

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)`

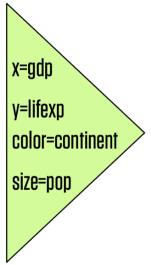
ggplot's FLOW OF ACTION

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



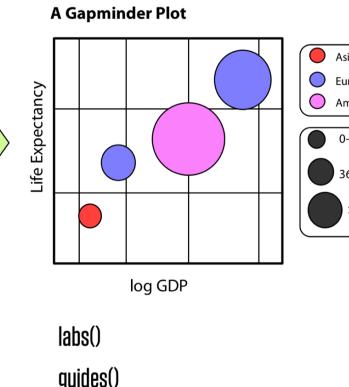
3. Geom

```
geom_point()
```

4. Co-ordinates, Scales

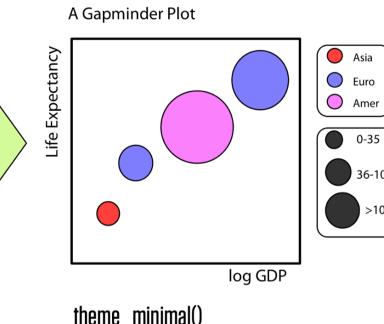
```
coord_cartesian()  
scale_x_log10()
```

5. Labels & Guides

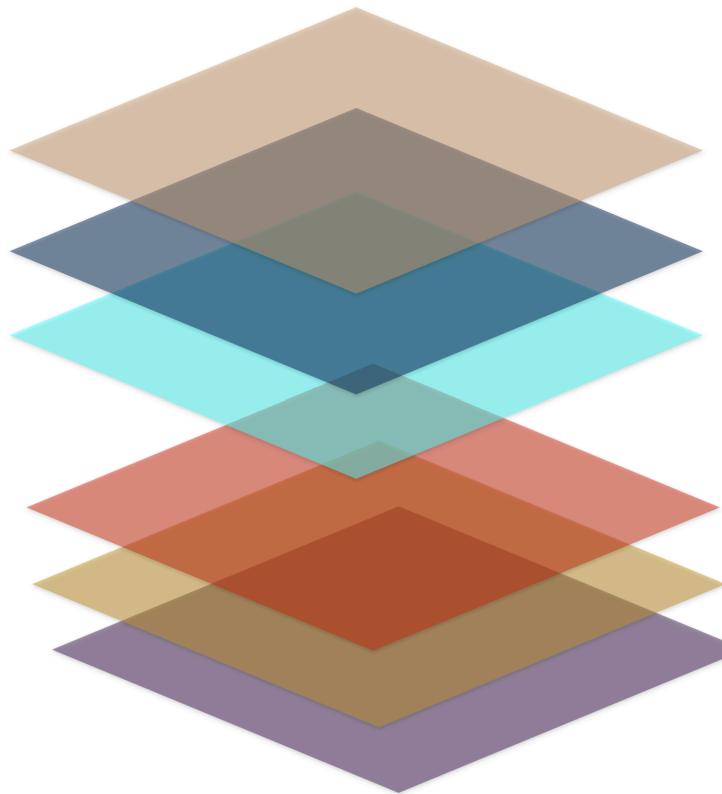


```
labs()  
guides()
```

6. Themes



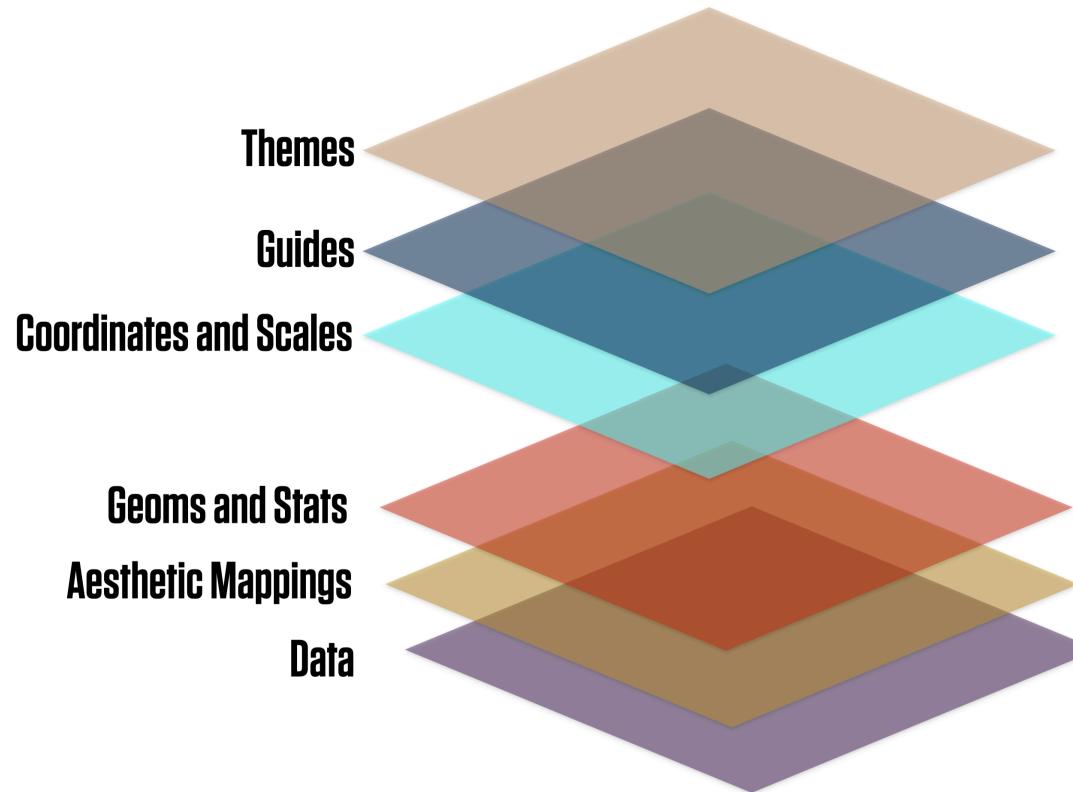
ggplot's flow of action



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>, padege <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

n-way tables

Race	Religion	Northeast	Midwest	South	West
White	Protestant	112	260	415	180
	Catholic	142	148	116	94
	Jewish	26	3	11	10
	None	85	126	123	147
	Other	16	19	26	31
	(Missing)	1	3	6	-
Black	Protestant	36	50	209	32
	Catholic	6	5	23	8
	Jewish	1	-	-	-
	None	14	25	33	17
	Other	3	8	14	1
Other	Protestant	10	15	26	26
	Catholic	14	19	21	53
	None	13	6	14	16
	Other	9	6	10	16
Black	(Missing)	-	1	3	1
Other	(Missing)	-	1	2	-

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

<code>id</code>	<code>bigregion</code>	<code>religion</code>
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

<code>bigregion</code>	<code>religion</code>	<code>N</code>
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

<code>bigregion</code>	<code>religion</code>	<code>N</code>	<code>pct</code>
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...
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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>,
```

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>
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 *one* column

```
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  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 ...  
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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>
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 x 32
# Groups:   bigregion, religion [24]
  year    id ballot      age child� sibs degree race sex   region income16
  <dbl> <dbl> <labelled> <dbl> <dbl> <dbl> <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 Femal... New E... $170000...
5 2016     5 3           55     2 2   Gradu... White Femal... New E... $170000...
6 2016     6 2           53     2 2   Junio... White Femal... 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 Femal... 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 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...
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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>  
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 ...  
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5 2016     5 3           55      2 2  Gradu... White Fema... New E... $170000...  
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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 ...  
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, which then “disappears”—i.e. it becomes the rows of in the summary table.

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 x 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
```

Use `tally()`

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

```
# A tibble: 24 x 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
```

Use `count()`

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

```
# A tibble: 24 x 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
```

Group it yourself;
result is grouped.

More compact; result
is grouped.

One step; result is
not grouped.

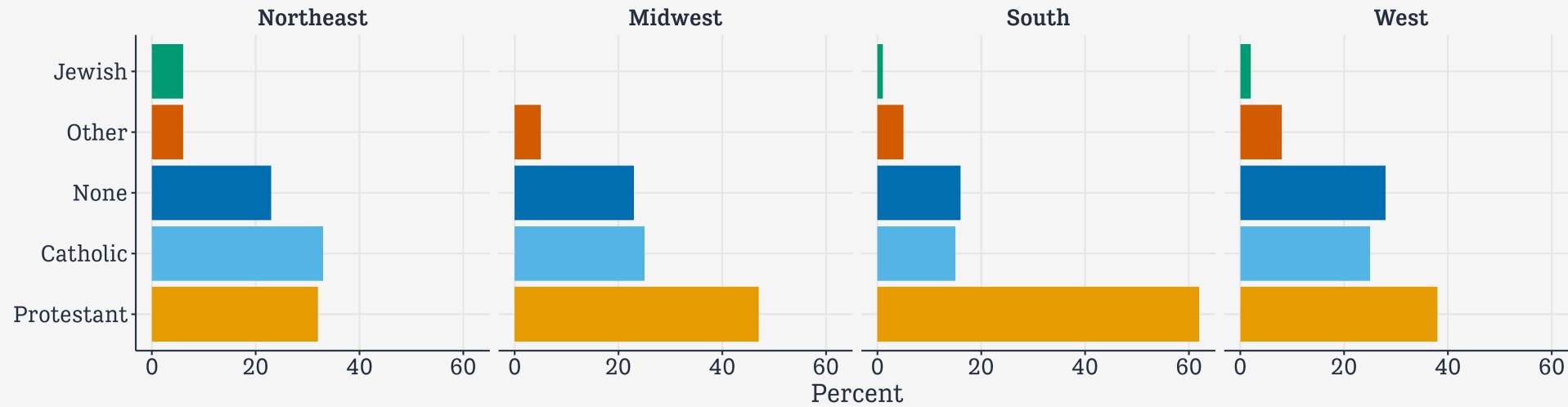
Pass results on to ... a **table**

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

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

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()
```

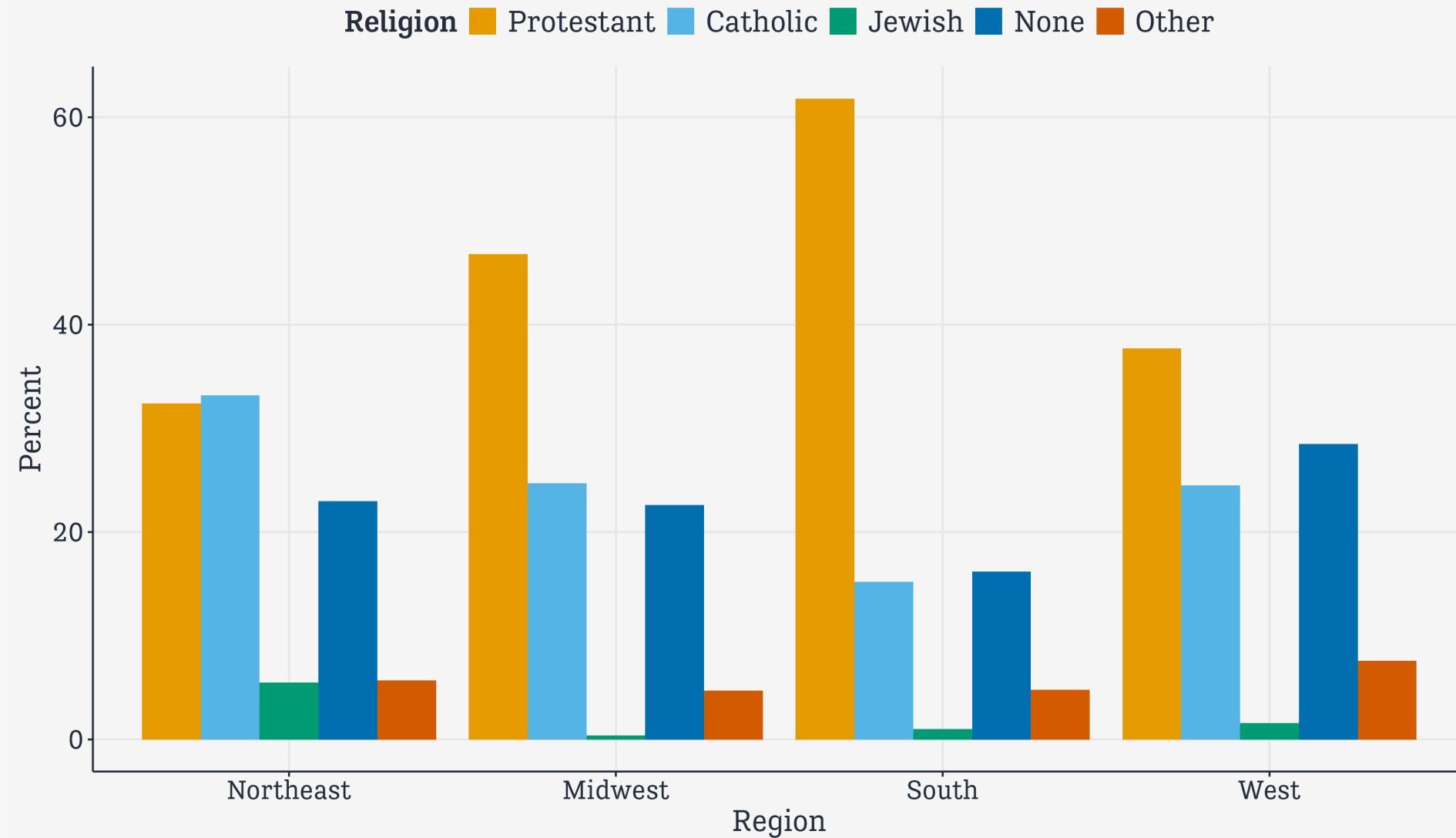
```
head(rel_by_region)
```

```
# 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
```

