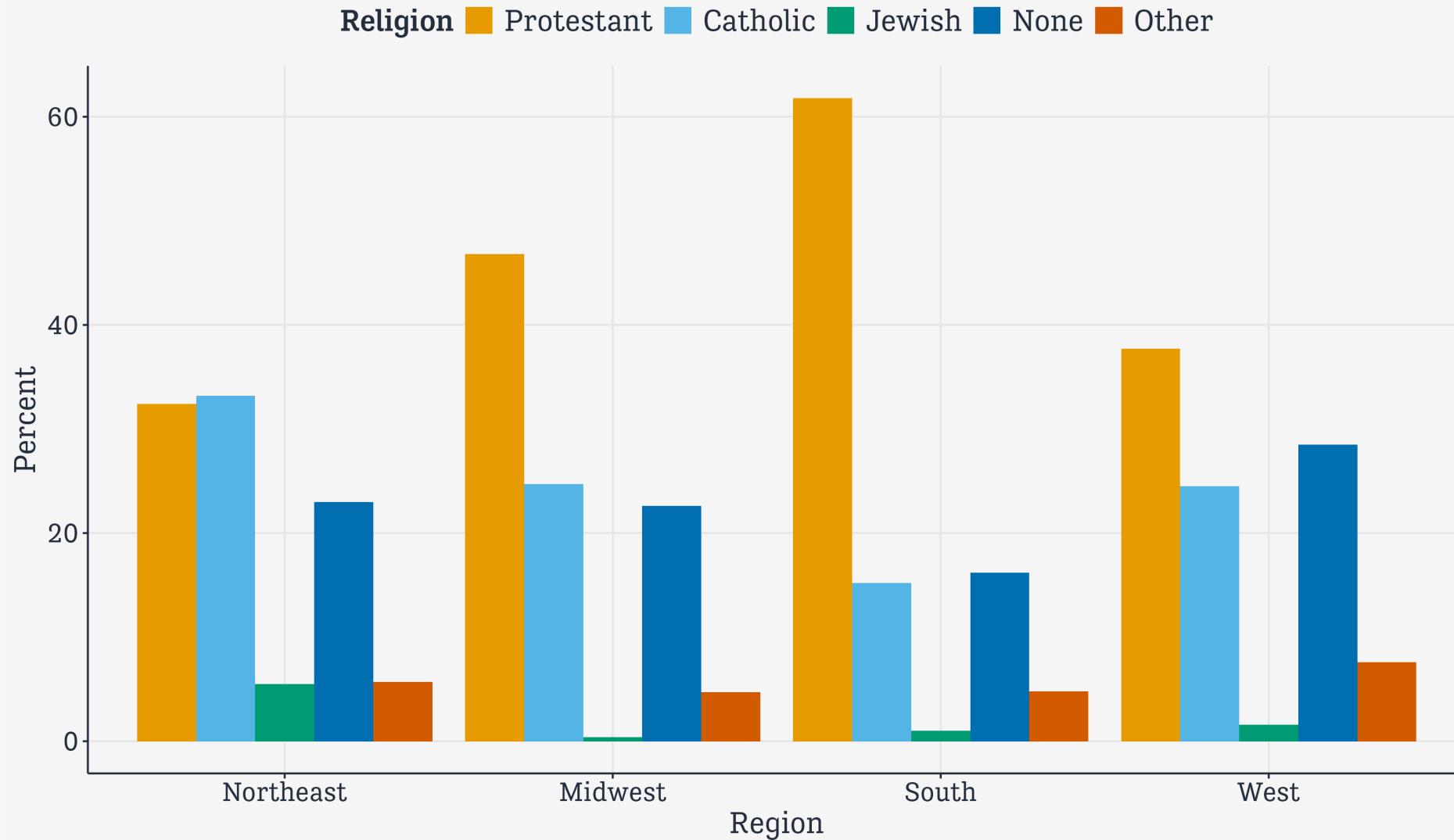
```
head(rel_by_region)
```

```
# A tibble: 6 × 4  
# Groups:   bigregion [2]  
  bigregion religion     n    pct  
  <fct>     <fct>     <int> <dbl>  
1 Northeast Protestant  158  32.4  
2 Northeast Catholic   162  33.2  
3 Northeast Jewish     27   5.5  
4 Northeast None        112  23  
5 Northeast Other       28   5.7  
6 Midwest   Protestant 325  46.8
```

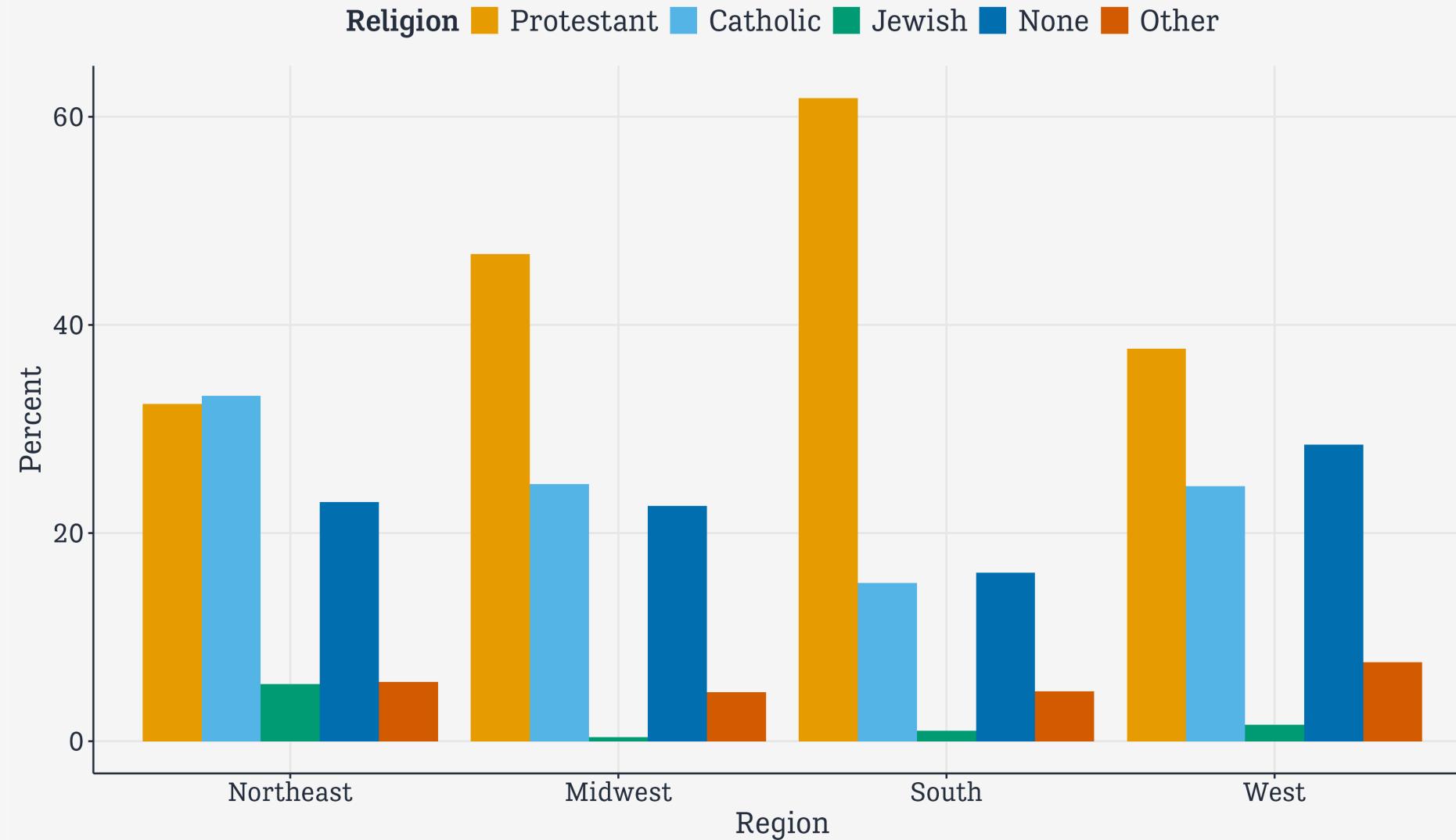
# We might write ...

```
p ← ggplot(data = rel_by_region,
             mapping = aes(x = bigregion,
                            y = pct,
                            fill = religion))
p_out ← p + geom_col(position = "dodge") +
  labs(x = "Region",
       y = "Percent",
       fill = "Religion")
```

# We might write ...



# Is this an effective graph? Not really!



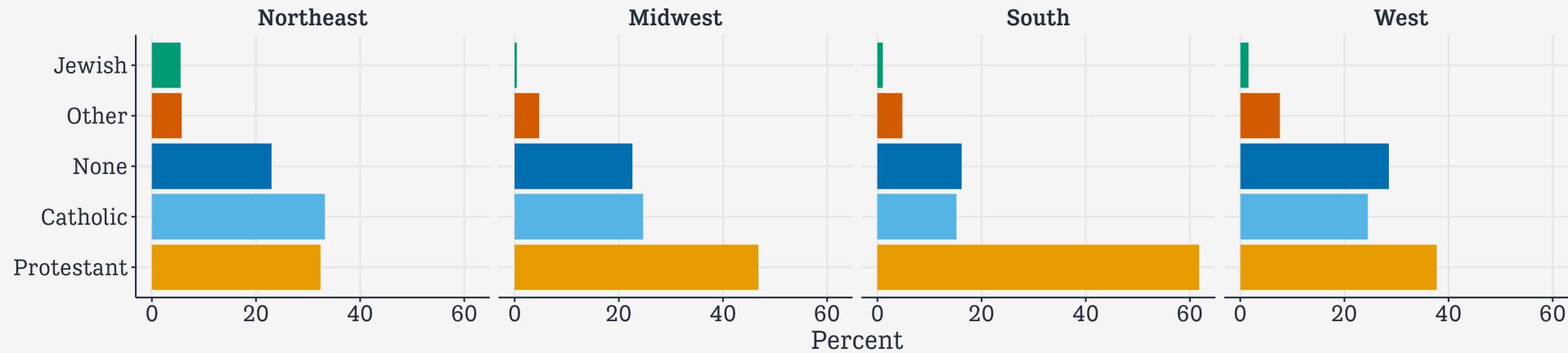
# Try faceting instead

```
p ← ggplot(data = rel_by_region,
            mapping = aes(x = pct,
                           y = reorder(religion, -pct),
                           fill = religion))
p_out_facet ← p + geom_col() +
  guides(fill = "none") +
  facet_wrap(~ bigregion, nrow = 1) +
  labs(x = "Percent",
       y = NULL)
```

Putting categories on the y-axis is a very useful trick.

Faceting reduces the number of guides the viewer needs to consult.

# Try faceting instead



## Try faceting instead

Try putting categories on the y-axis. (And reorder them by x.)

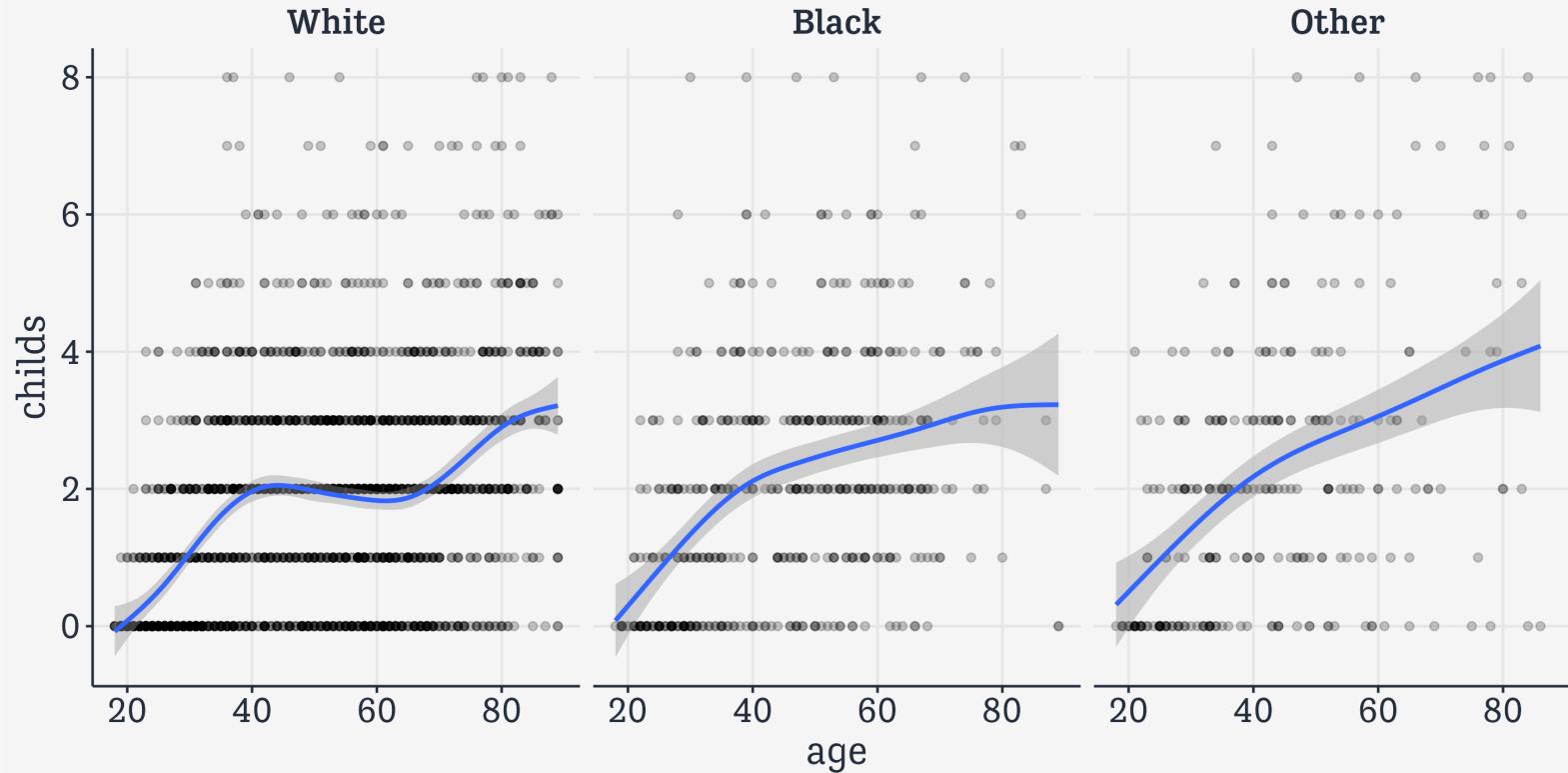
Try facetting variables instead of mapping them to color or shape.

Try to minimize the need for guides and legends.