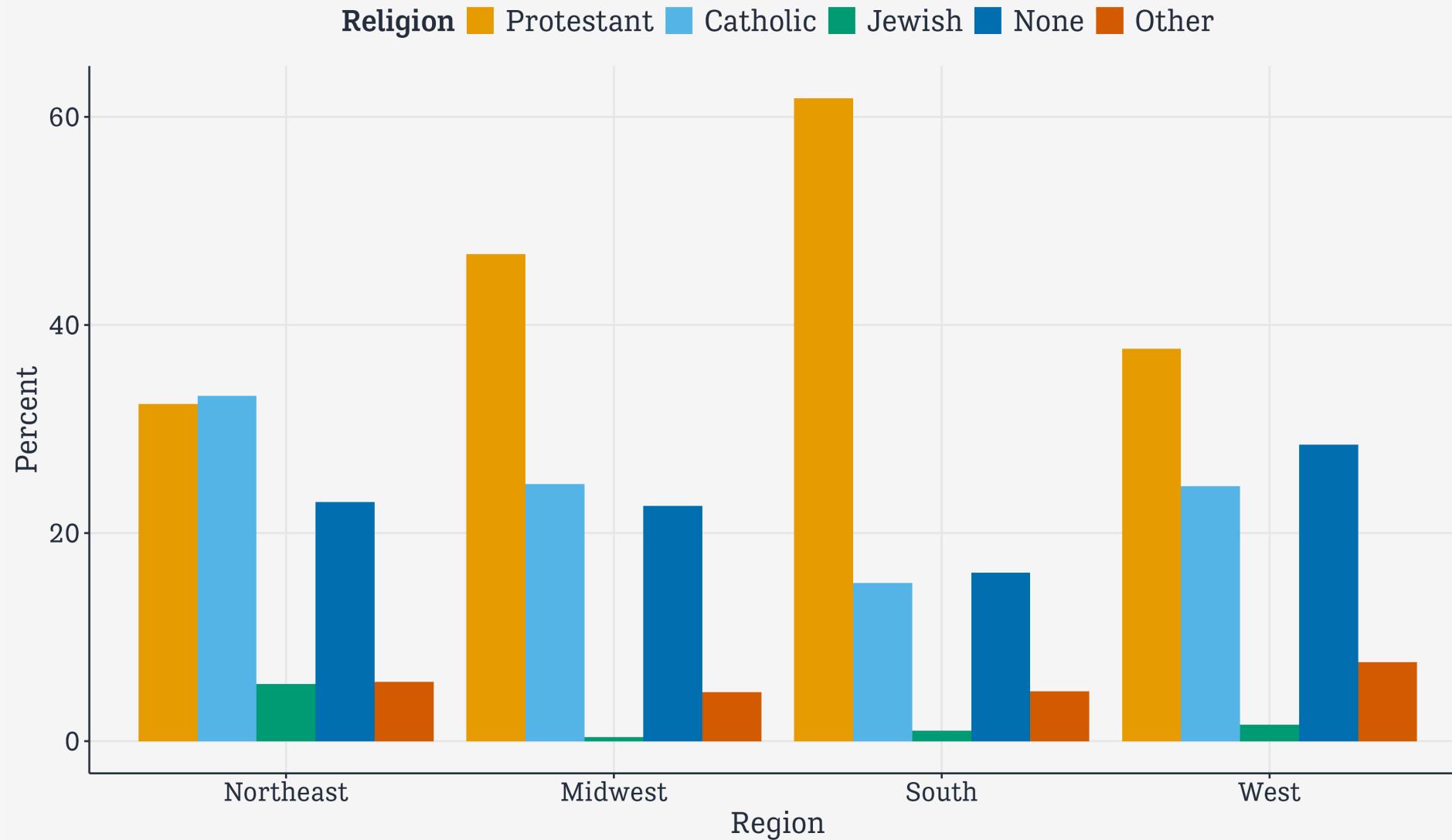
We might write ...

```
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!



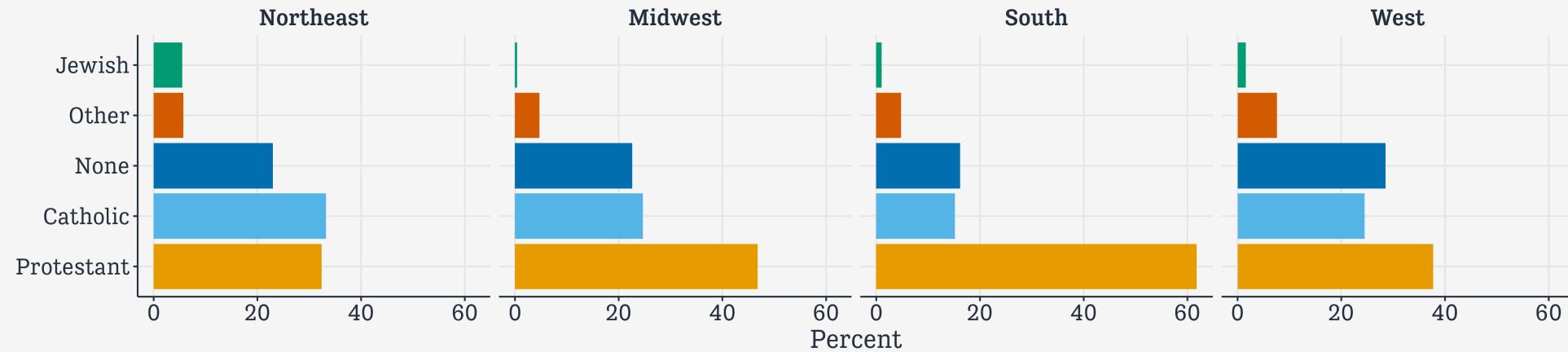
Try faceting instead

```
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.)

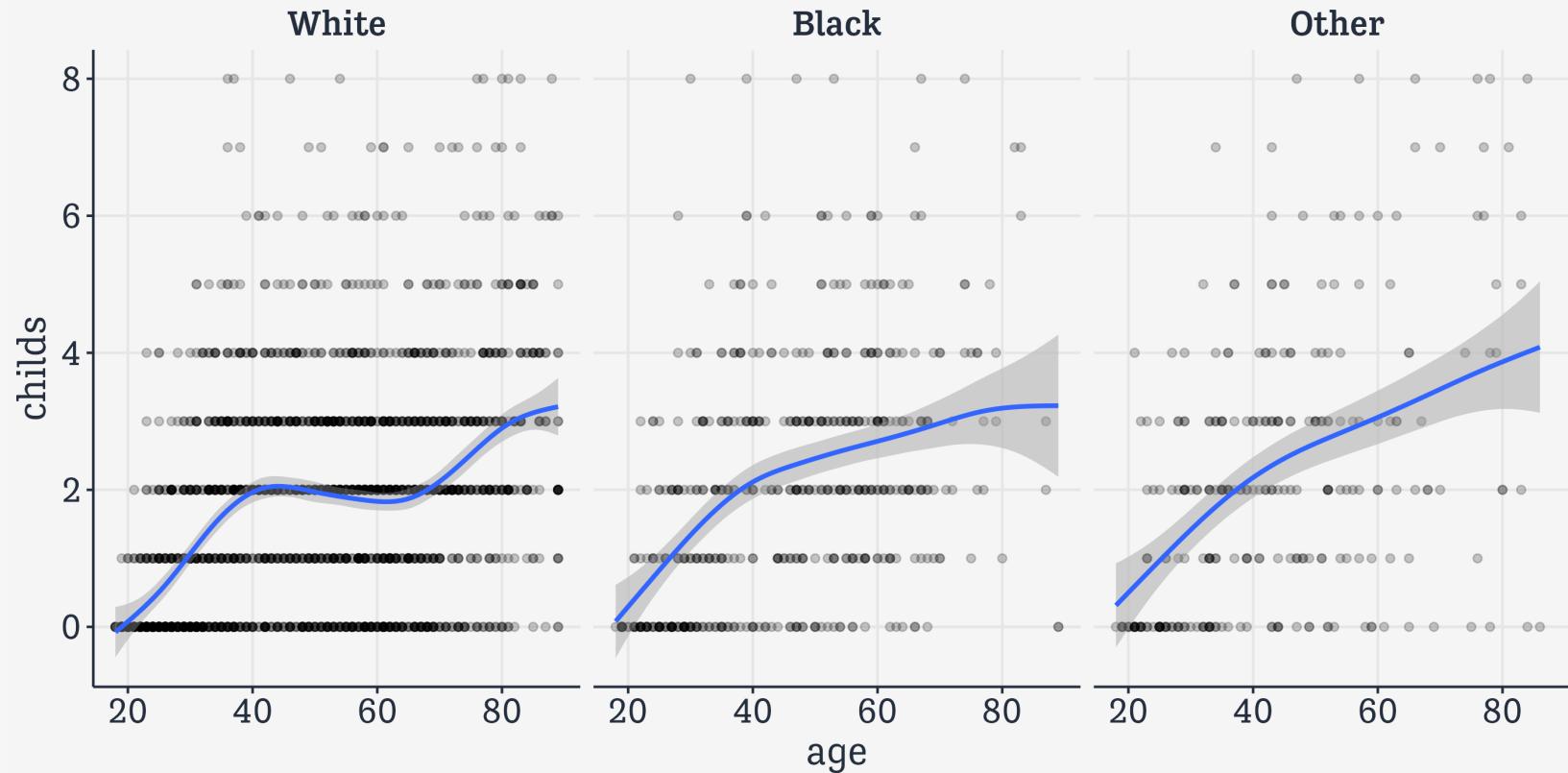
Try faceting variables instead of mapping them to color or shape.

Try to minimize the need for guides and legends.

Two kinds of facet

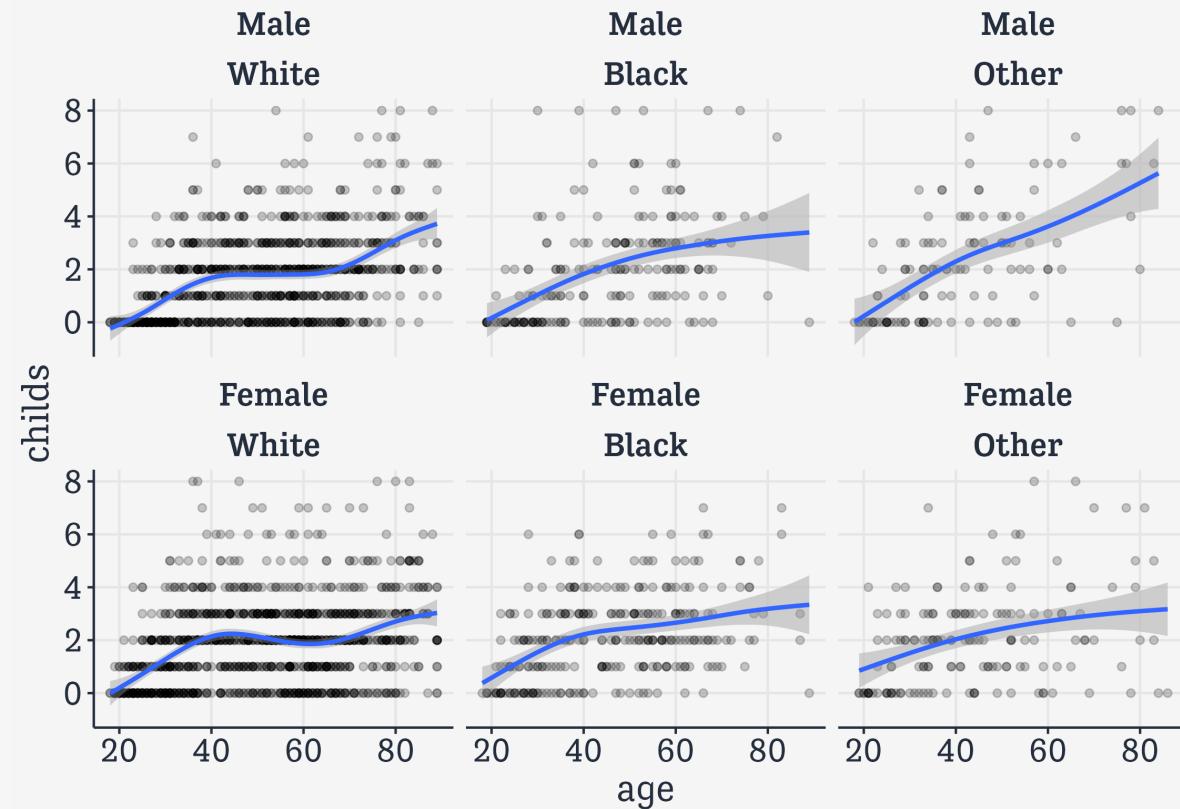
Facet Children vs Age, by Race

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



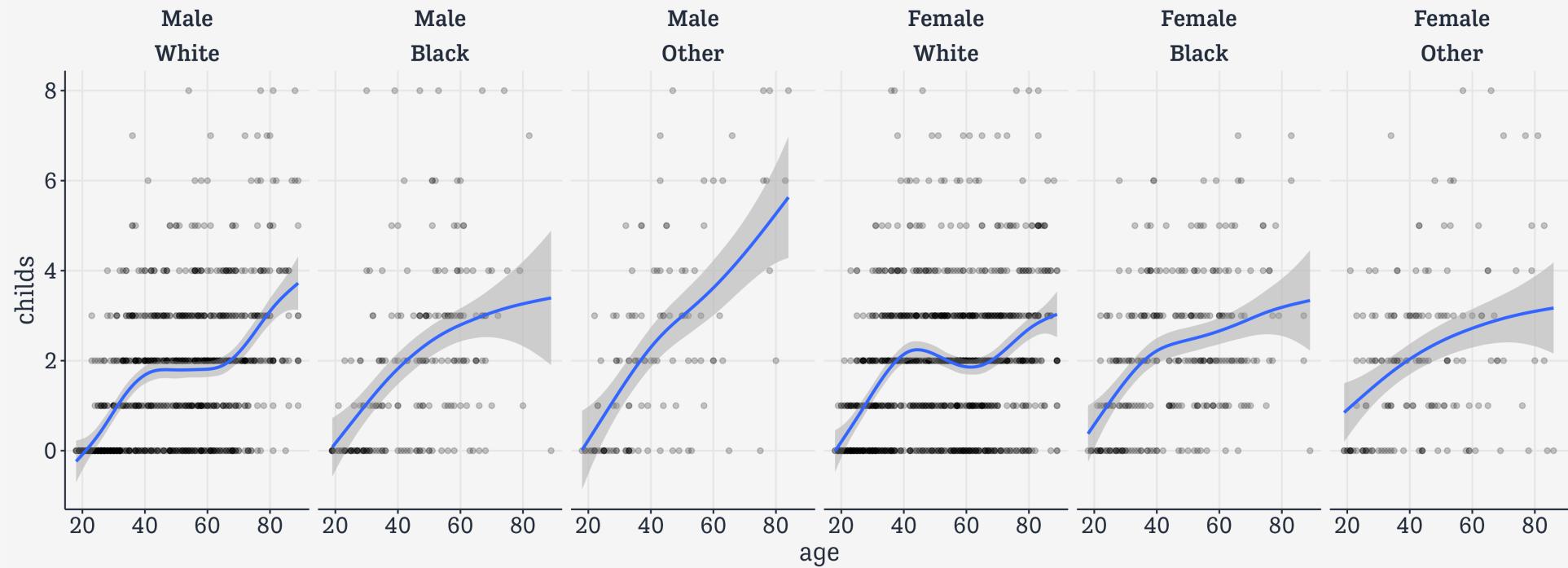
Facet by more than one variable

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



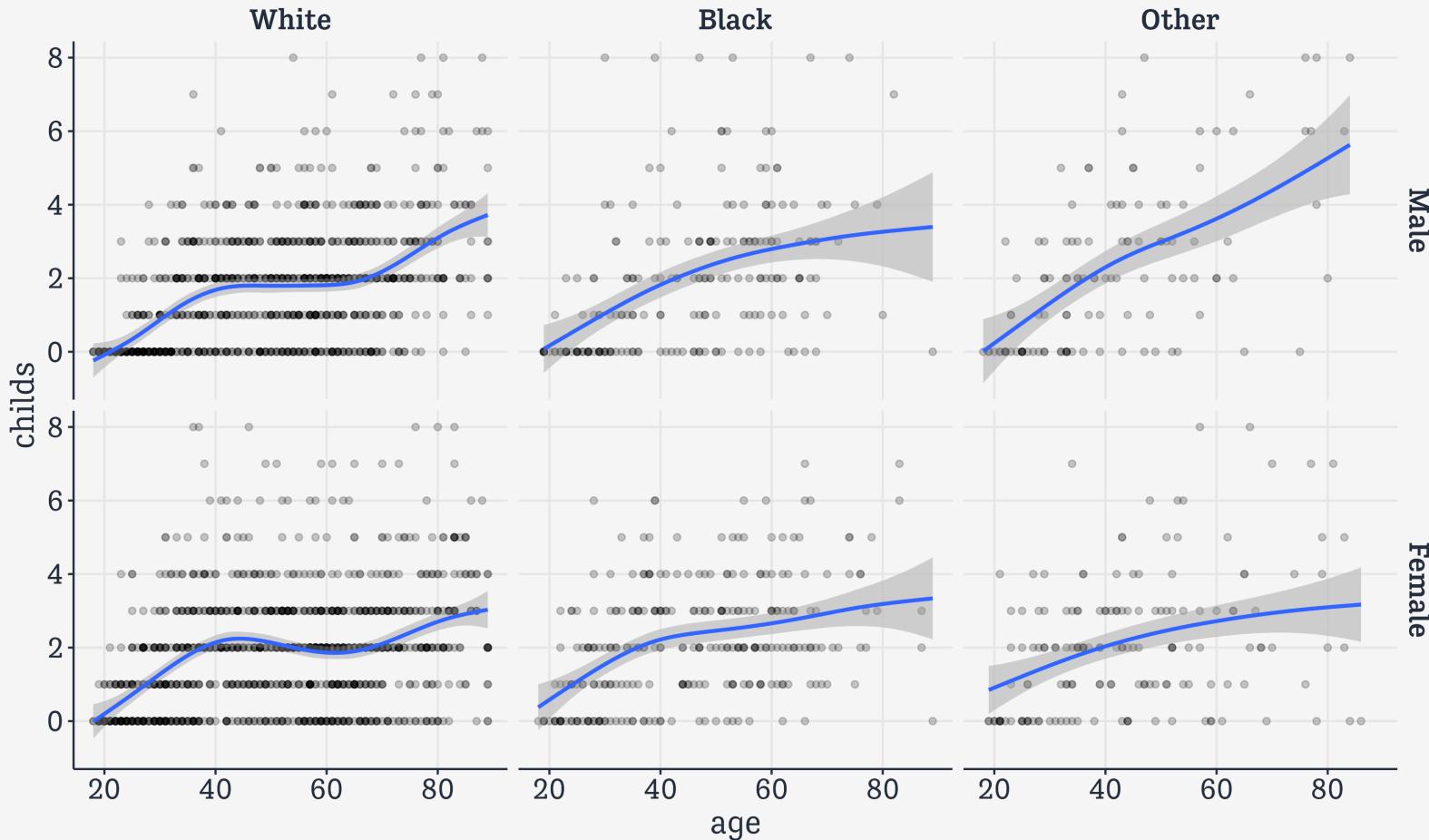
Arrange `facet_wrap()` quite freely

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



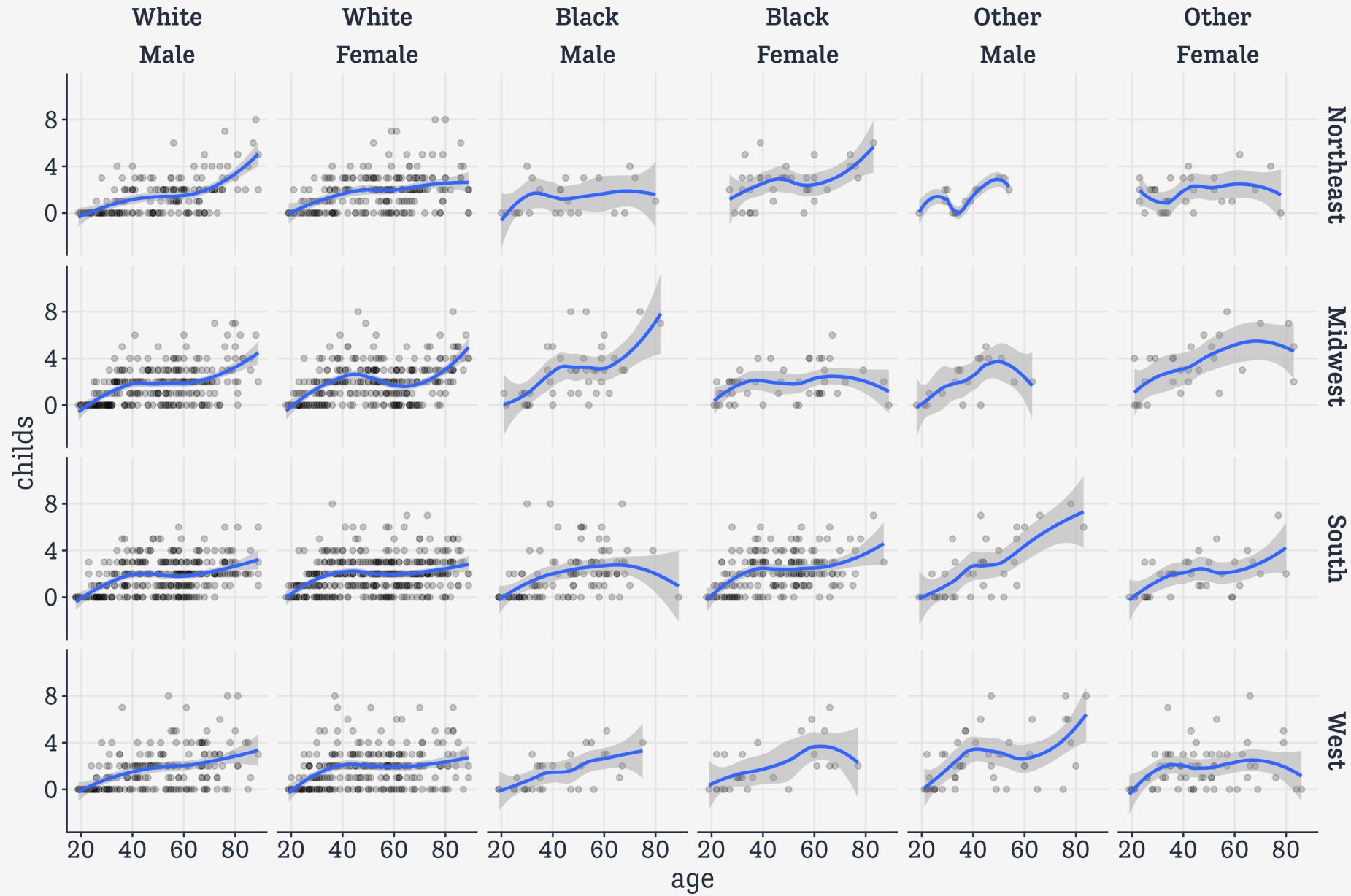
facet_grid() is more like a true crosstab

```
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

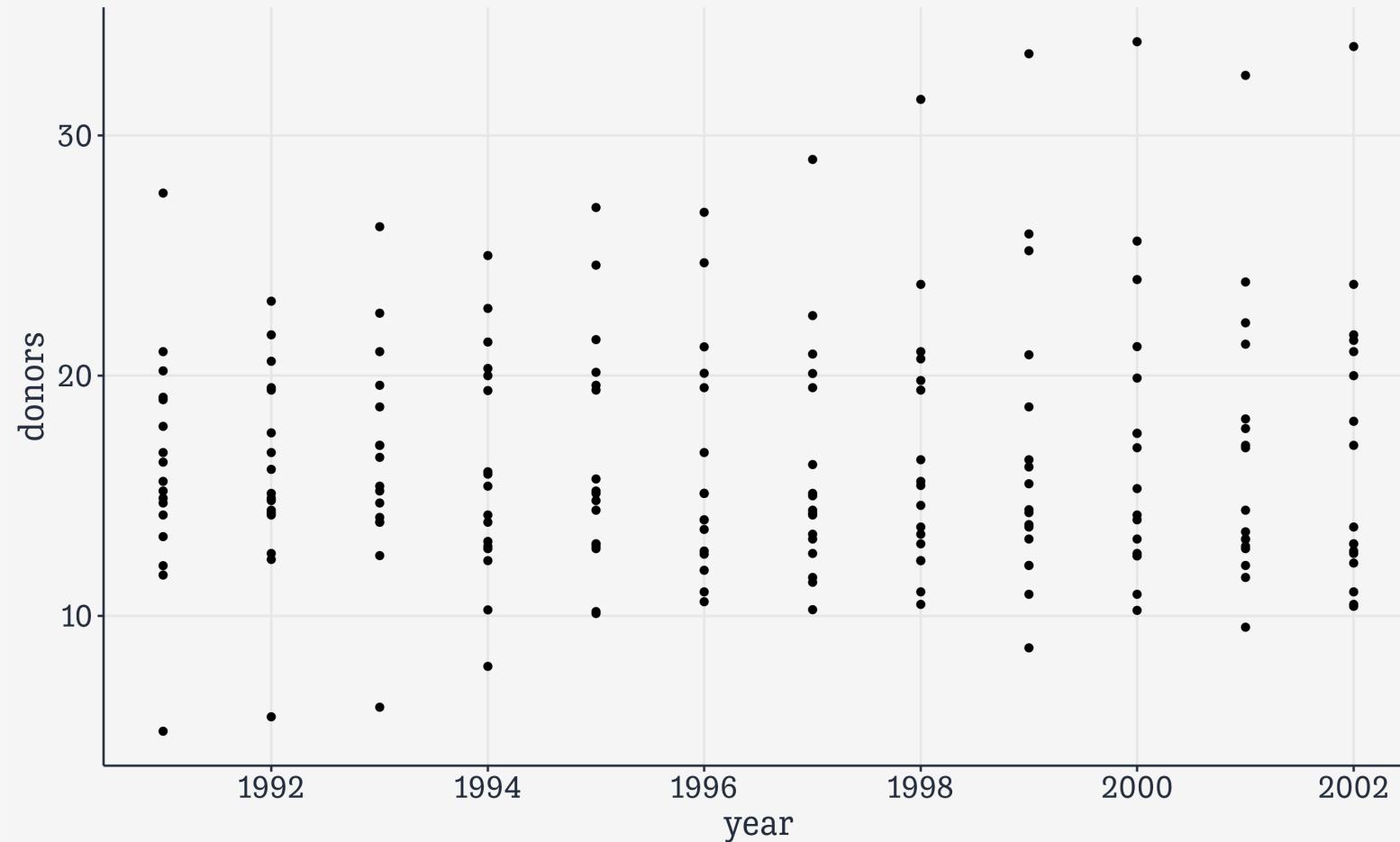
organdata is in the socviz package