Two kinds of facet

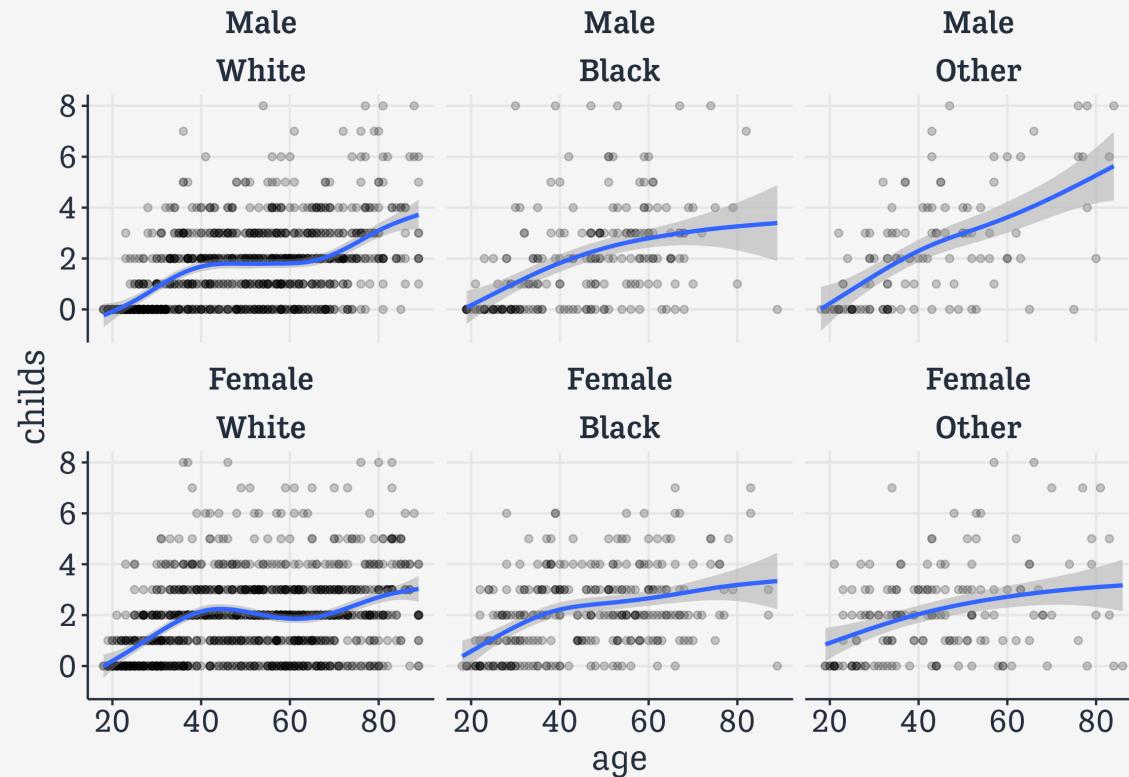
# Facet Children vs Age, by Race

```
p ← ggplot(data = gss_sm,  
            mapping = aes(x = age, y = child))  
  
p + geom_point(alpha = 0.2) +  
  geom_smooth() +  
  facet_wrap(~ race)
```



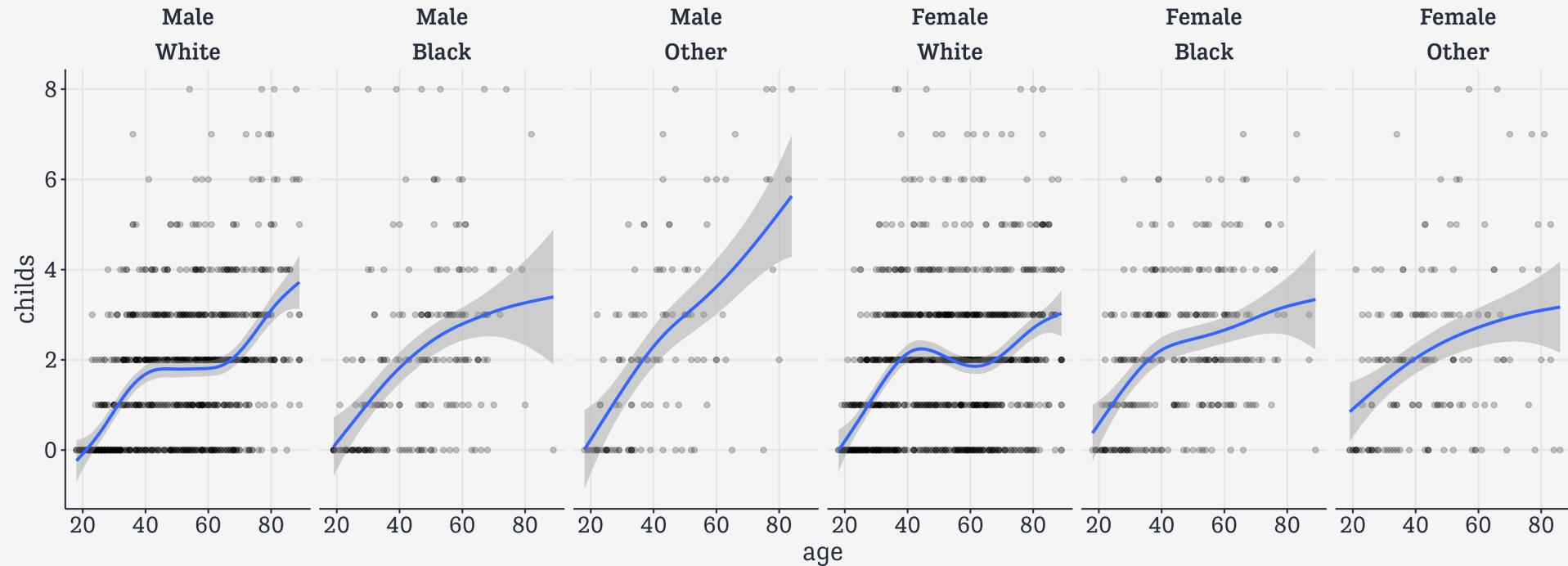
# Facet by more than one variable

```
p ← ggplot(data = gss_sm,  
            mapping = aes(x = age, y = childs))  
  
p + geom_point(alpha = 0.2) +  
  geom_smooth() +  
  facet_wrap(~ sex + race)
```



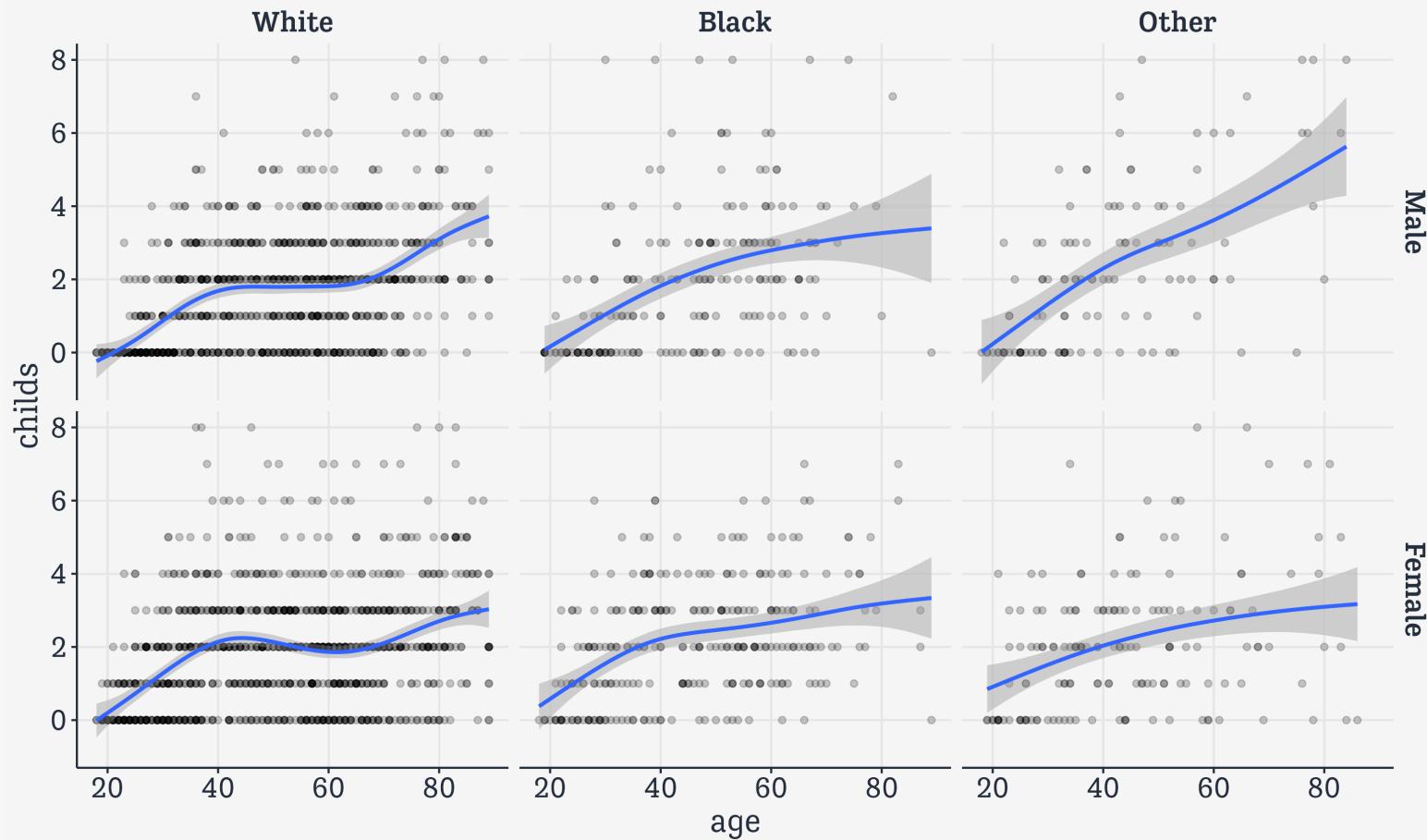
# Arrange `facet_wrap()` quite freely

```
p ← ggplot(data = gss_sm,  
            mapping = aes(x = age, y = child))  
  
p + geom_point(alpha = 0.2) +  
  geom_smooth() +  
  facet_wrap(~ sex + race, nrow = 1)
```



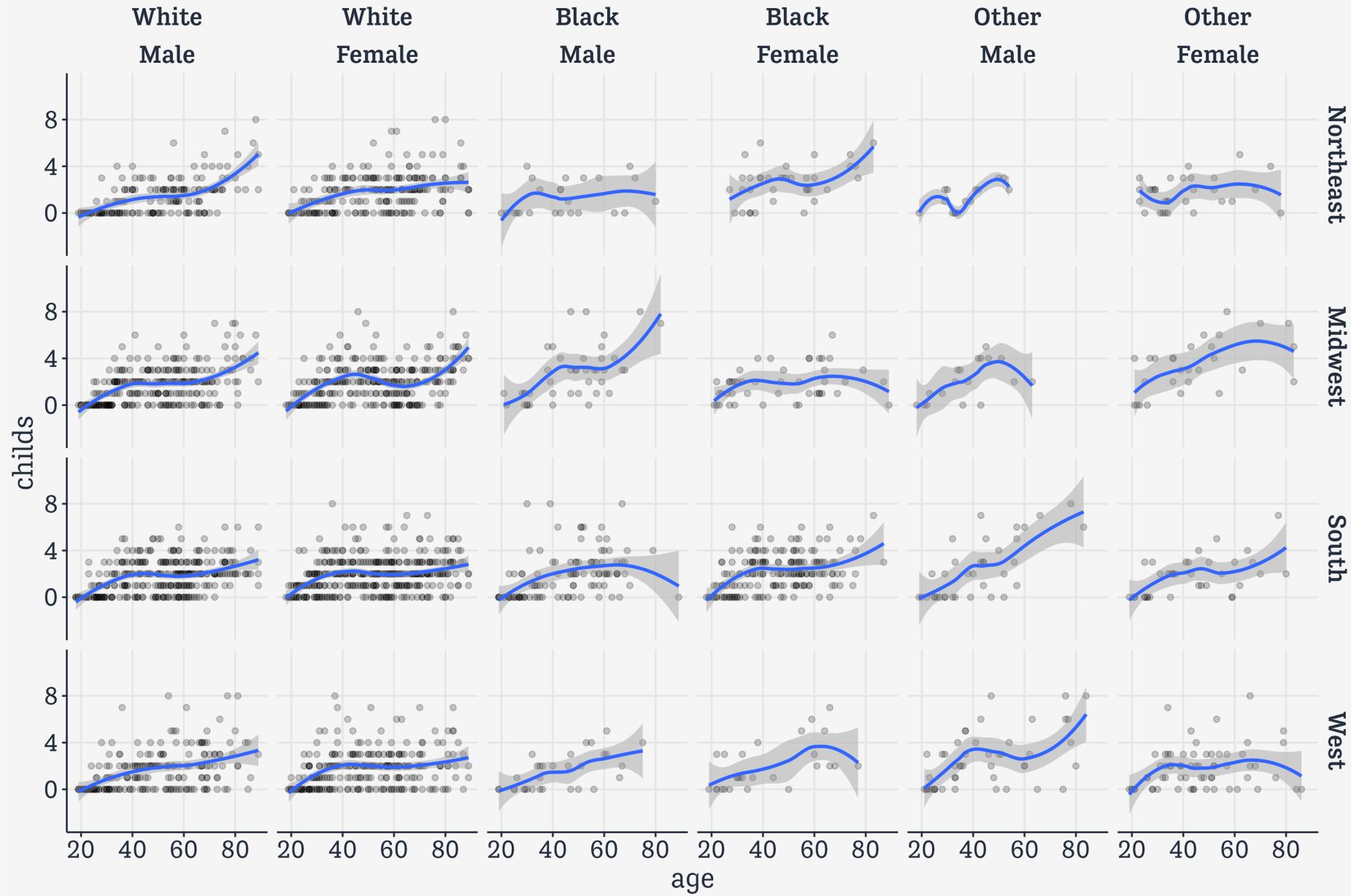
# facet\_grid() is more like a true crosstab

```
p + geom_point(alpha = 0.2) +  
  geom_smooth() +  
  facet_grid(sex ~ race)
```



# Extend both to multi-way views

```
p_out ← p + geom_point(alpha = 0.2) +  
  geom_smooth() +  
  facet_grid(bigregion ~ race + sex)
```



**What we've  
built-up**

# Core Grammar

```
p <- ggplot(data = <DATA>,
              mapping=aes(<MAPPINGS>)) +
  <GEOM_FUNCTION>(
    mapping = aes(<MAPPINGS>),
    stat = <STAT>,
    position = <POSITION>) +
  <SCALE_FUNCTION> +
  <COORDINATE_FUNCTION> +
  <FACET_FUNCTION> +
  <THEME_FUNCTION>
```

# Grouped data; faceting

Along with a few peeks at scale transformations, guide adjustments, and theme adjustment

```
p <- ggplot(data = gapminder,  
             mapping = aes(x = year,  
                            y = gdpPercap))  
  
p + geom_line(aes(group = country)) +  
  scale_y_log10() +  
  coord_cartesian() +  
  facet_wrap(~ continent) +  
  theme_minimal()
```