```
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>
```

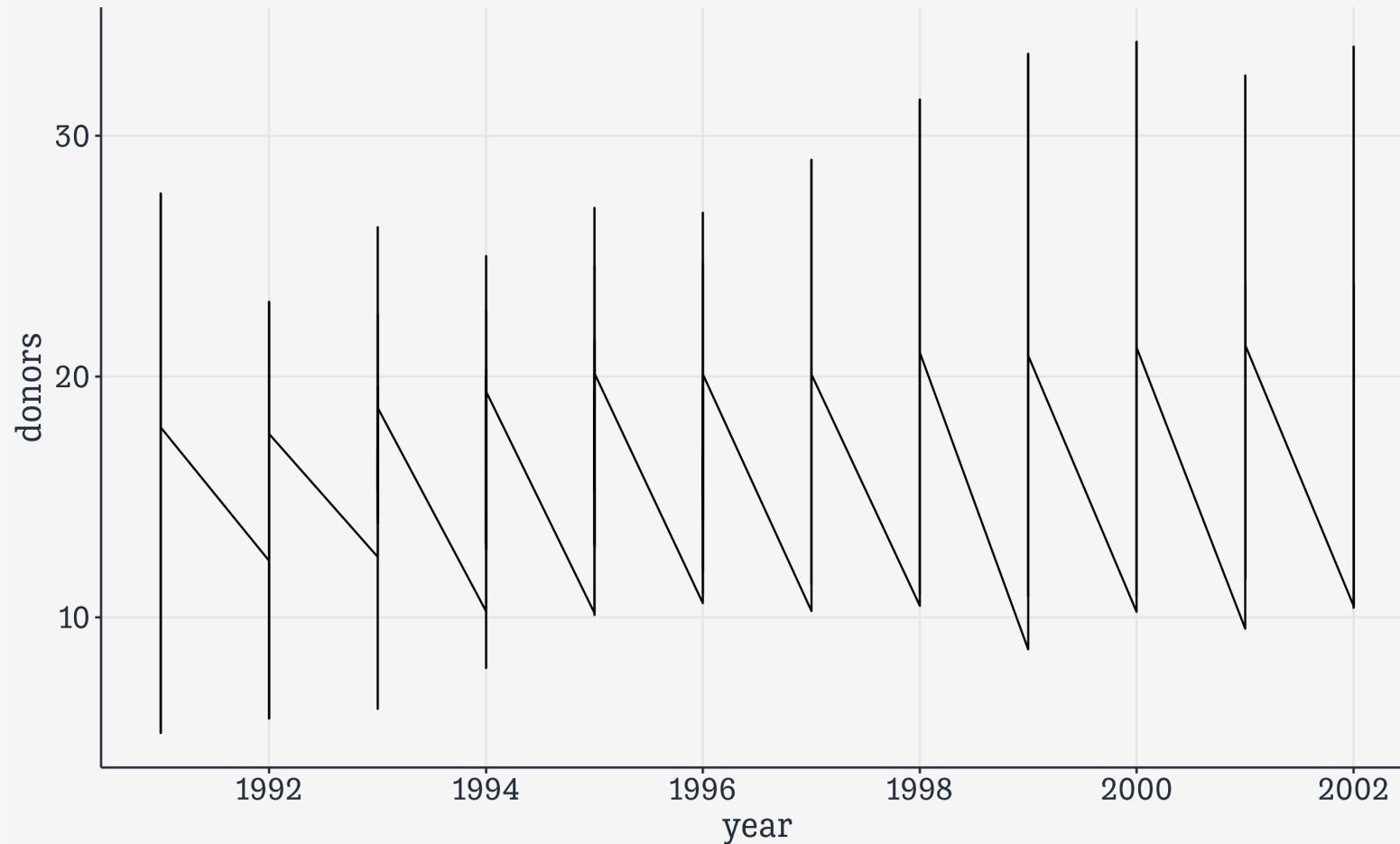
First look

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



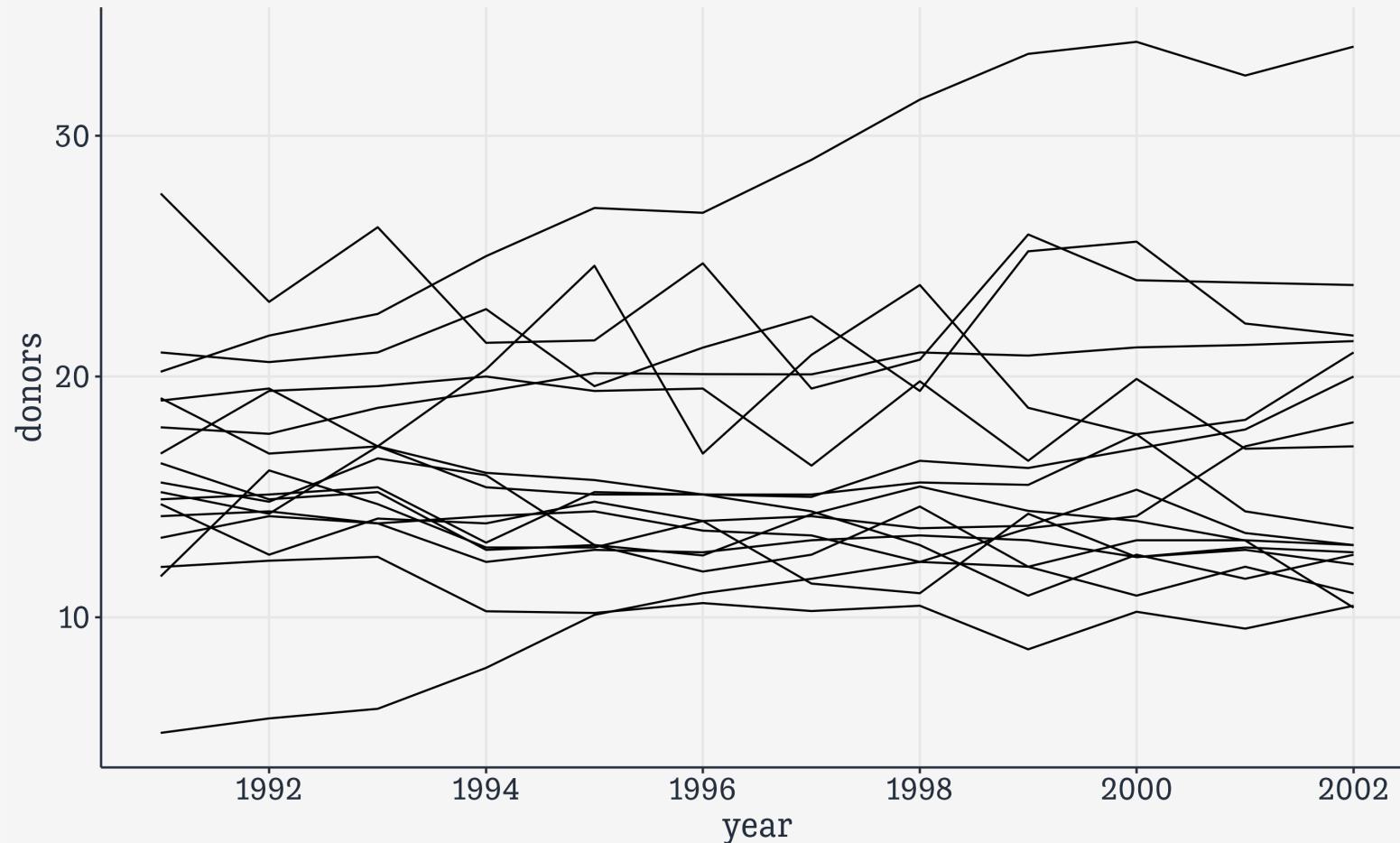
First look

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



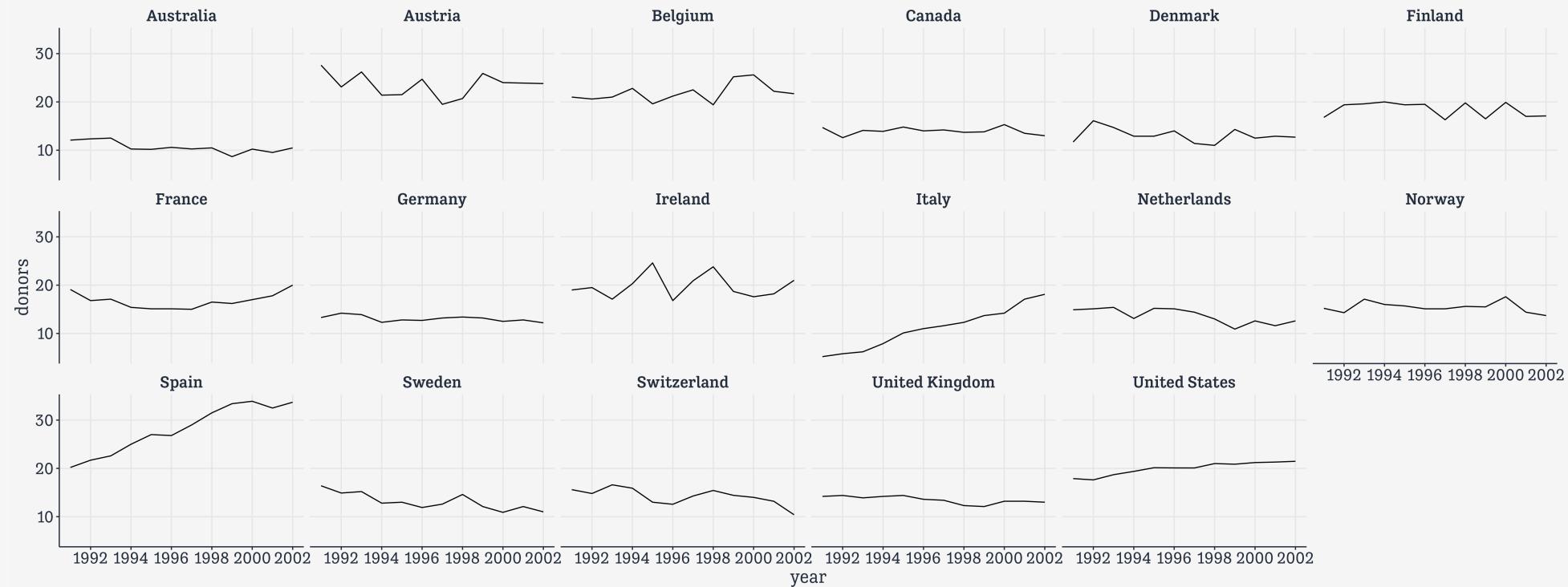
First look

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



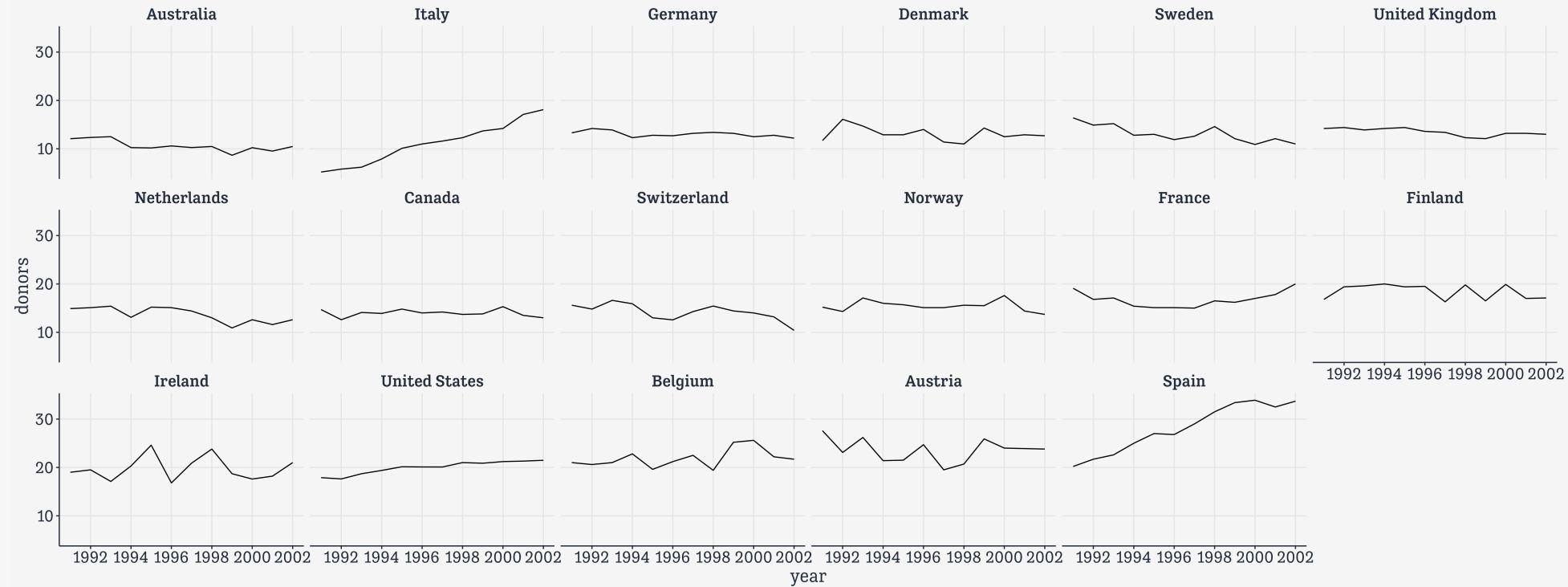
First look

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



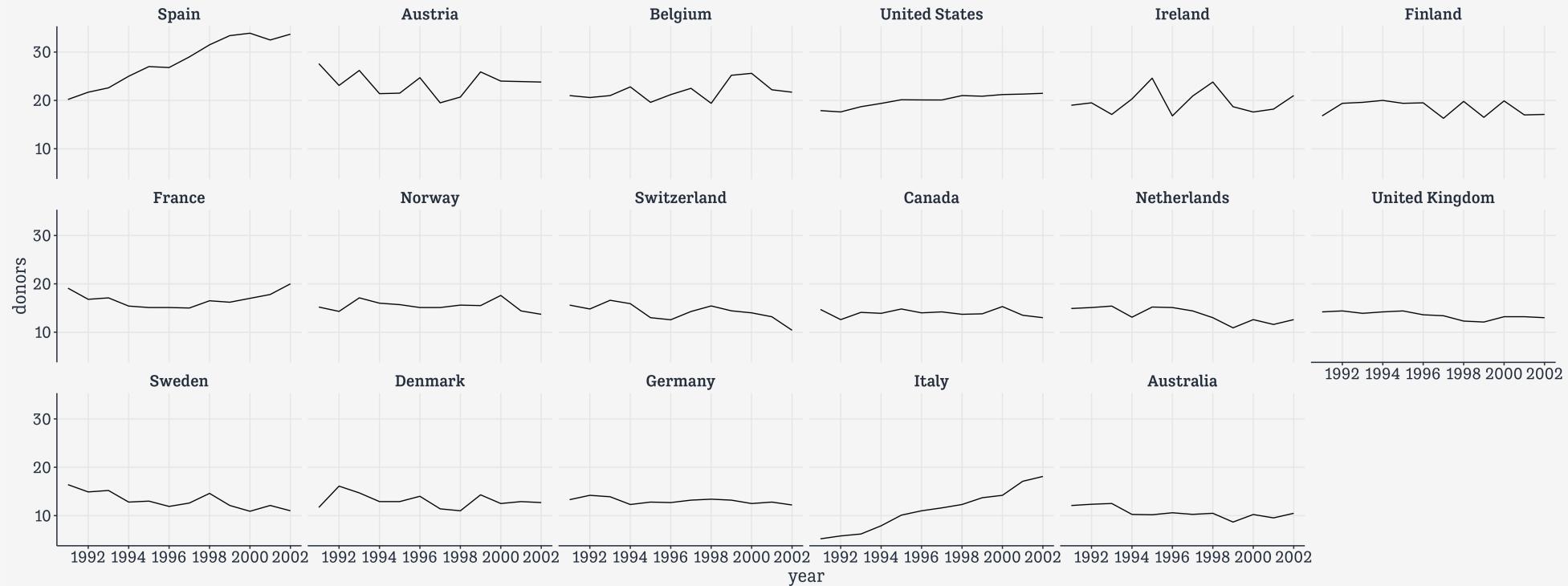
First look

```
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>,
# i gdp_lag_mean <dbl>, gdp_lag_sd <dbl>, health_mean <dbl>, health_sd <dbl>,
# i health_lag_mean <dbl>, health_lag_sd <dbl>, pubhealth_mean <dbl>,
# i pubhealth_sd <dbl>, roads_mean <dbl>, roads_sd <dbl>, cerebvas_mean <dbl>,
# i cerebvas_sd <dbl>, assault_mean <dbl>, assault_sd <dbl>,
# i external_mean <dbl>, external_sd <dbl>, txp_pop_mean <dbl>,
# i txp_pop_sd <dbl>
```

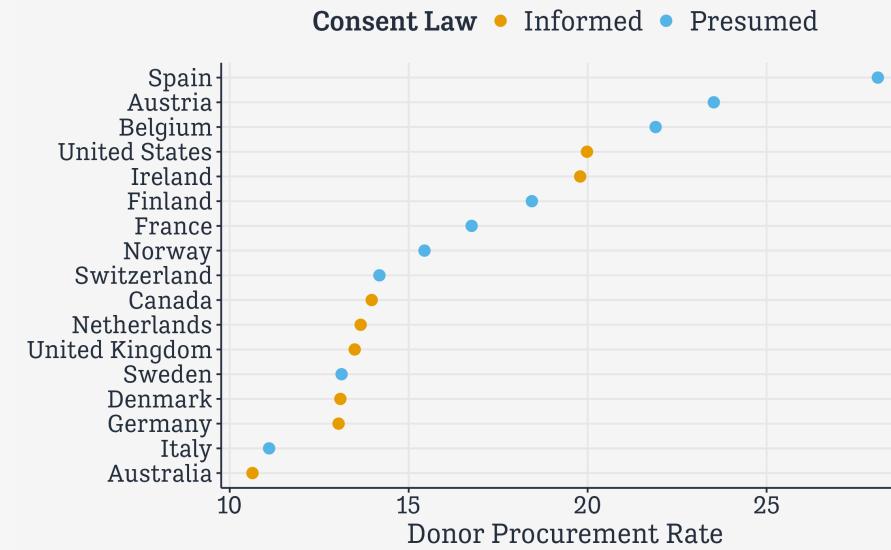
Use `across()` and `where()` instead

```
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

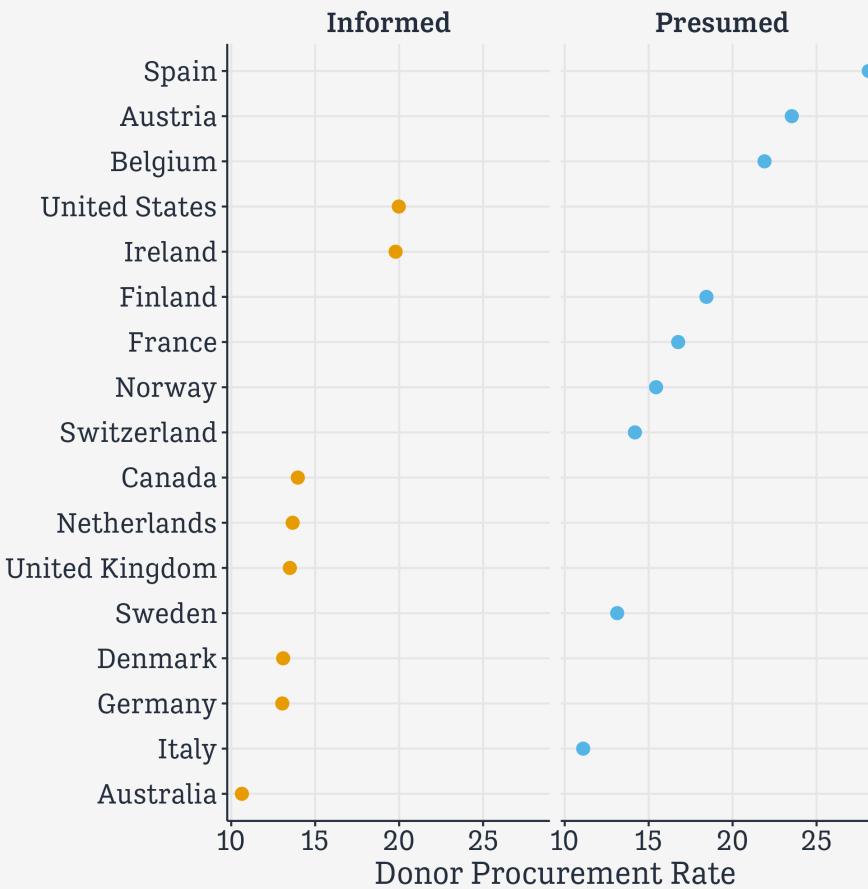
```
by_country %>%  
  ggplot(mapping =  
    aes(x = donors_mean,  
        y = reorder(country, donors_mean),  
        color = consent_law)) +  
  geom_point(size=3) +  
  labs(x = "Donor Procurement Rate",  
       y = NULL,  
       color = "Consent Law")
```



What about faceting it instead?

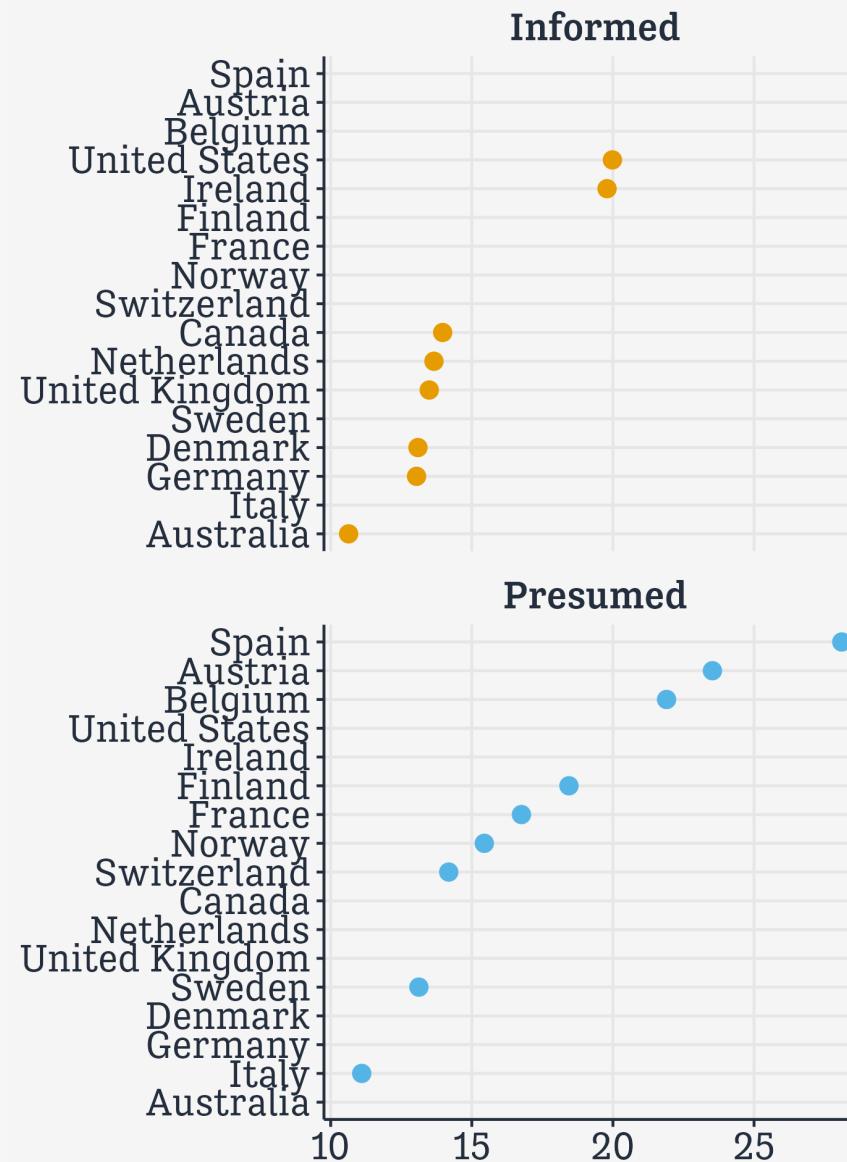
The problem is that countries can only be in one Consent Law category.

```
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?

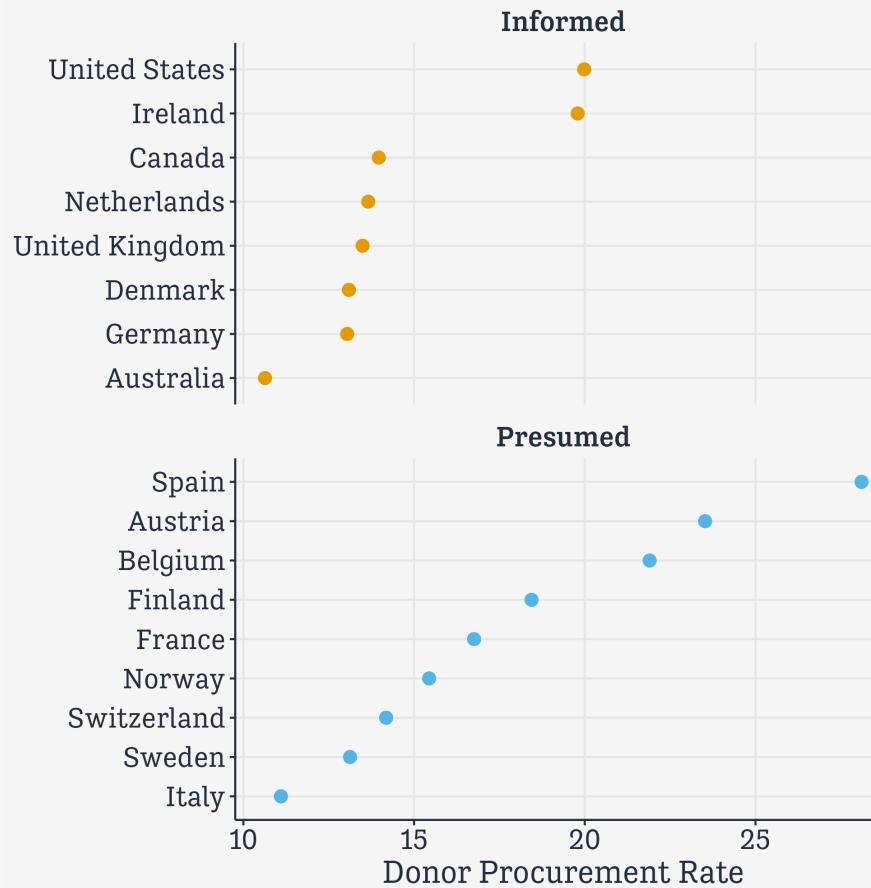
```
by_country >  
  ggplot(mapping =  
    aes(x = donors_mean,  
        y = reorder(country, donors_mean),  
        color = consent_law)) +  
  geom_point(size=3) +  
  guides(color = "none") +  
  facet_wrap(~ consent_law, ncol = 1) +  
  labs(x = "Donor Procurement Rate",  
       y = NULL,  
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