All basic steps

# dplyr and Pipelining

The elements of filtering and summarizing

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

# A tibble: 24 × 5
# Groups:   bigregion [4]
  bigregion religion     n    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
```



# **Example and extension: Organ Donation data**

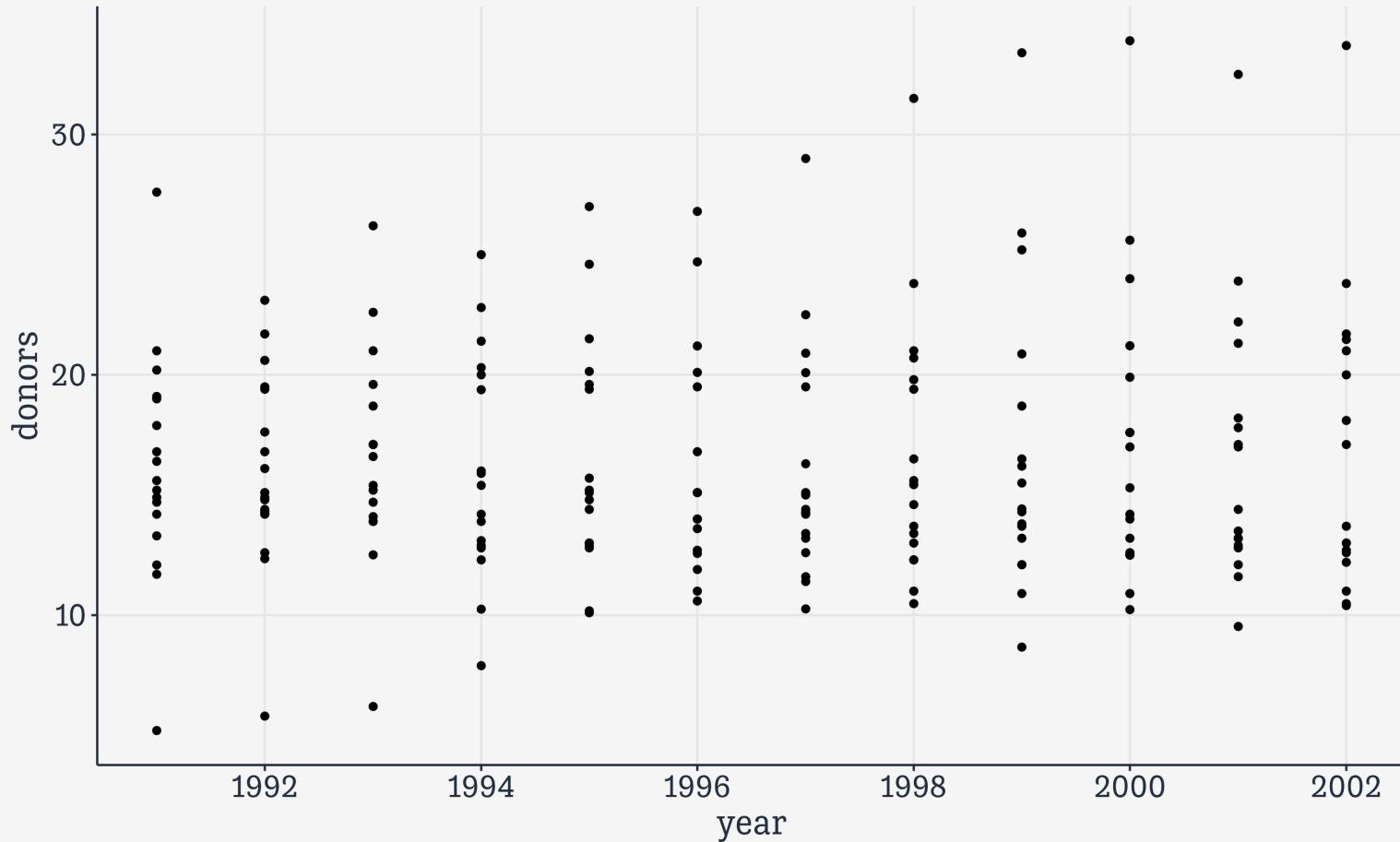
# organdata is in the socviz package

```
organdata
```

```
# A tibble: 238 × 21
  country     year    donors    pop  pop_dens    gdp gdp_lag health health_lag
  <chr>     <date>   <dbl>   <int>    <dbl> <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>
```

# First look

```
p ← ggplot(data = organdata,  
            mapping = aes(x = year, y = donors))  
p + geom_point()
```



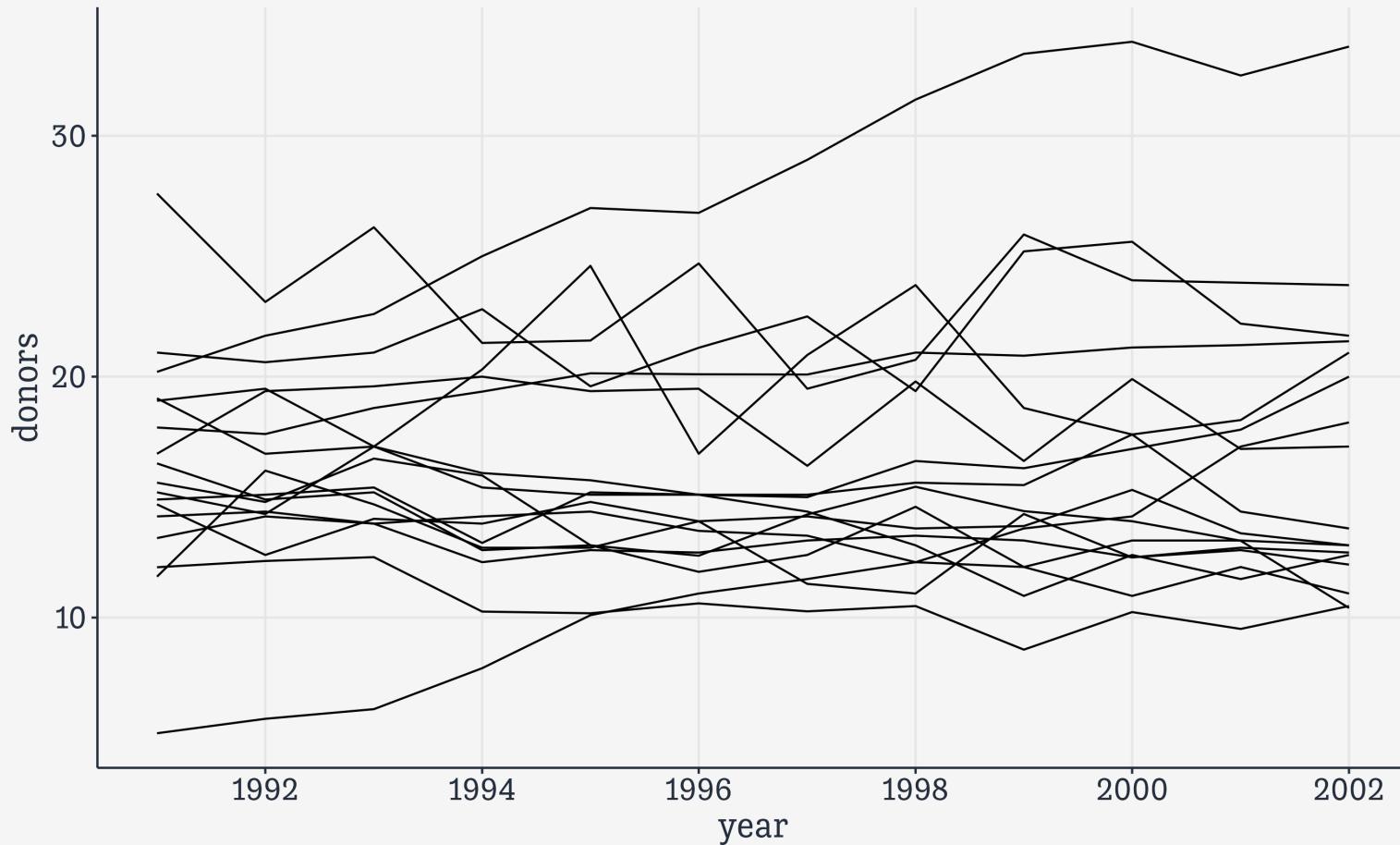
# First look

```
p ← ggplot(data = organdata,  
            mapping = aes(x = year, y = donors))  
p + geom_line()
```



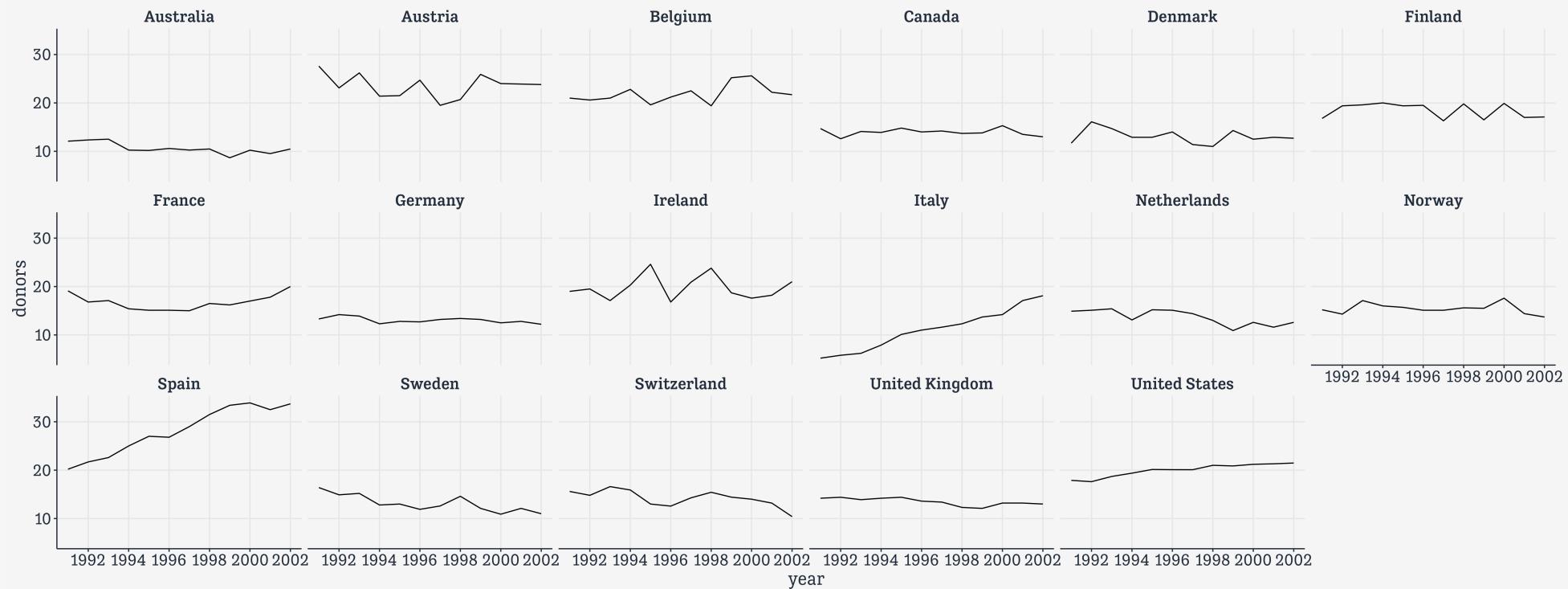
# First look

```
p ← ggplot(data = organdata,  
            mapping = aes(x = year, y = donors))  
p + geom_line(aes(group = country))
```



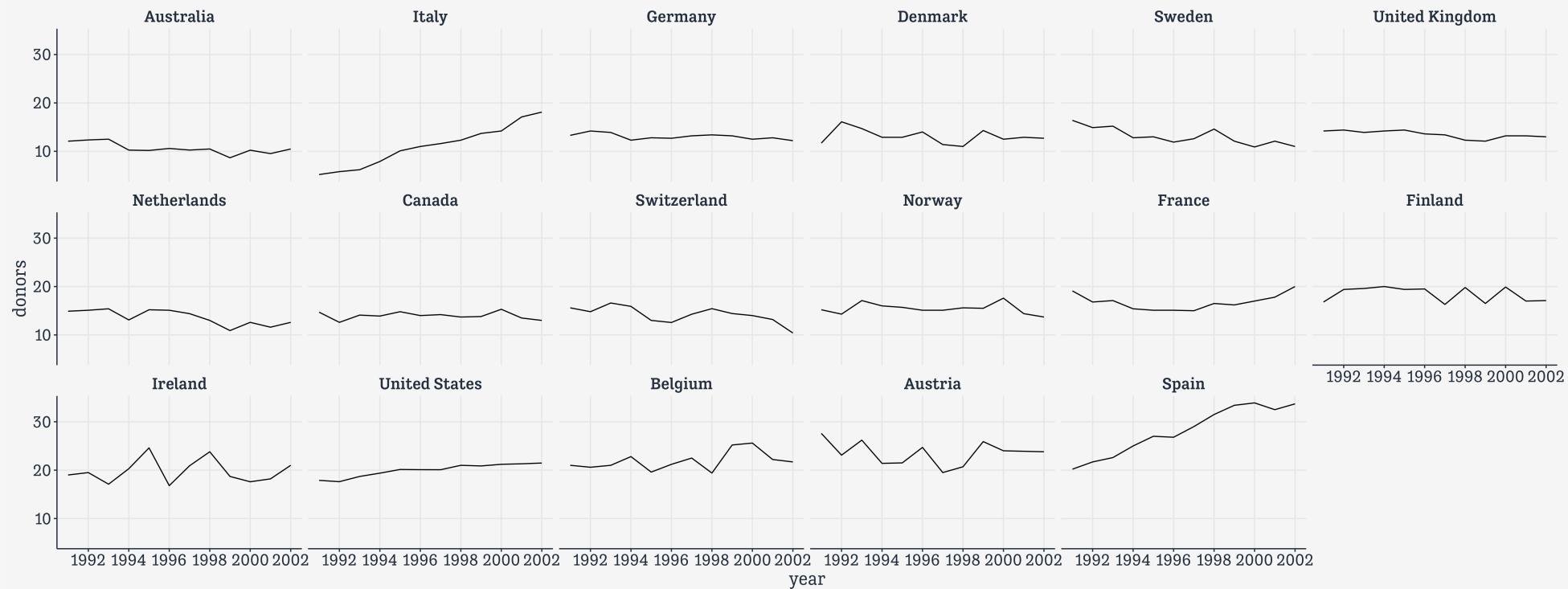
# First look