Allow the y-scale to vary

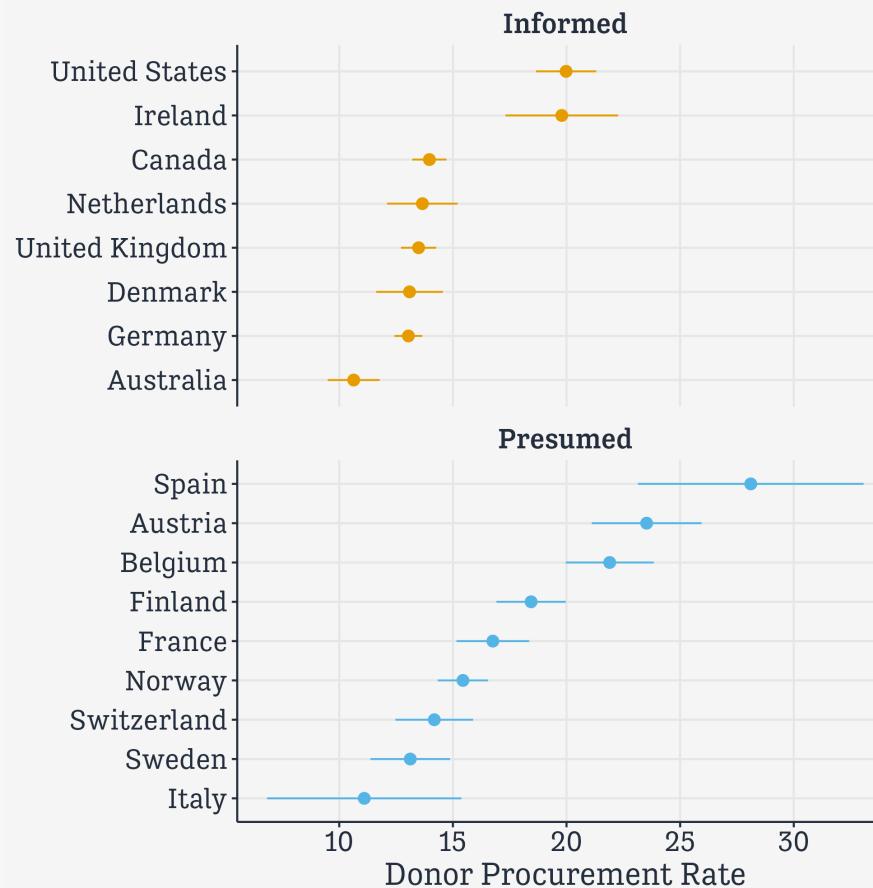
Normally the point of a facet is to preserve comparability between panels by not allowing the scales to vary. But for categorical measures it can be useful to allow this.

```
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

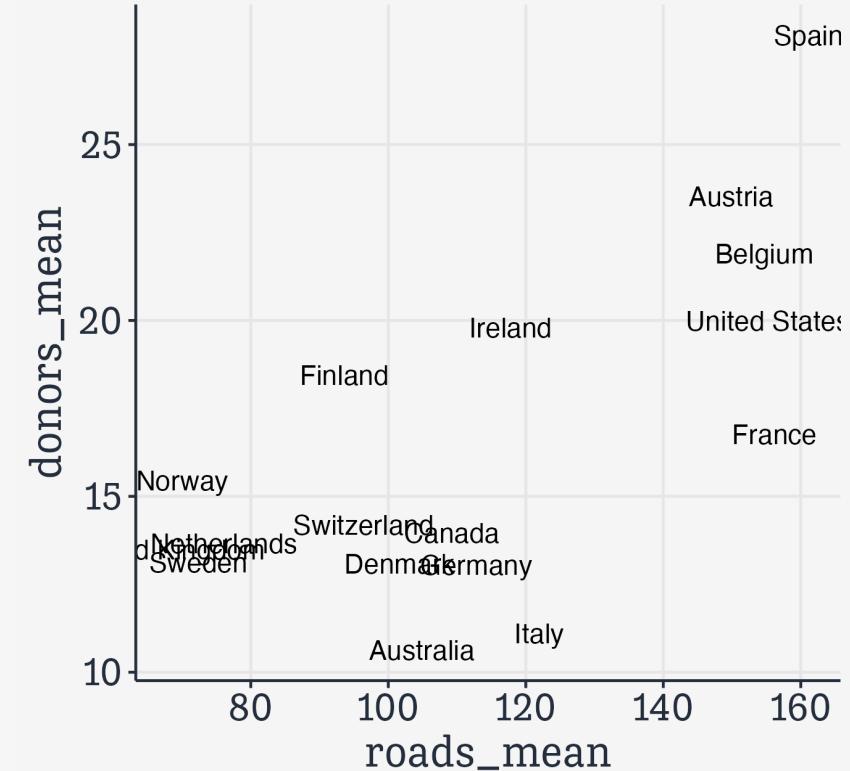
```
by_country >
  ggplot(mapping =
    aes(x = donors_mean,
        y = reorder(country, donors_mean),
        color = consent_law)) +
  geom_pointrange(mapping =
    aes(xmin = donors_mean - donors_sd,
        xmax = donors_mean + donors_sd))
guides(color = "none") +
facet_wrap(~ consent_law,
    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



Plot text directly

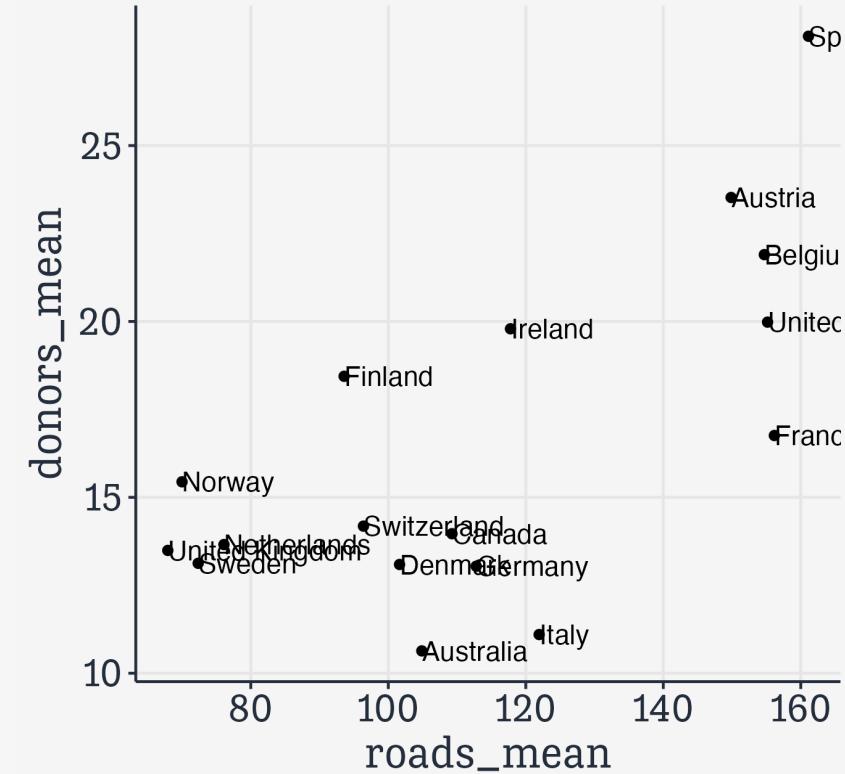
geom_text() for basic labels

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



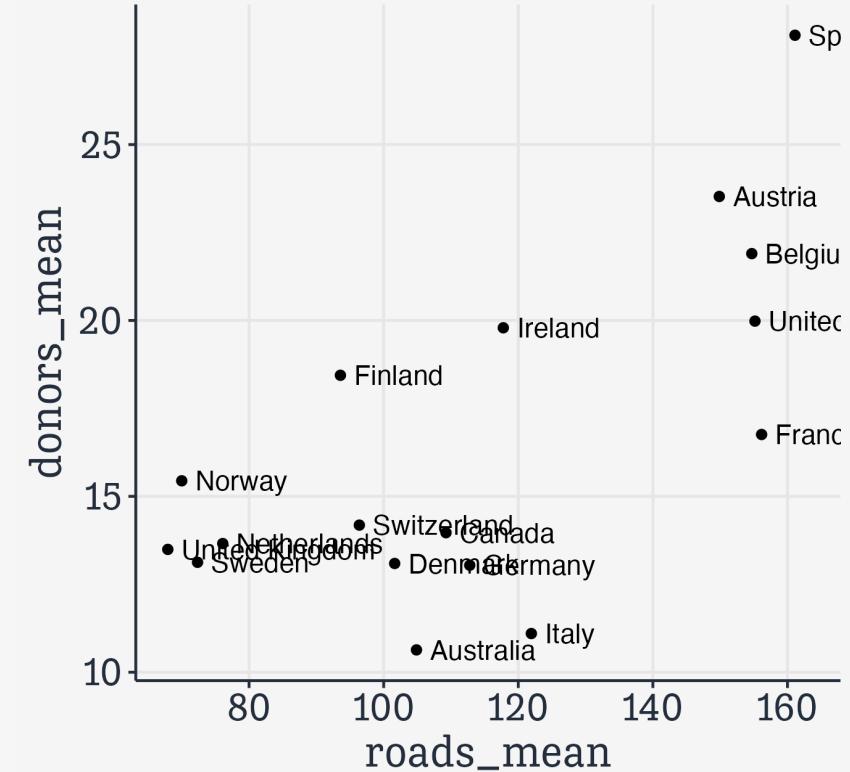
It's not very flexible

```
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()`

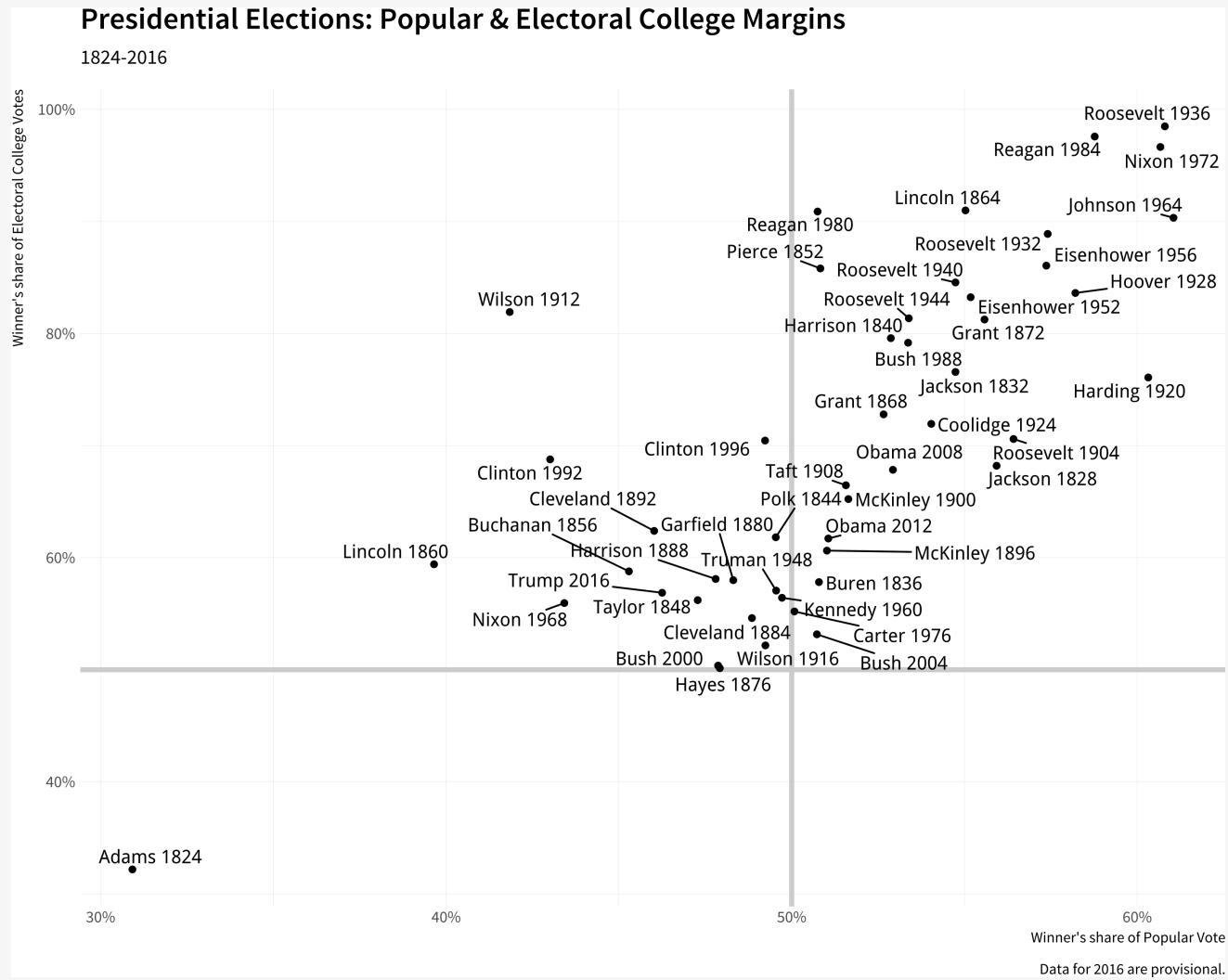
Example: U.S. Historic Presidential Elections

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 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

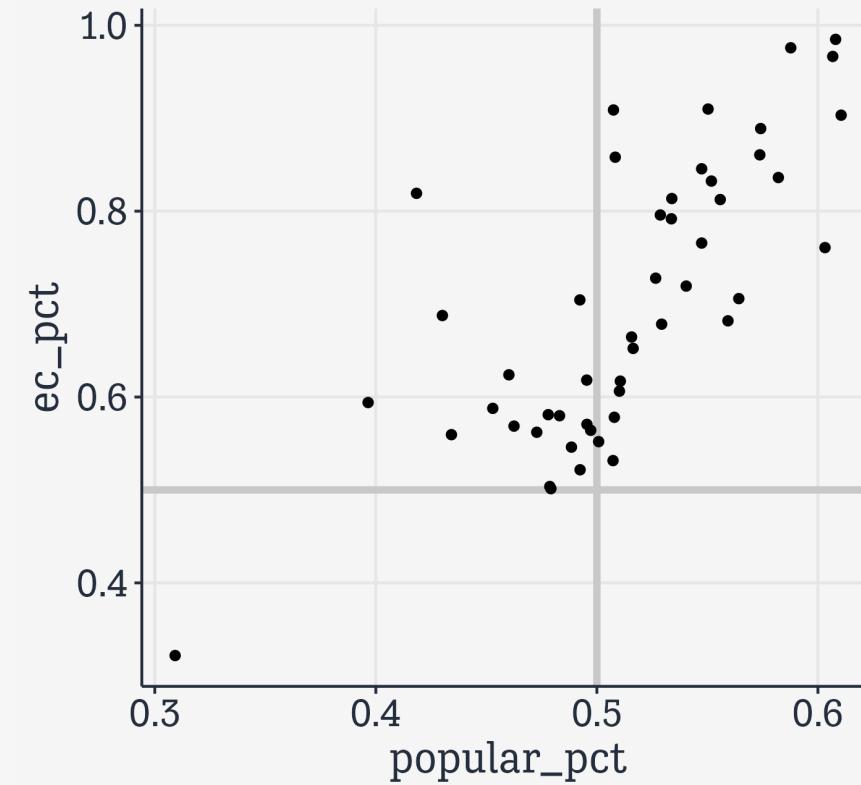
Keep things neat

```
## 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()
```

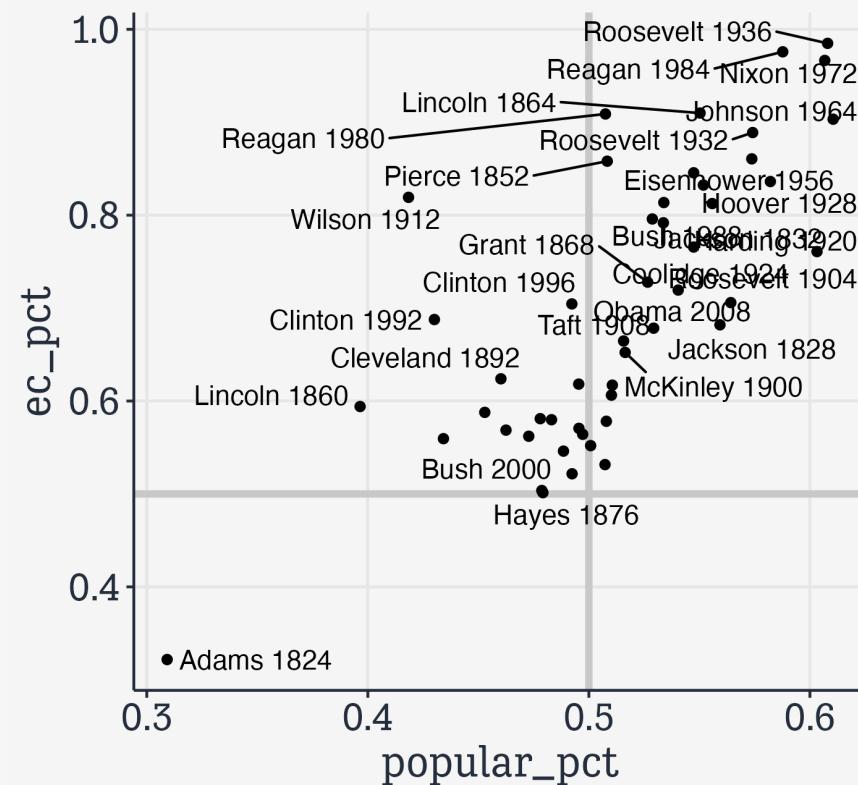


Add the labels

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.

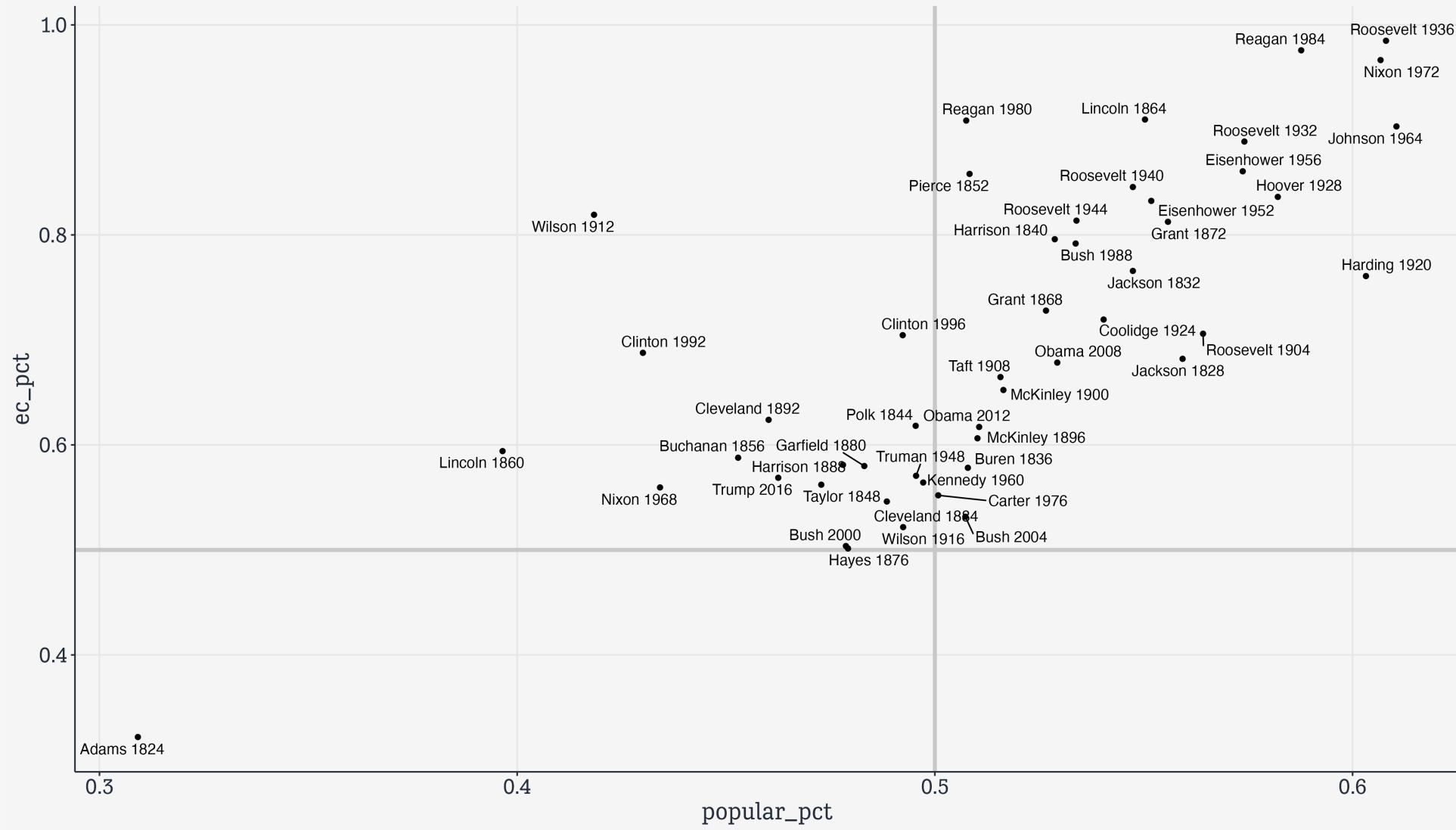
```
p <- ggplot(data = elections_historic,
             mapping = aes(x = popular_pct,
                           y = ec_pct,
                           label = winner_label))

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()
```



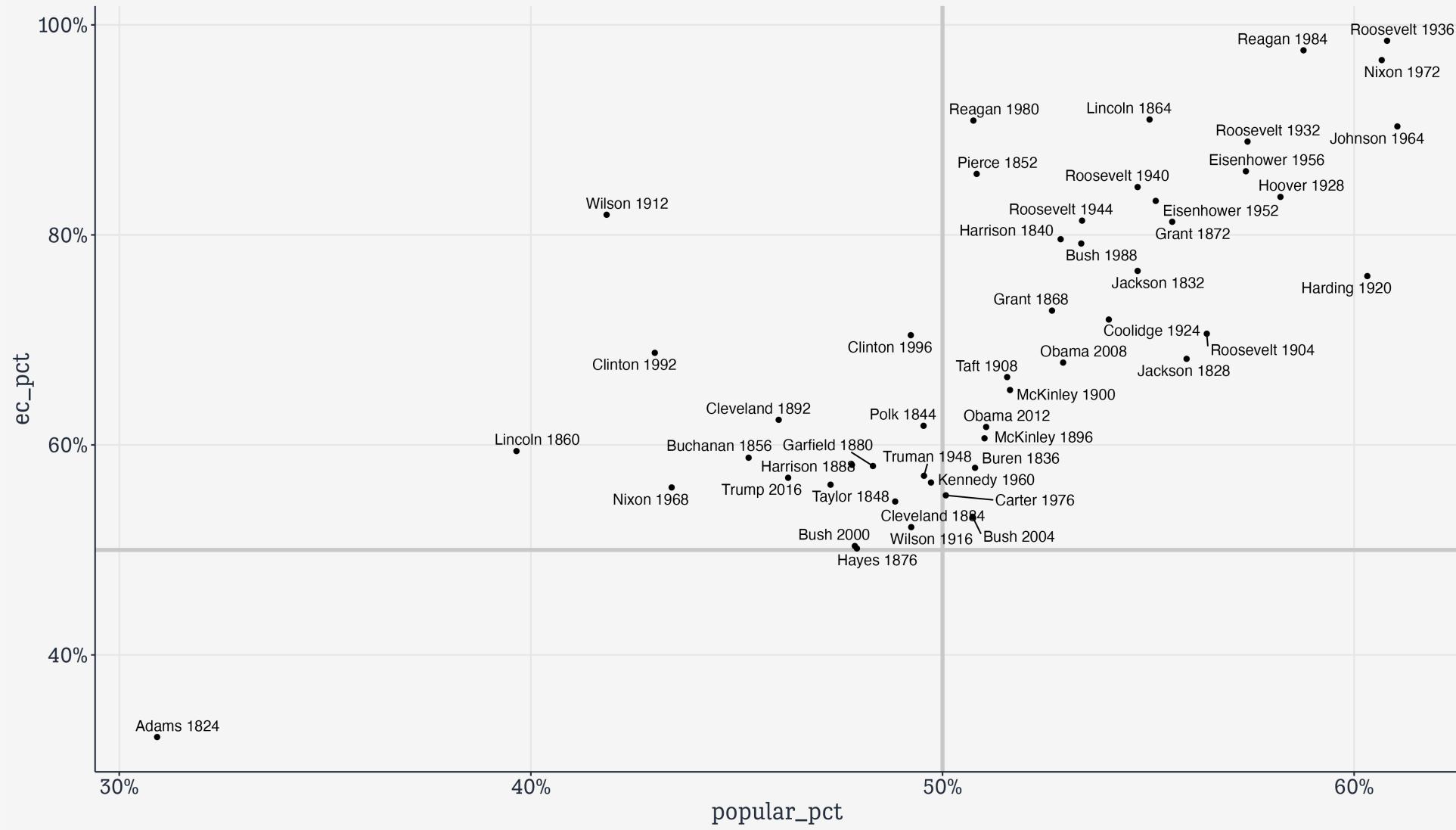
Labeling is with respect to the plot size