```
p ← ggplot(data = organdata,  
            mapping = aes(x = year, y = donors))  
p + geom_line() +  
  facet_wrap(~ country, nrow = 3)
```



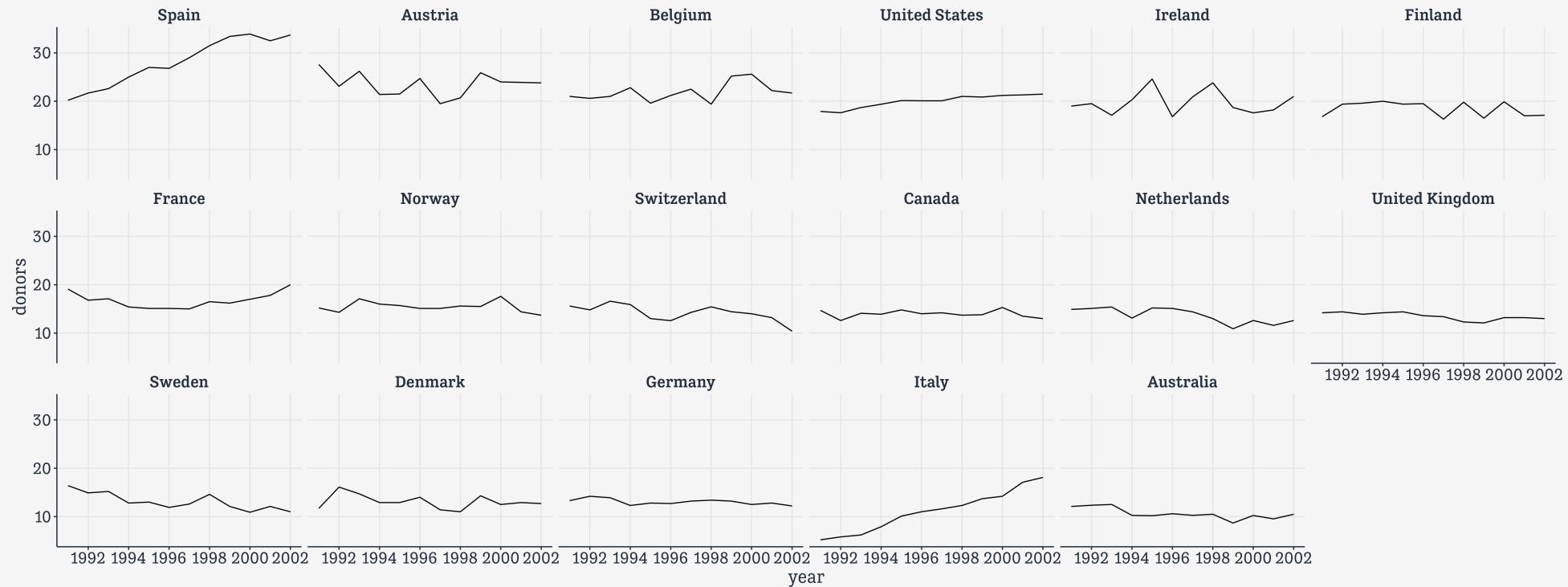
# First look

```
p ← ggplot(data = organdata,  
            mapping = aes(x = year, y = donors))  
p + geom_line() +  
  facet_wrap(~ reorder(country, donors, na.rm = TRUE), nrow = 3)
```



# First look

```
p ← ggplot(data = organdata,  
            mapping = aes(x = year, y = donors))  
p + geom_line() +  
  facet_wrap(~ reorder(country, -donors, na.rm = TRUE), nrow = 3)
```



Summarize better  
with `dplyr`

# Summarize a bunch of variables

```
by_country ← 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),  
            cerebvas_mean = mean(cerebvas, na.rm = TRUE))  
  
head(by_country)  
  
# A tibble: 6 × 8  
# Groups: consent_law [1]  
  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  
# i 1 more variable: cerebvas_mean <dbl>
```

This works, but there's so much repetition! It's an open invitation to make mistakes copying and pasting.

**DRY:**  
**Don't Repeat**  
**Yourself**

# Use `across()` and `where()` instead

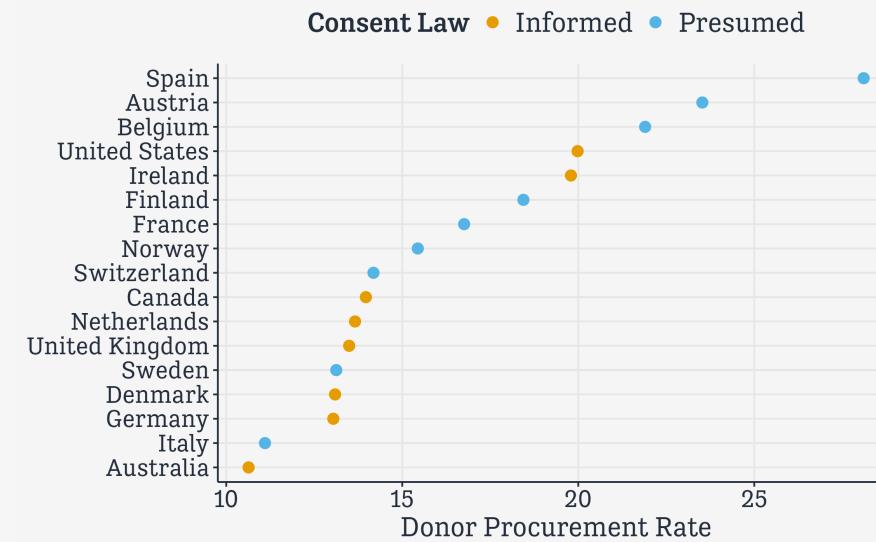
```
by_country ← organdata ▷  
  group_by(consent_law, country) ▷  
  summarize(across(where(is.numeric),  
    list(mean = ~ mean(.x, na.rm = TRUE),  
        sd = ~ sd(.x, na.rm = TRUE))))  
  
head(by_country)  
  
# A tibble: 6 × 28  
# Groups: consent_law [1]  
  consent_law country      donors_mean donors_sd pop_mean pop_sd pop_dens_mean  
  <chr>       <chr>          <dbl>     <dbl>    <dbl>    <dbl>      <dbl>  
1 Informed    Australia      10.6      1.14    18318.   831.      0.237  
2 Informed    Canada        14.0      0.751    29608.   1193.      0.297  
3 Informed    Denmark       13.1      1.47     5257.    80.6       12.2  
4 Informed    Germany       13.0      0.611    80255.   5158.      22.5  
5 Informed    Ireland       19.8      2.48     3674.    132.       5.23  
6 Informed    Netherlands   13.7      1.55    15548.   373.      37.4  
# i 21 more variables: pop_dens_sd <dbl>, gdp_mean <dbl>, gdp_sd <dbl>,  
#   gdp_lag_mean <dbl>, gdp_lag_sd <dbl>, health_mean <dbl>, health_sd <dbl>,  
#   health_lag_mean <dbl>, health_lag_sd <dbl>, pubhealth_mean <dbl>,  
#   pubhealth_sd <dbl>, roads_mean <dbl>, roads_sd <dbl>, cerebvas_mean <dbl>,  
#   cerebvas_sd <dbl>, assault_mean <dbl>, assault_sd <dbl>,  
#   external_mean <dbl>, external_sd <dbl>, txp_pop_mean <dbl>,  
#   txp_pop_sd <dbl>
```

# Use `across()` and `where()` instead

```
by_country ← organdata ▷  
  group_by(consent_law, country) ▷  
  summarize(across(where(is.numeric),  
    list(mean = ~ mean(.x, na.rm = TRUE),  
         sd = ~ sd(.x, na.rm = TRUE))),  
    .groups = "drop")  
head(by_country)  
  
# A tibble: 6 × 28  
  consent_law country     donors_mean donors_sd pop_mean pop_sd pop_dens_mean  
  <chr>       <chr>        <dbl>      <dbl>   <dbl>    <dbl>      <dbl>  
1 Informed    Australia     10.6       1.14   18318.   831.      0.237  
2 Informed    Canada       14.0       0.751   29608.   1193.      0.297  
3 Informed    Denmark      13.1       1.47    5257.    80.6       12.2  
4 Informed    Germany      13.0       0.611   80255.   5158.      22.5  
5 Informed    Ireland      19.8       2.48    3674.    132.       5.23  
6 Informed    Netherlands   13.7       1.55    15548.   373.      37.4  
# i 21 more variables: pop_dens_sd <dbl>, gdp_mean <dbl>, gdp_sd <dbl>,  
#   gdp_lag_mean <dbl>, gdp_lag_sd <dbl>, health_mean <dbl>, health_sd <dbl>,  
#   health_lag_mean <dbl>, health_lag_sd <dbl>, pubhealth_mean <dbl>,  
#   pubhealth_sd <dbl>, roads_mean <dbl>, roads_sd <dbl>, cerebvas_mean <dbl>,  
#   cerebvas_sd <dbl>, assault_mean <dbl>, assault_sd <dbl>,  
#   external_mean <dbl>, external_sd <dbl>, txp_pop_mean <dbl>,  
#   txp_pop_sd <dbl>
```

# Plot our summary data

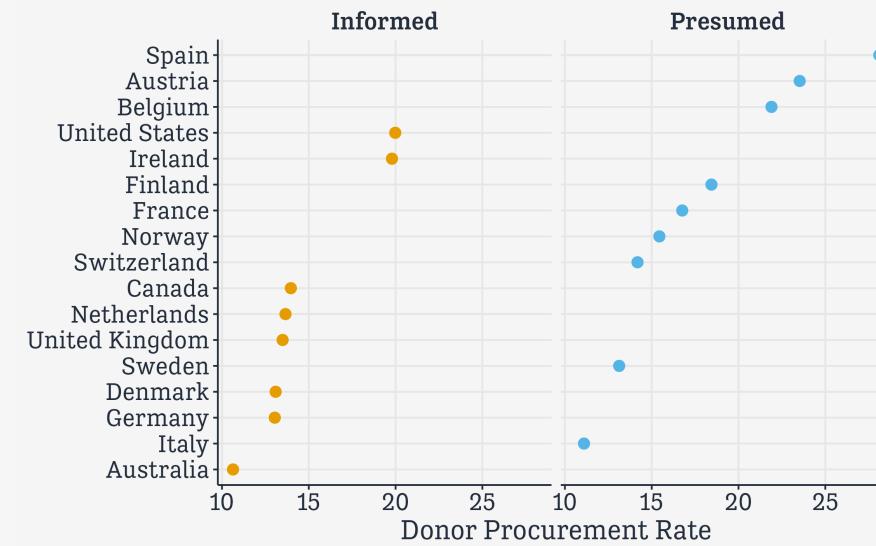
```
by_country %>%  
  ggplot(mapping =  
    aes(x = donors_mean,  
        y = reorder(country, donors_mean),  
        color = consent_law)) +  
  geom_point(size=3) +  
  labs(x = "Donor Procurement Rate",  
       y = NULL,  
       color = "Consent Law")
```



# What about faceting it instead?

The problem is that countries can only be in one Consent Law category.

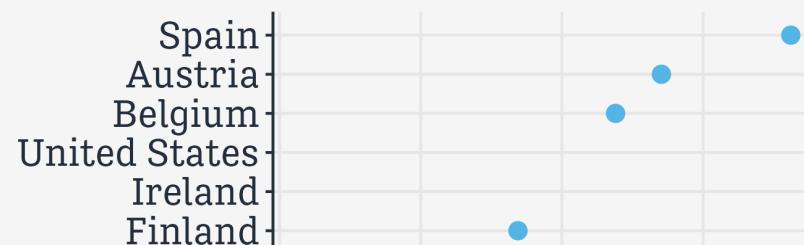
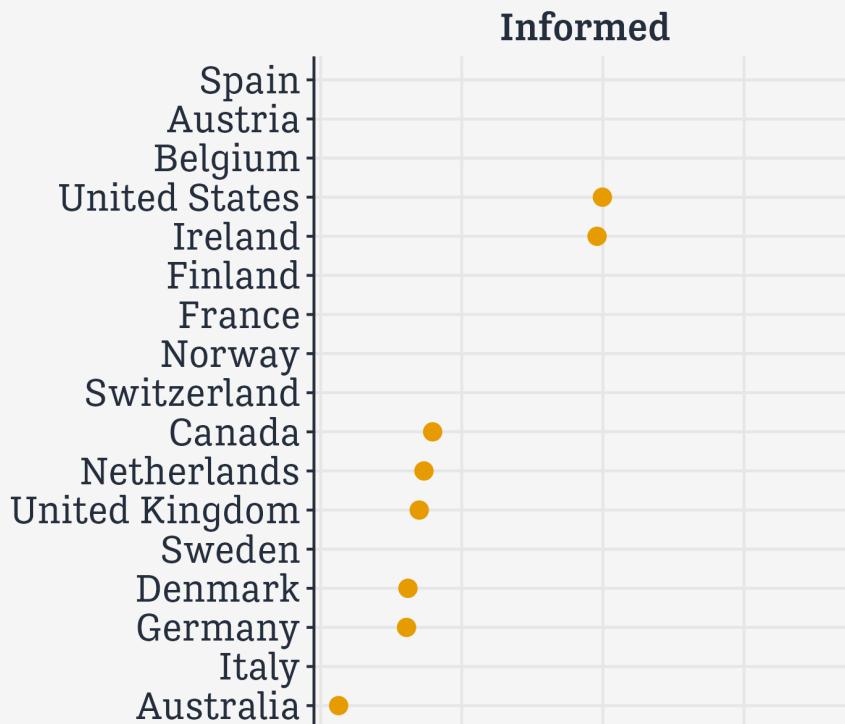
```
by_country >
  ggplot(mapping =
    aes(x = donors_mean,
        y = reorder(country, donors_mean),
        color = consent_law)) +
  geom_point(size=3) +
  guides(color = "none") +
  facet_wrap(~ consent_law) +
  labs(x = "Donor Procurement Rate",
       y = NULL,
       color = "Consent Law")
```



# What about faceting it instead?

Restricting to one column doesn't fix it.

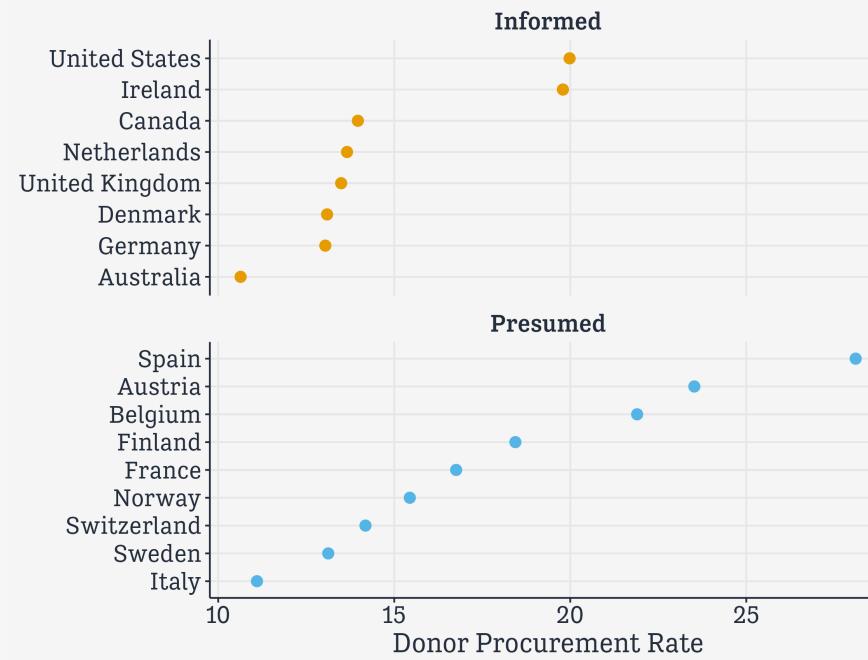
```
by_country %>%  
  ggplot(mapping =  
    aes(x = donors_mean,  
        y = reorder(country, donors_mean  
                    color = consent_law)) +  
  geom_point(size=3) +  
  guides(color = "none") +  
  facet_wrap(~ consent_law, ncol = 1) +  
  labs(x = "Donor Procurement Rate",  
       y = NULL,  
       color = "Consent Law")
```



# Allow the y-scale to vary

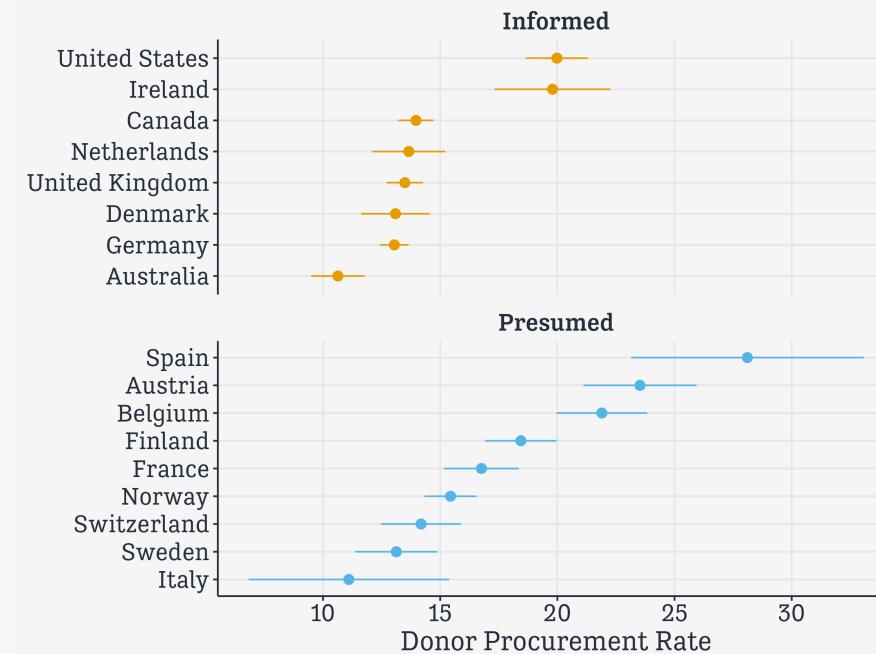
Normally the point of a facet is to preserve comparability between panels by not allowing the scales to vary. But for categorical measures it can be useful to allow this.

```
by_country >  
  ggplot(mapping =  
    aes(x = donors_mean,  
        y = reorder(country, donors_mean),  
        color = consent_law)) +  
  geom_point(size=3) +  
  guides(color = "none") +  
  facet_wrap(~ consent_law,  
            ncol = 1,  
            scales = "free_y") +  
  labs(x = "Donor Procurement Rate",  
       y = NULL,  
       color = "Consent Law")
```



# Again, these methods are general

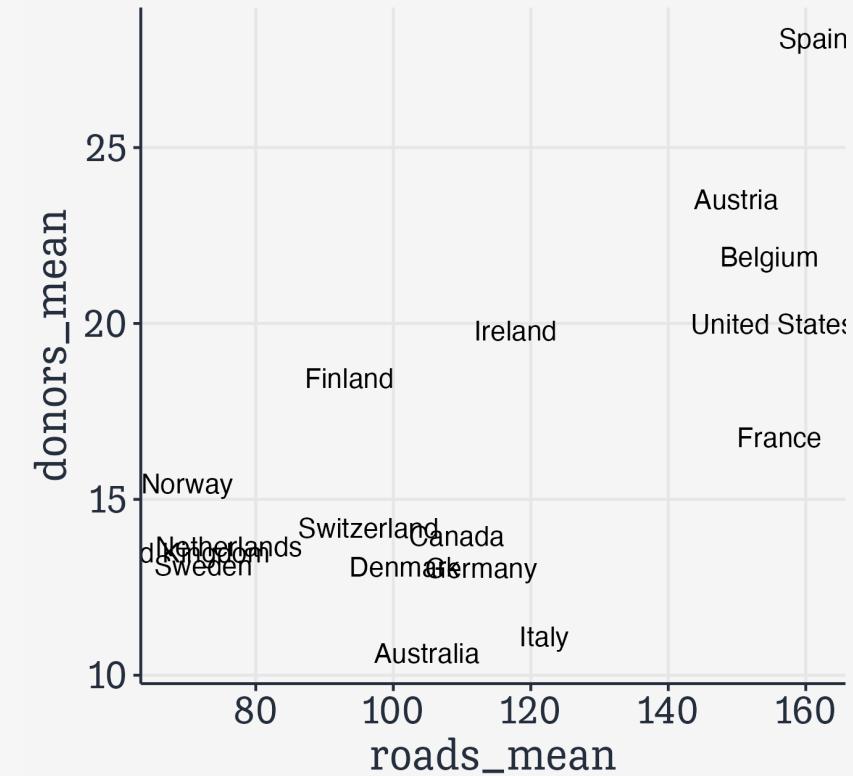
```
by_country %>%  
  ggplot(mapping =  
    aes(x = donors_mean,  
        y = reorder(country, donors_mean),  
        color = consent_law)) +  
  geom_pointrange(mapping =  
    aes(xmin = donors_mean - do  
        nmax = donors_mean + do  
        guides(color = "none") +  
        facet_wrap(~ consent_law,  
                  ncol = 1,  
                  scales = "free_y") +  
        labs(x = "Donor Procurement Rate",  
              y = NULL,  
              color = "Consent Law")
```



# Plot text directly

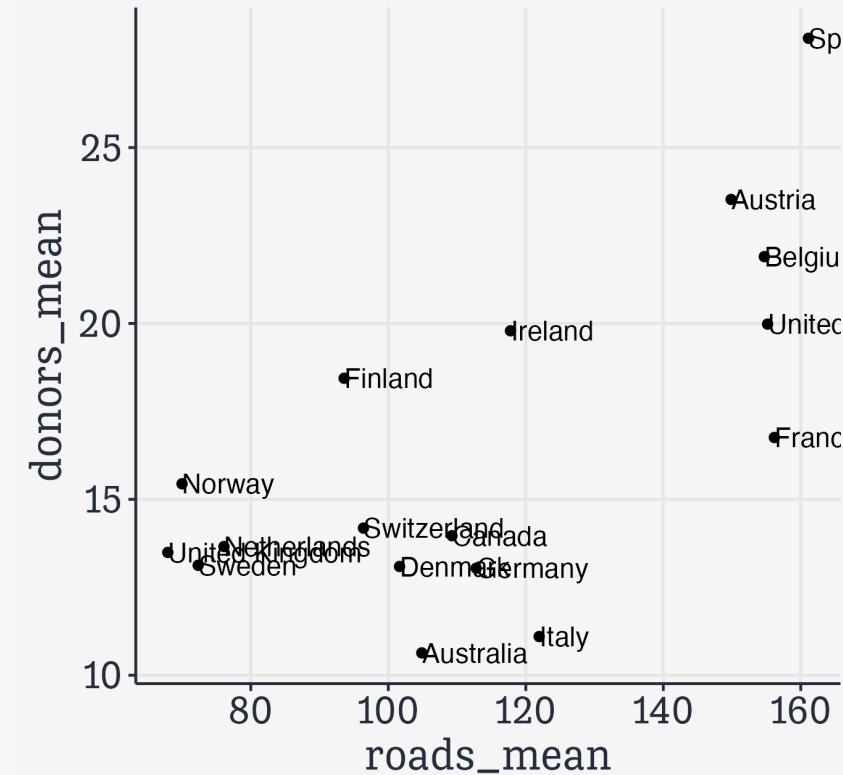
# geom\_text() for basic labels

```
by_country %>%  
  ggplot(mapping = aes(x = roads_mean,  
                      y = donors_mean)) +  
  geom_text(mapping = aes(label = country))
```



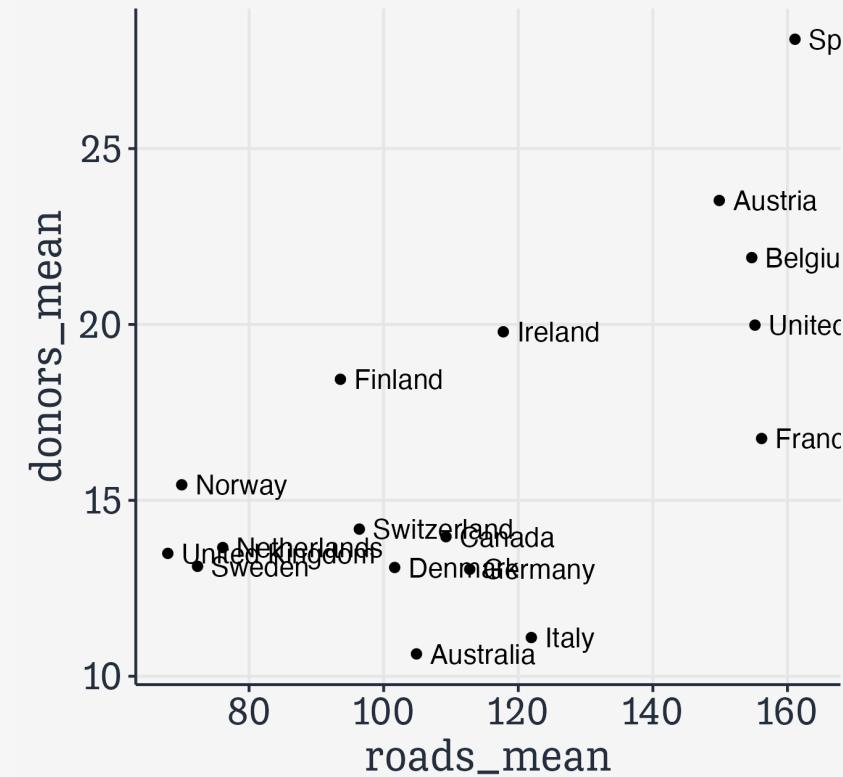
# It's not very flexible

```
by_country %>%  
  ggplot(mapping = aes(x = roads_mean,  
                      y = donors_mean)) +  
  geom_point() +  
  geom_text(mapping = aes(label = country),  
            hjust = 0)
```



# There are tricks, but they're limited

```
by_country %>%  
  ggplot(mapping = aes(x = roads_mean,  
                        y = donors_mean)) +  
  geom_point() +  
  geom_text(mapping = aes(x = roads_mean + 2,  
                          label = country),  
            hjust = 0)
```



# We'll use `ggrepel` instead

The `ggrepel` package provides  
`geom_text_repel()` and  
`geom_label_repel()`

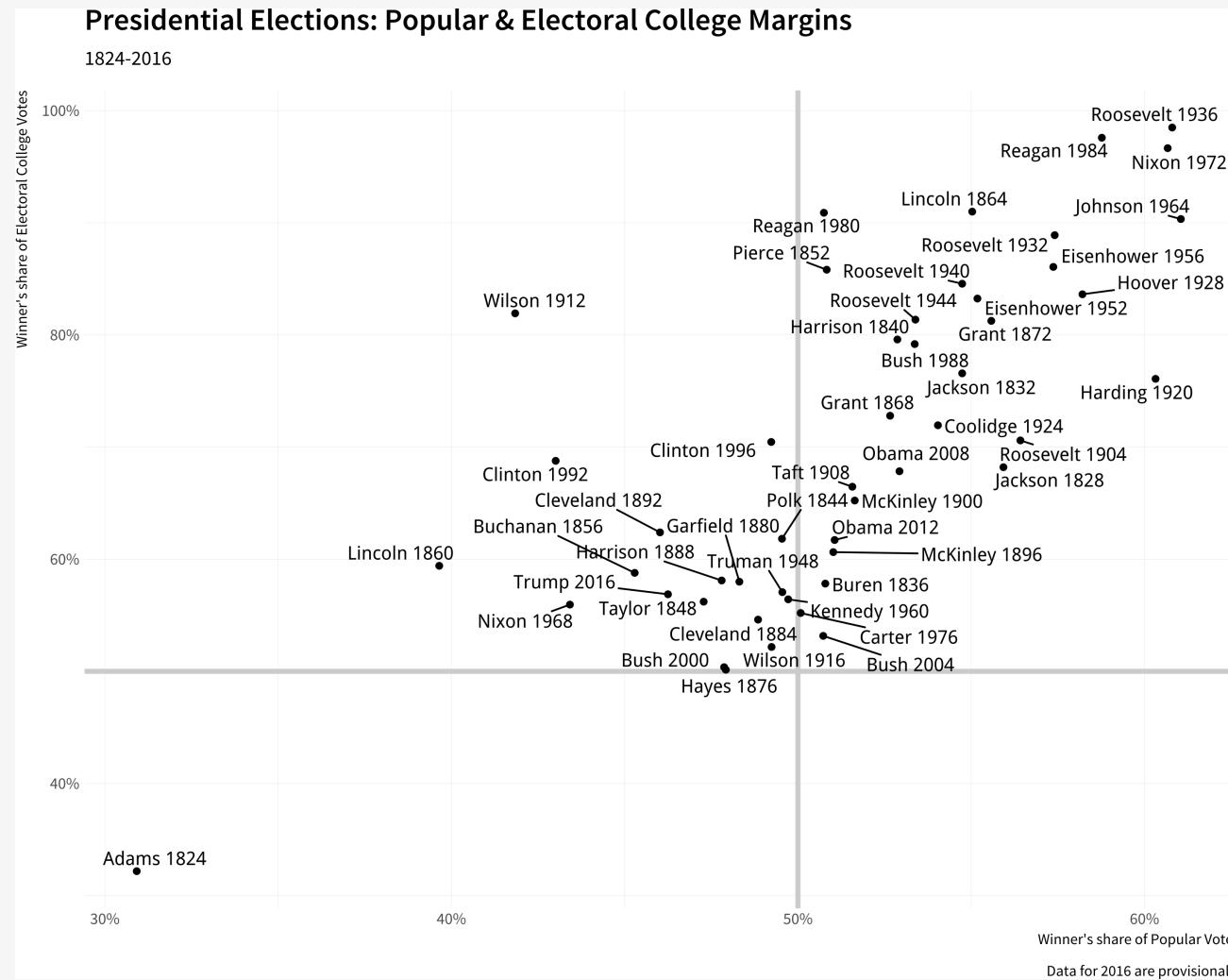
# Example: U.S. Historic Presidential Elections

# elections\_historic is in socviz

```
elections_historic
```

```
# A tibble: 49 × 19
  election year winner      win_party ec_pct popular_pct popular_margin   votes
  <int> <int> <chr>       <chr>     <dbl>      <dbl>           <dbl>    <int>
1      10  1824 John Quincy Adams D.-R.    0.322      0.309        -0.104 1.13e5
2      11  1828 Andrew Jackson Dem.      0.682      0.559         0.122 6.43e5
3      12  1832 Andrew Jackson Dem.      0.766      0.547         0.178 7.03e5
4      13  1836 Martin Van Buren Dem.    0.578      0.508         0.142 7.63e5
5      14  1840 William Henry Harrison Whig    0.796      0.529         0.0605 1.28e6
6      15  1844 James Polk Dem.          0.618      0.495         0.0145 1.34e6
7      16  1848 Zachary Taylor Whig        0.562      0.473         0.0479 1.36e6
8      17  1852 Franklin Pierce Dem.      0.858      0.508         0.0695 1.61e6
9      18  1856 James Buchanan Dem.      0.588      0.453         0.122 1.84e6
10     19  1860 Abraham Lincoln Rep.      0.594      0.396         0.101 1.86e6
# i 39 more rows
# i 11 more variables: margin <int>, runner_up <chr>, ru_part <chr>,
# turnout_pct <dbl>, winner_lname <chr>, winner_label <chr>, ru_lname <chr>,
# ru_label <chr>, two_term <lgl>, ec_votes <dbl>, ec_denom <dbl>
```

# We'll draw a plot like this



Presidential elections

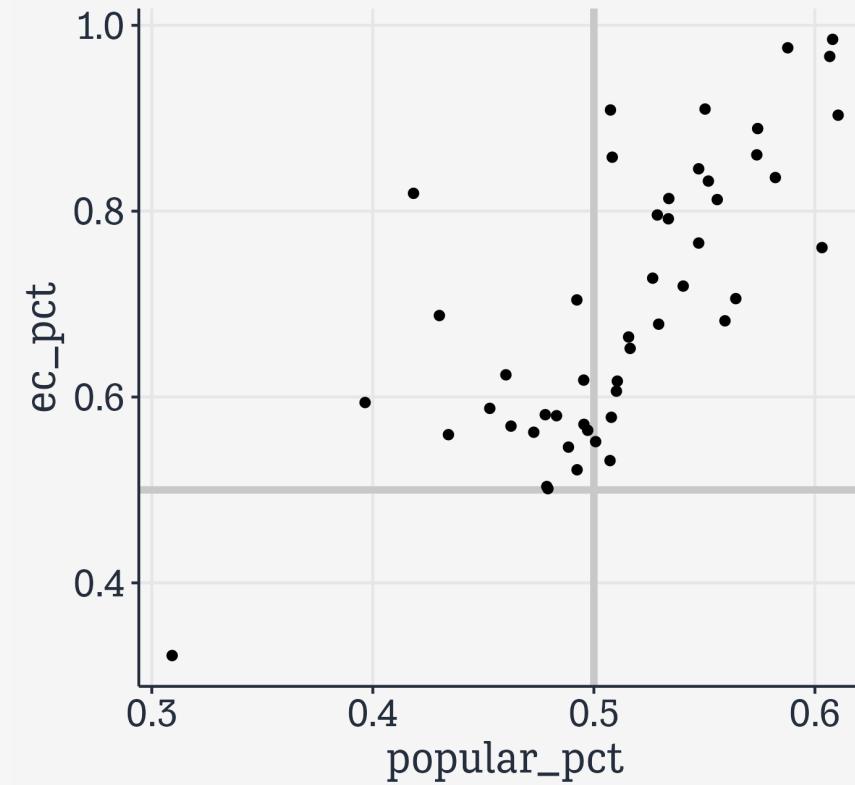
# Keep things neat

```
## The packages we'll use in addition to ggplot
library(ggrepel)
library(scales)

p_title ← "Presidential Elections: Popular & Electoral College Margins"
p_subtitle ← "1824-2016"
p_caption ← "Data for 2016 are provisional."
x_label ← "Winner's share of Popular Vote"
y_label ← "Winner's share of Electoral College Votes"
```

# Base Layer, Lines, Points

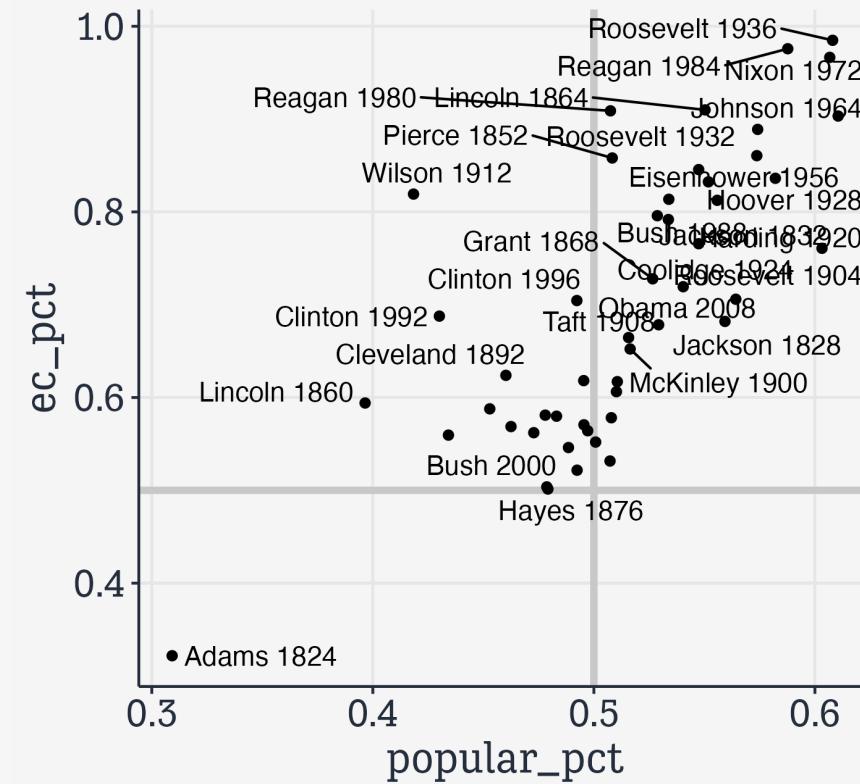
```
p ← ggplot(data = elections_historic,  
            mapping = aes(x = popular_pct,  
                           y = ec_pct,  
                           label = winner_label))  
  
p + geom_hline(yintercept = 0.5,  
                 linewidth = 1.4,  
                 color = "gray80") +  
  geom_vline(xintercept = 0.5,  
             linewidth = 1.4,  
             color = "gray80") +  
  geom_point()
```



# Add the labels

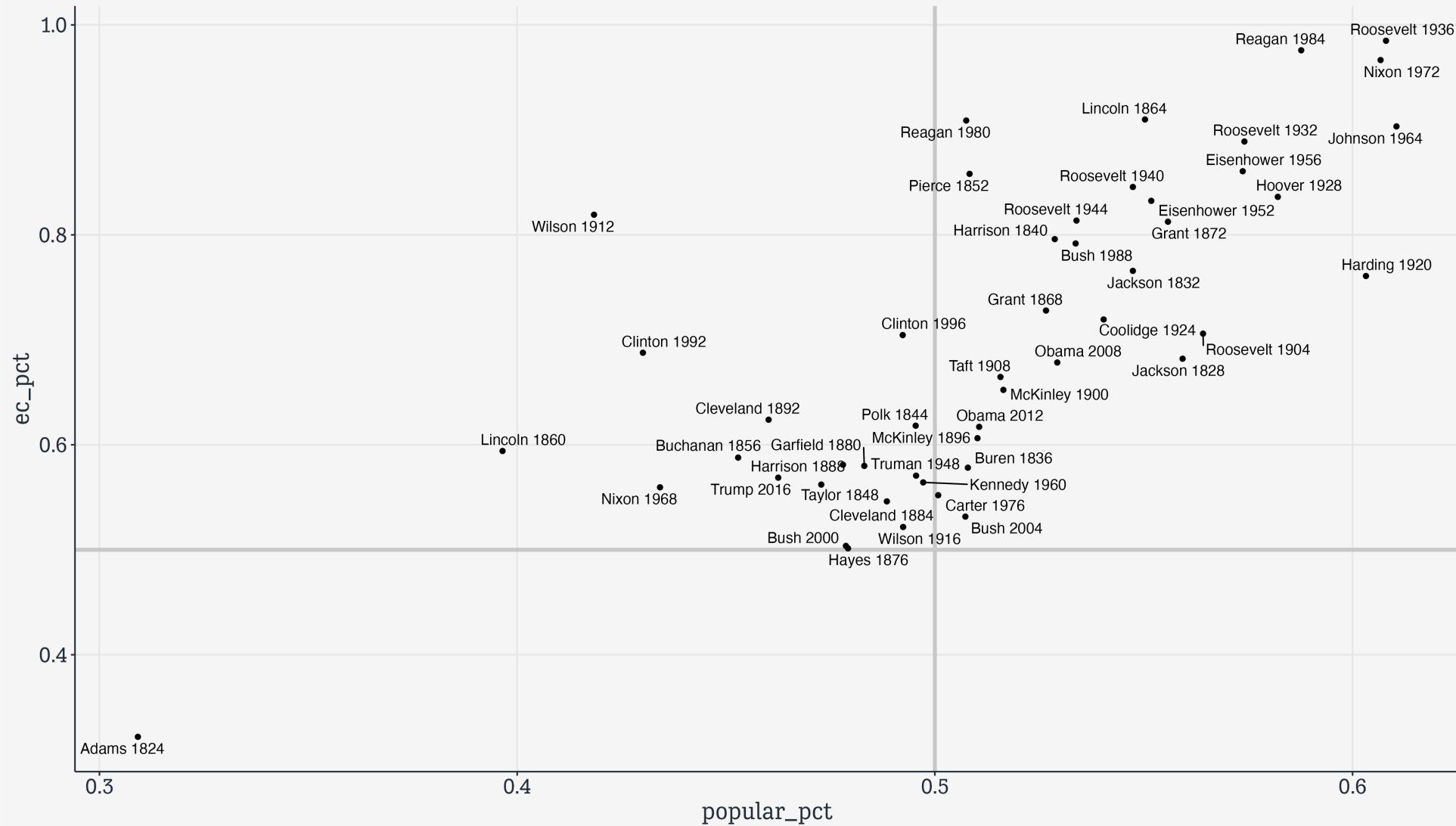
This looks terrible here because `geom_text_repel()` uses the dimensions of the available graphics device to iteratively figure out the labels. Let's allow it to draw on the whole slide.

```
p ← ggplot(data = elections_historic,  
            mapping = aes(x = popular_pct,  
                           y = ec_pct,  
                           label = winner_label))  
  
p + geom_hline(yintercept = 0.5,  
                 linewidth = 1.4, color = "gray80")  
  geom_vline(xintercept = 0.5,  
             linewidth = 1.4, color = "gray80")  
  geom_point() +  
  geom_text_repel()
```



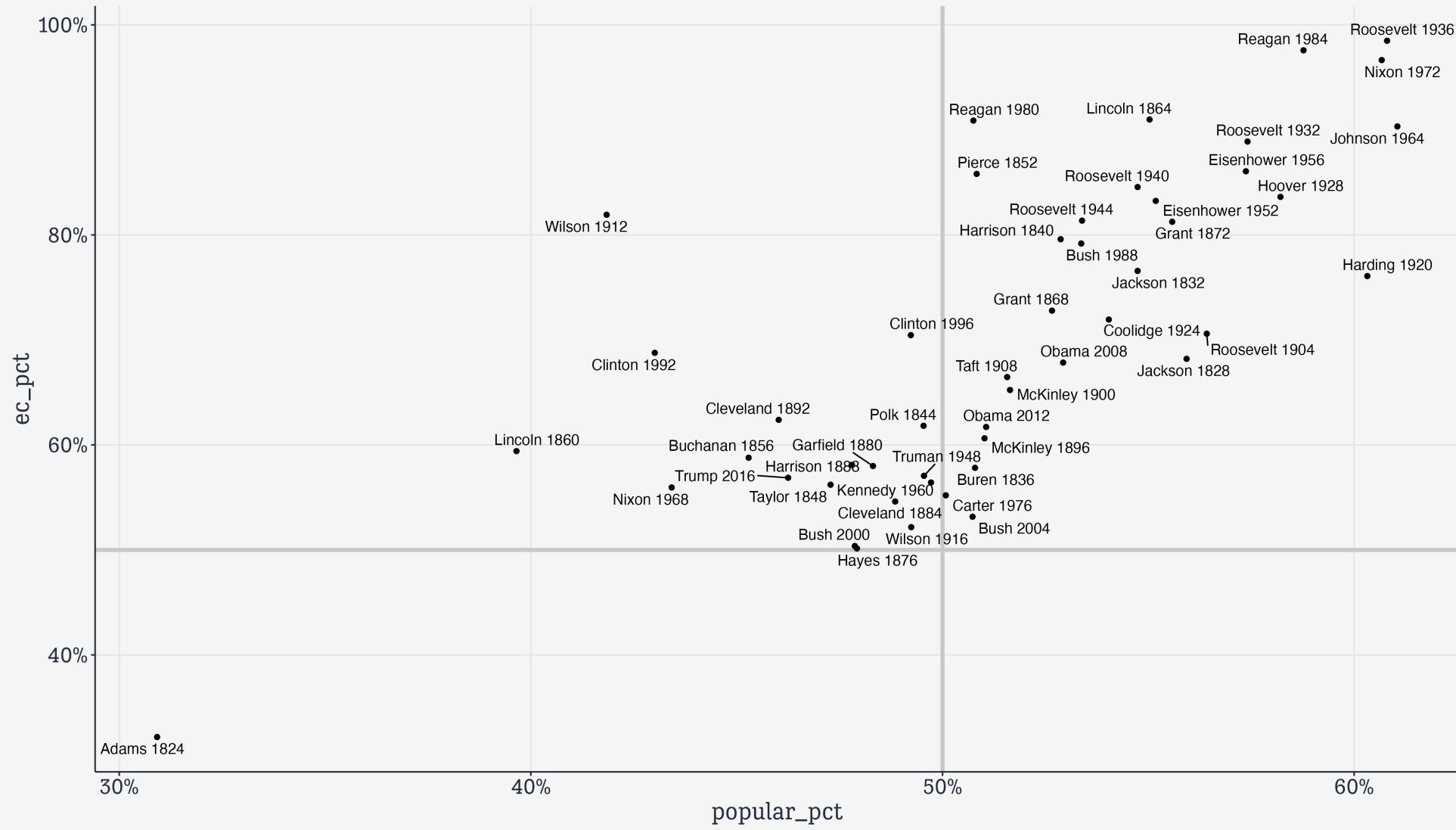
# Labeling is with respect to the plot size

```
p ← ggplot(data = elections_historic,  
            mapping  = aes(x = popular_pct,  
                            y = ec_pct,  
                            label = winner_label))  
  
p_out ← p +  
    geom_hline(yintercept = 0.5,  
                linewidth = 1.4,  
                color = "gray80") +  
    geom_vline(xintercept = 0.5,  
                linewidth = 1.4,  
                color = "gray80") +  
    geom_point() +  
    geom_text_repel()
```



# Adjust the Scales

```
p ← ggplot(data = elections_historic,  
            mapping  = aes(x = popular_pct,  
                            y = ec_pct,  
                            label = winner_label))  
p_out ← p + geom_hline(yintercept = 0.5,  
                        linewidth = 1.4,  
                        color = "gray80") +  
        geom_vline(xintercept = 0.5,  
                    linewidth = 1.4,  
                    color = "gray80") +  
        geom_point() +  
        geom_text_repel() +  
        scale_x_continuous(labels = label_percent()) +  
        scale_y_continuous(labels = label_percent())
```

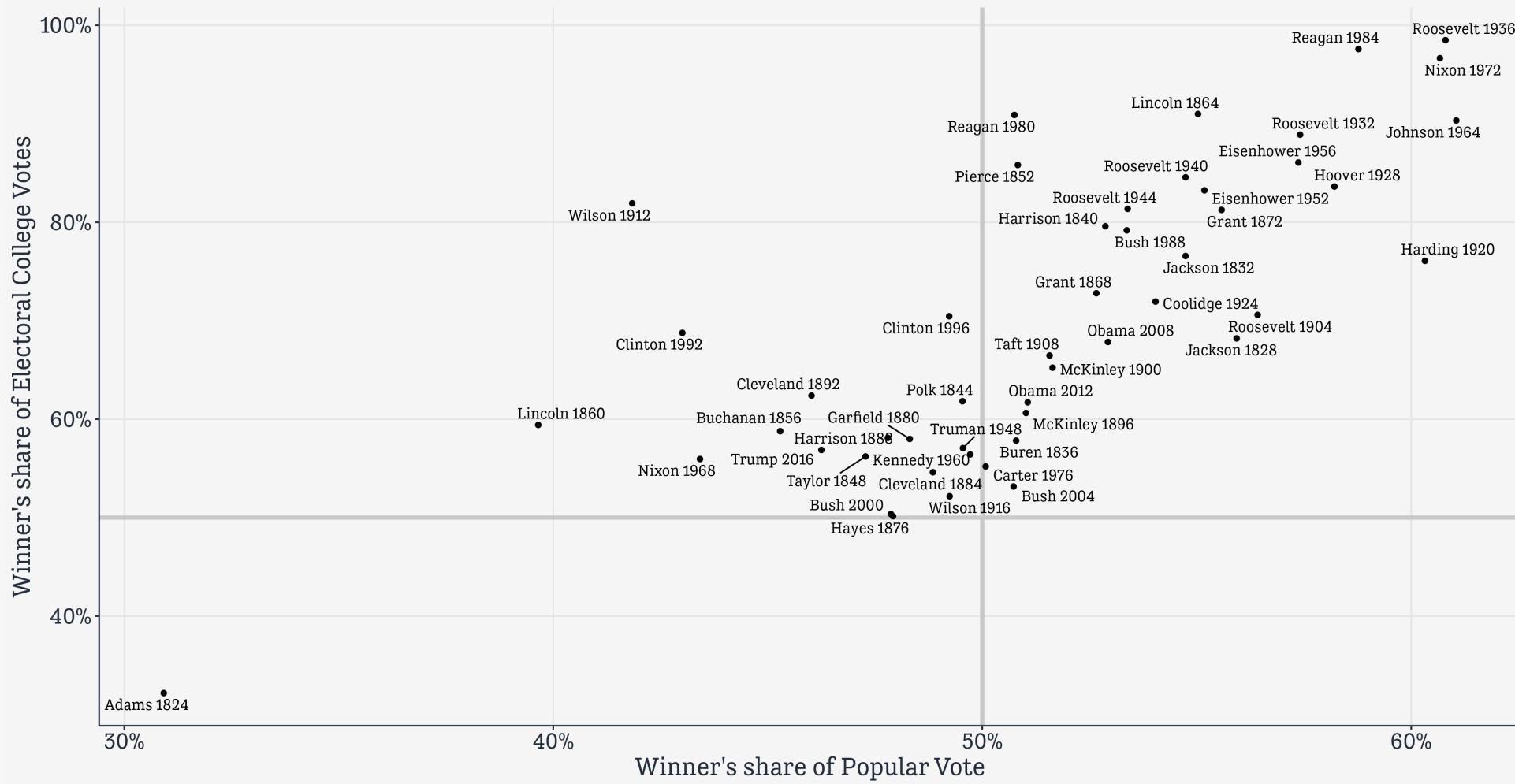


# Add the labels

```
p ← ggplot(data = elections_historic,
             mapping  = aes(x = popular_pct,
                            y = ec_pct,
                            label = winner_label))
p_out ← p + geom_hline(yintercept = 0.5,
                        linewidth = 1.4,
                        color = "gray80") +
  geom_vline(xintercept = 0.5,
             linewidth = 1.4,
             color = "gray80") +
  geom_point() +
  geom_text_repel(mapping = aes(family = "Tenso Slide")) +
  scale_x_continuous(labels = label_percent()) +
  scale_y_continuous(labels = label_percent()) +
  labs(x = x_label, y = y_label,
       title = p_title,
       subtitle = p_subtitle,
       caption = p_caption)
```

## Presidential Elections: Popular & Electoral College Margins

1824-2016

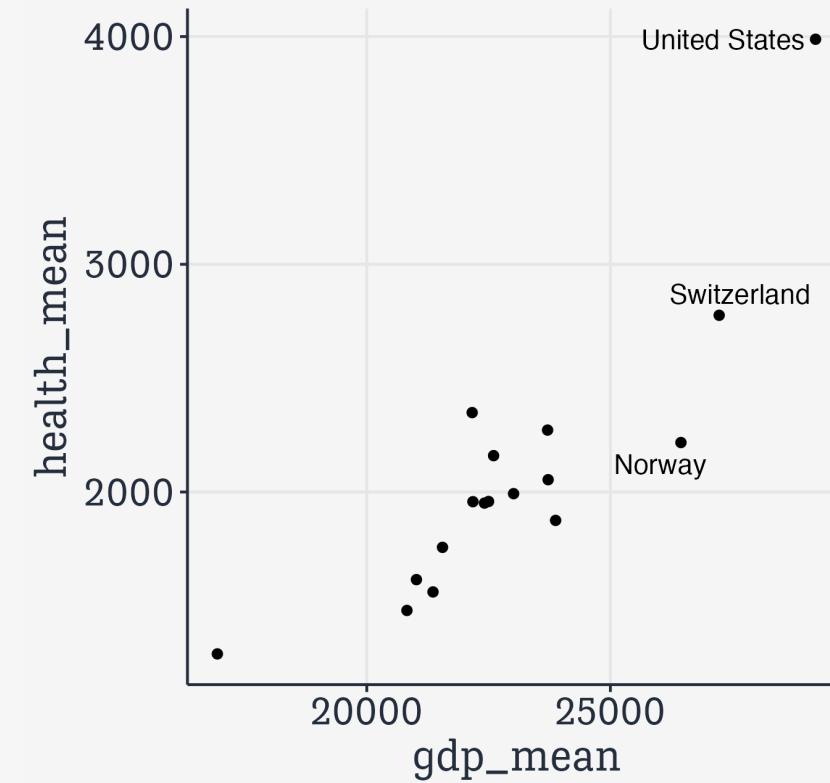


Data for 2016 are provisional.

# Labeling points of interest

# Option 1: On the fly in `ggplot`

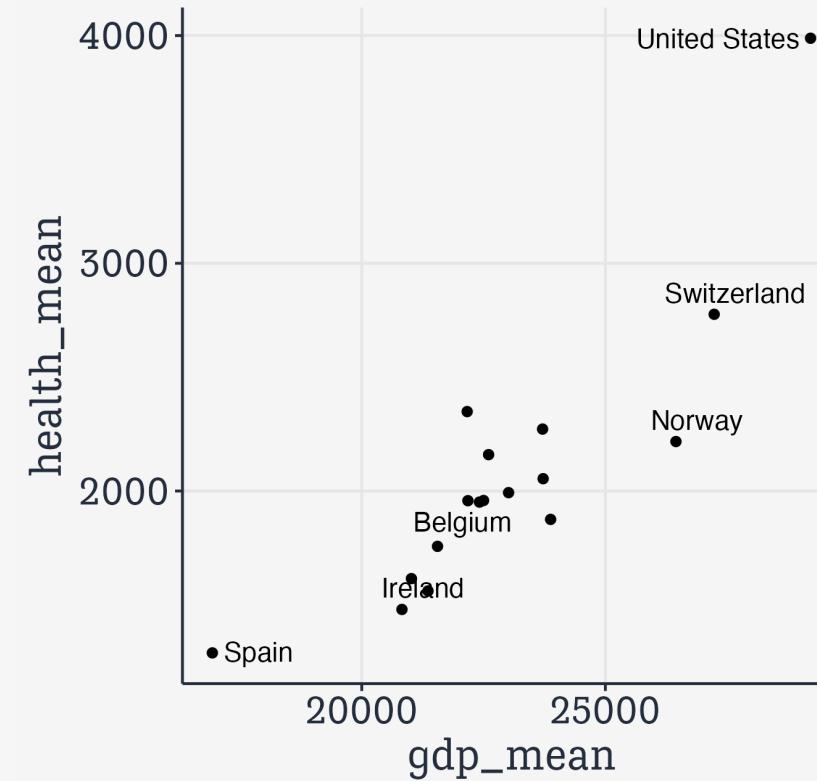
```
by_country %>%  
  ggplot(mapping = aes(x = gdp_mean,  
                      y = health_mean)) +  
  geom_point() +  
  geom_text_repel(data = subset(by_country, gdp_mean > 18000),  
                  mapping = aes(label = country))
```



# Option 1: On the fly inside `ggplot`

Stuffing everything into the `subset()` call might get messy

```
by_country >  
  ggplot(mapping = aes(x = gdp_mean,  
                        y = health_mean)) +  
  geom_point() +  
  geom_text_repel(data = subset(by_country,  
                                gdp_mean > 2500  
                                health_mean <  
                                country %in%  
                                mapping = aes(label = country
```



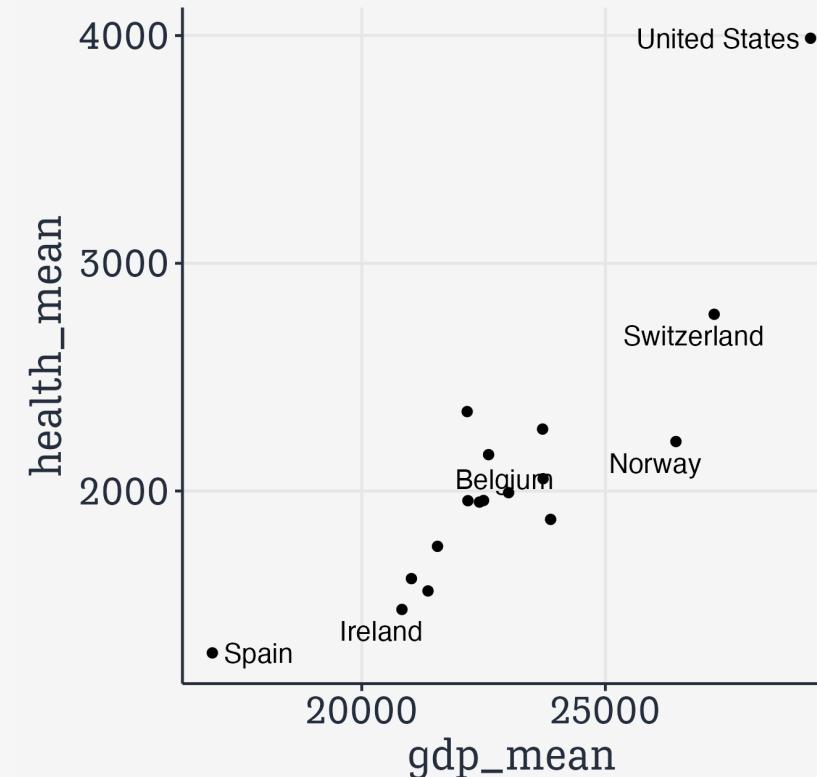
# Option 2: Use `dplyr` first

```
df_hl ← by_country %>%  
  filter(gdp_mean > 25000 |  
         health_mean < 1500 |  
         country %in% "Belgium")  
  
df_hl  
  
# A tibble: 6 × 28  
  consent_law country      donors_mean donors_sd pop_mean  pop_sd pop_dens_mean  
  <chr>       <chr>        <dbl>     <dbl>    <dbl>    <dbl>      <dbl>  
1 Informed    Ireland      19.8      2.48    3674.   132.      5.23  
2 Informed    United States 20.0      1.33   269330. 12545.     2.80  
3 Presumed    Belgium      21.9      1.94    10153.   109.      30.7  
4 Presumed    Norway       15.4      1.11    4386.   97.3      1.35  
5 Presumed    Spain        28.1      4.96    39666.   951.      7.84  
6 Presumed    Switzerland  14.2      1.71    7037.   170.      17.0  
# i 21 more variables: pop_dens_sd <dbl>, gdp_mean <dbl>, gdp_sd <dbl>,  
#   gdp_lag_mean <dbl>, gdp_lag_sd <dbl>, health_mean <dbl>, health_sd <dbl>,  
#   health_lag_mean <dbl>, health_lag_sd <dbl>, pubhealth_mean <dbl>,  
#   pubhealth_sd <dbl>, roads_mean <dbl>, roads_sd <dbl>, cerebvas_mean <dbl>,  
#   cerebvas_sd <dbl>, assault_mean <dbl>, assault_sd <dbl>,  
#   external_mean <dbl>, external_sd <dbl>, txp_pop_mean <dbl>,  
#   txp_pop_sd <dbl>
```

## Option 2: Use `dplyr` first

This makes things neater. A `geom` can be fully “autonomous”. Each one can have its own `mapping` call *and* its own `data` source. This can be very useful when building up plots overlaying several sources or subsets of data.

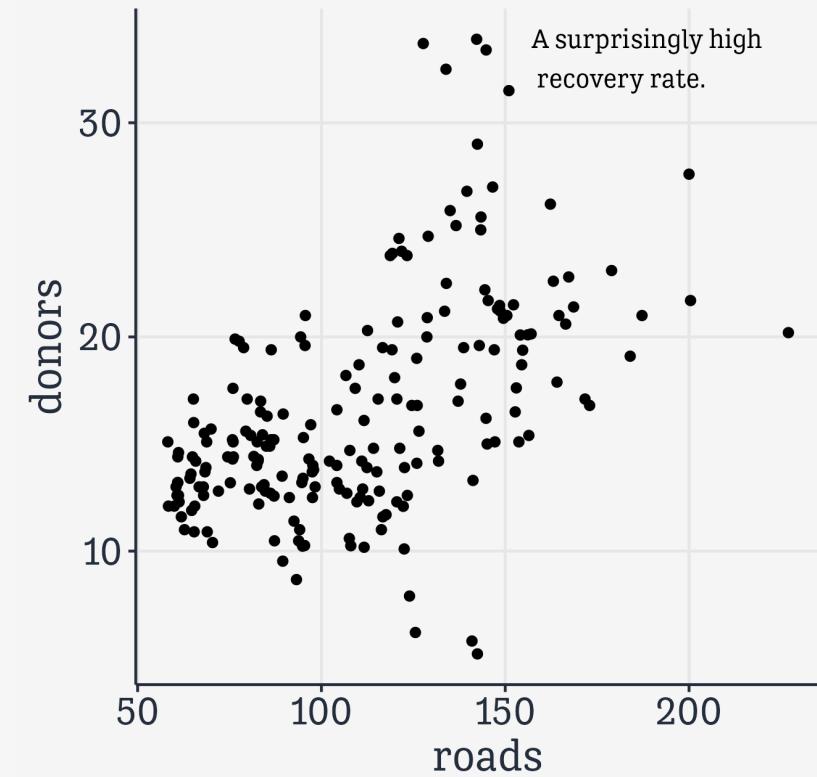
```
by_country %>%  
  ggplot(mapping = aes(x = gdp_mean,  
                        y = health_mean)) +  
  geom_point() +  
  geom_text_repel(data = df_hl,  
                  mapping = aes(label = country
```



**Write and draw  
inside the plot area**

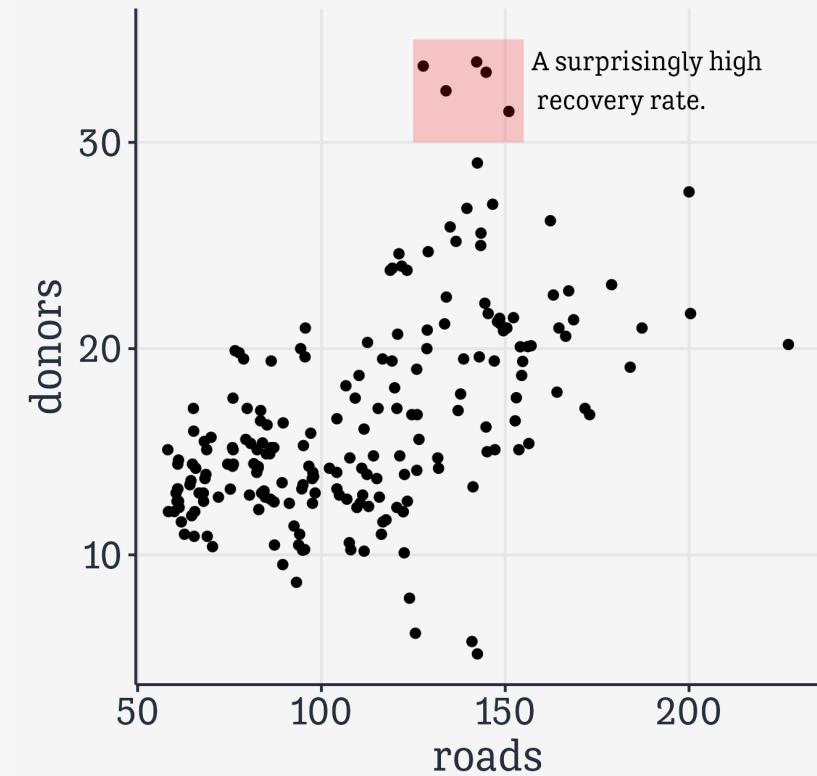
# annotate() can imitate geoms

```
organdata >  
  ggplot(mapping = aes(x = roads,  
                        y = donors)) +  
  geom_point() +  
  annotate(geom = "text",  
          family = "Tenso Slide",  
          x = 157,  
          y = 33,  
          label = "A surprisingly high \n recovery rate.",  
          hjust = 0)
```



# annotate() can imitate geoms

```
organdata >  
  ggplot(mapping = aes(x = roads,  
                        y = donors)) +  
  geom_point() +  
  annotate(geom = "rect",  
          xmin = 125, xmax = 155,  
          ymin = 30, ymax = 35,  
          fill = "red",  
          alpha = 0.2) +  
  annotate(geom = "text",  
          x = 157, y = 33,  
          family = "Tenso Slide",  
          label = "A surprisingly high \n recovery rate.",  
          hjust = 0)
```



# Scales, Guides, and Themes

# Every mapped variable has a scale

Aesthetic mappings link quantities or categories in your data to things you can see on the graph. Thus, they have a scale associated with that representation.

Scale functions manage this relationship. Remember: not just `x` and `y` but also `color`, `fill`, `shape`, `size`, and `alpha` are scales.

If it can represent your data, it has a scale, and a *scale function* to manage it.

This means you control things like color schemes *for data mappings* through scale functions

Because those colors are representing features of your data.

# Naming conventions for scale functions

In general, scale functions are named like this:

**scale\_<MAPPING>\_<KIND>()**

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We already know there are a lot of **mappings**

*x, y, color, size, shape, and so on.*

# Naming conventions

In general, scale functions are named like this:

**scale\_<MAPPING>\_<KIND>()**

We already know there are a lot of **mappings**

*x, y, color, size, shape, and so on.*

And there are many **kinds** of scale as well.

*discrete, continuous, log10, date, binned, and many others.*

So there's a whole zoo of scale functions.

*The naming convention helps us keep track.*

# Naming conventions

**scale\_<MAPPING>\_<KIND>()**

scale\_x\_continuous()

scale\_y\_continuous()

scale\_x\_discrete()

scale\_y\_discrete()

scale\_x\_log10()

scale\_x\_sqrt()

# Naming conventions

**scale\_<MAPPING>\_<KIND>()**

scale\_x\_continuous()

scale\_color\_discrete()

scale\_y\_continuous()

scale\_color\_gradient()

scale\_x\_discrete()

scale\_color\_gradient2()

scale\_y\_discrete()

scale\_color\_brewer()

scale\_x\_log10()

scale\_fill\_discrete()

scale\_x\_sqrt()

scale\_fill\_gradient()

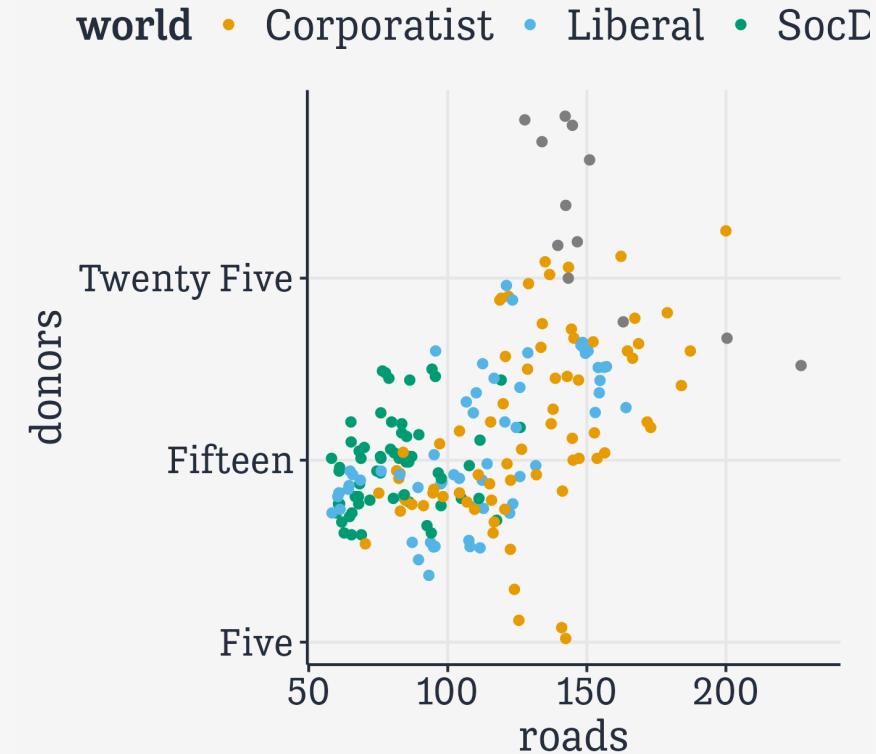
scale\_fill\_gradient2()

scale\_fill\_brewer()

# Scale functions in practice

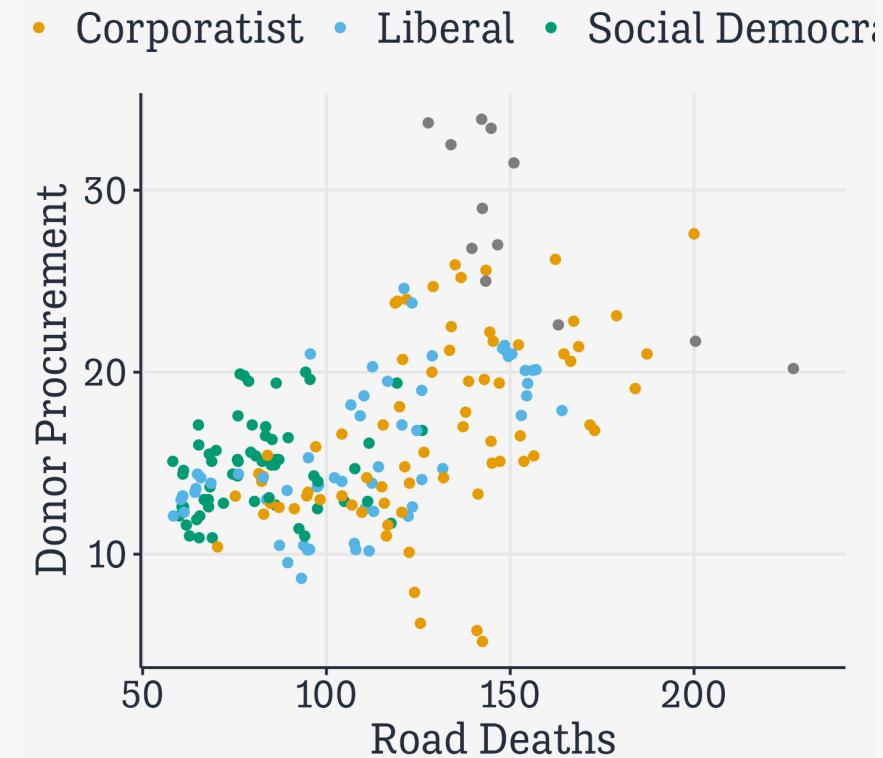
Scale functions take arguments appropriate to their mapping and kind

```
organdata %>%
  ggplot(mapping = aes(x = roads,
                        y = donors,
                        color = world)) +
  geom_point() +
  scale_y_continuous(breaks = c(5, 15, 25),
                     labels = c("Five",
                               "Fifteen",
                               "Twenty Five"))
```



# More usefully ...

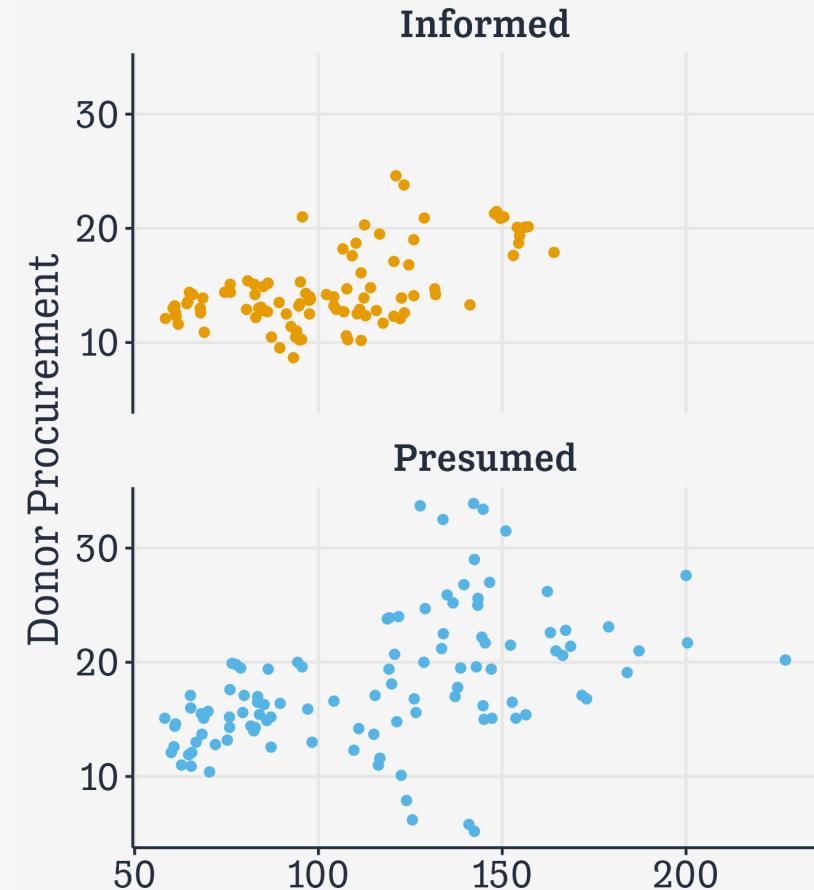
```
organdata %>  
  ggplot(mapping = aes(x = roads,  
                        y = donors,  
                        color = world)) +  
  geom_point() +  
  scale_color_discrete(labels =  
    c("Corporatist",  
      "Liberal",  
      "Social Democratic",  
      "Unclassified")) +  
  labs(x = "Road Deaths",  
       y = "Donor Procurement",  
       color = "Welfare State")
```



# The `guides()` function

Controls overall properties of the guide labels. Common use: turning it off. We'll see more advanced uses later.

```
organdata %>  
  ggplot(mapping = aes(x = roads,  
                        y = donors,  
                        color = consent_law)) +  
  geom_point() +  
  facet_wrap(~ consent_law, ncol = 1) +  
  guides(color = "none") +  
  labs(x = "Road Deaths",  
       y = "Donor Procurement")
```



# The `theme()` function

`theme()` styles parts of your plot that are *not* directly representing your data. Often the first thing people want to adjust; but logically it's the *last* thing.

```
## Using the "classic" ggplot theme here
organdata >
  ggplot(mapping = aes(x = roads,
                        y = donors,
                        color = consent_law)) +
  geom_point() +
  labs(title = "By Consent Law",
       x = "Road Deaths",
       y = "Donor Procurement",
       color = "Legal Regime:") +
  theme(legend.position = "bottom",
        plot.title = element_text(color = "dark",
                                   face = "bold")
```