```
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())
```

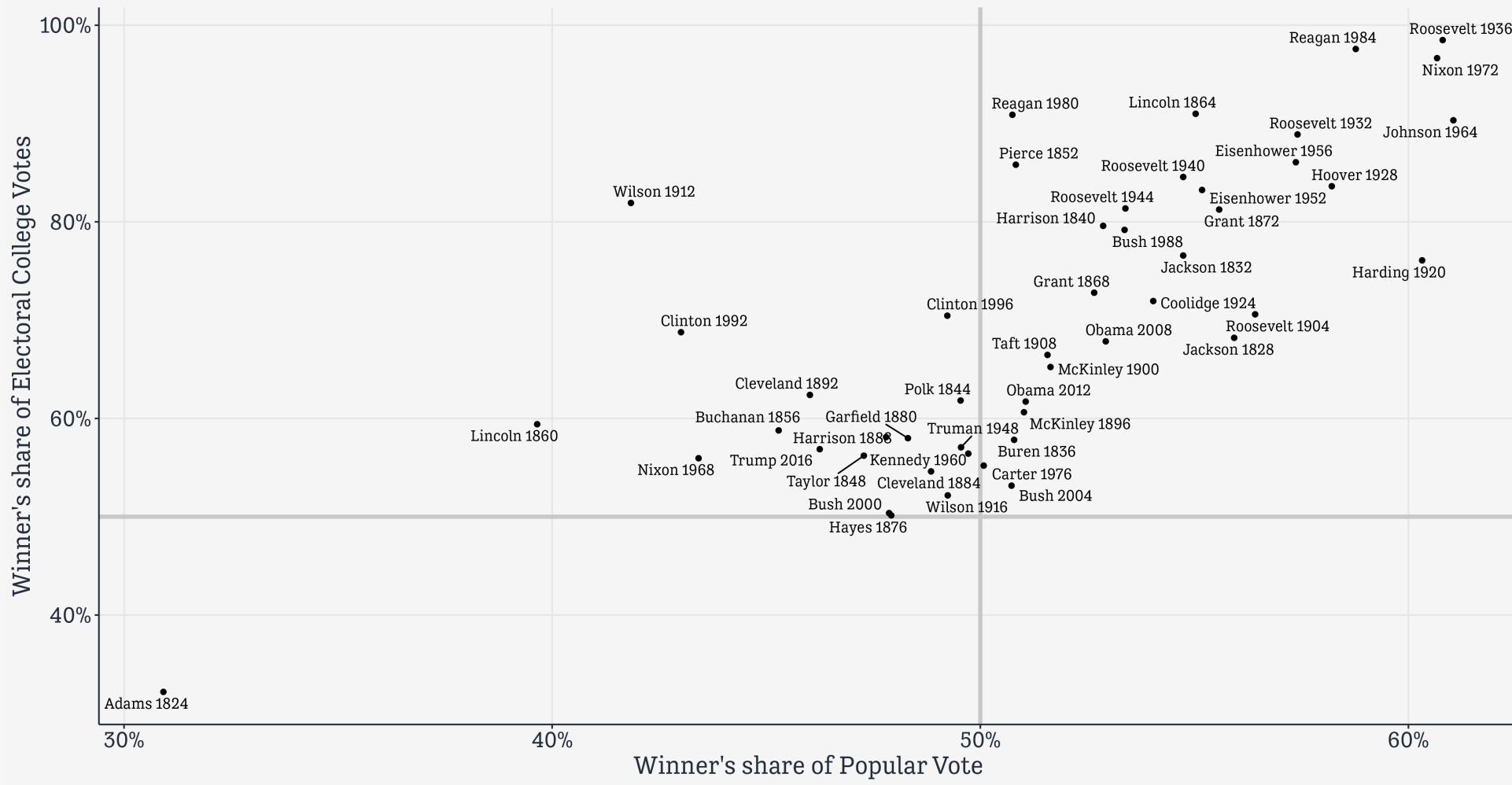


Add the labels

```
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

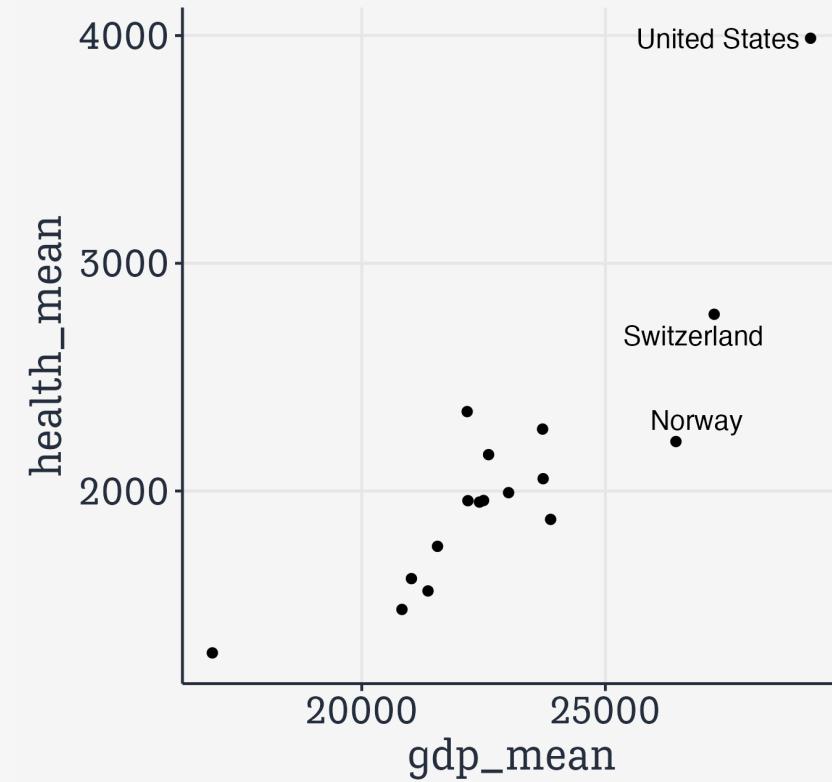


Data for 2016 are provisional.

Labeling points of interest

Option 1: On the fly in `ggplot`

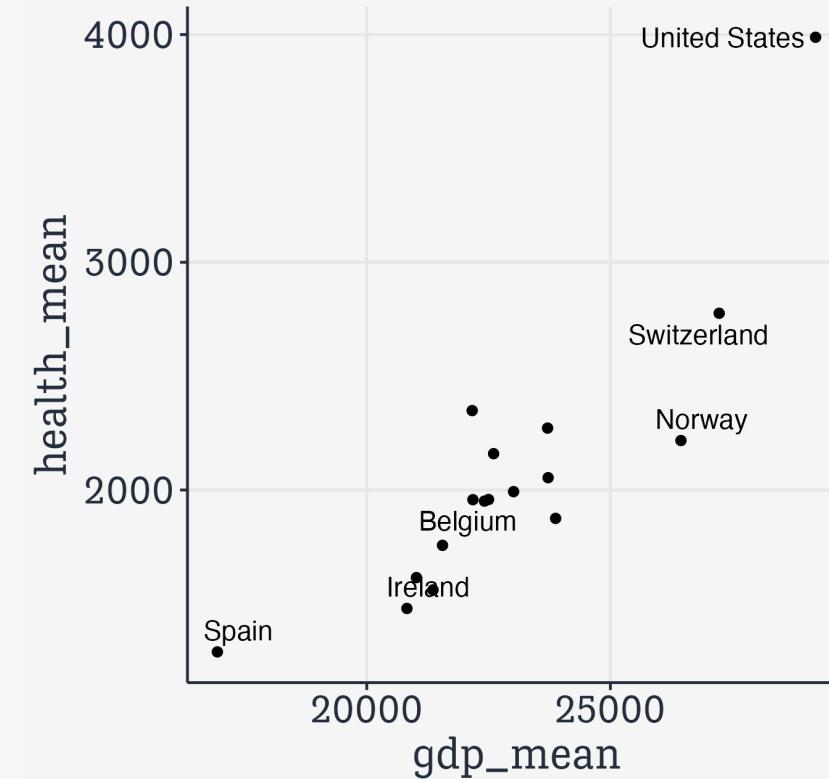
```
by_country %>%  
  ggplot(mapping = aes(x = gdp_mean,  
                      y = health_mean)) +  
  geom_point() +  
  geom_text_repel(data = subset(by_country, gdp_mean > 20000),  
                  mapping = aes(label = country))
```



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 > 25000 |  
                               health_mean < 1500 |  
                               country %in% "Belgium"  
                               mapping = aes(label = country)))
```



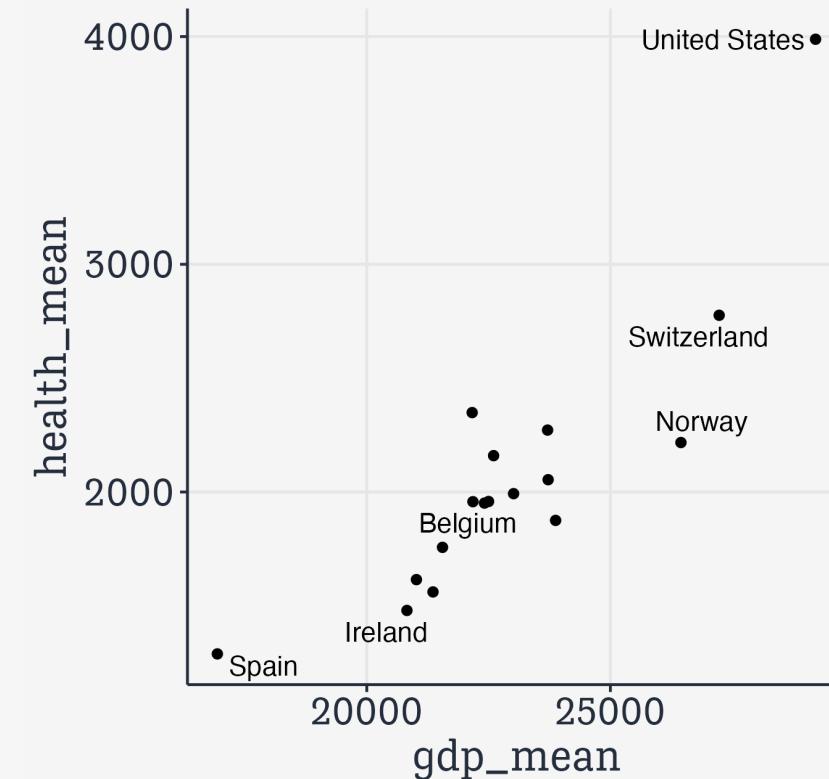
Option 2: Use `dplyr` first

```
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.

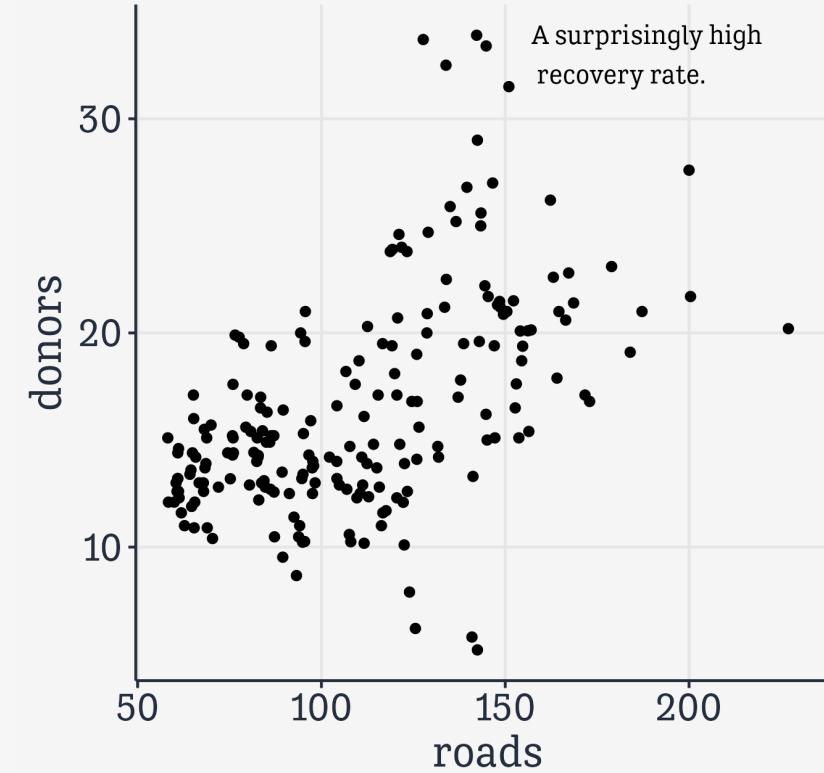
```
by_country %>%
  ggplot(mapping = aes(x = gdp_mean,
                       y = health_mean)) +
  geom_point() +
  geom_text_repel(data = df_hl,
                  mapping = aes(label = country))
```



**Write and draw
inside the plot area**

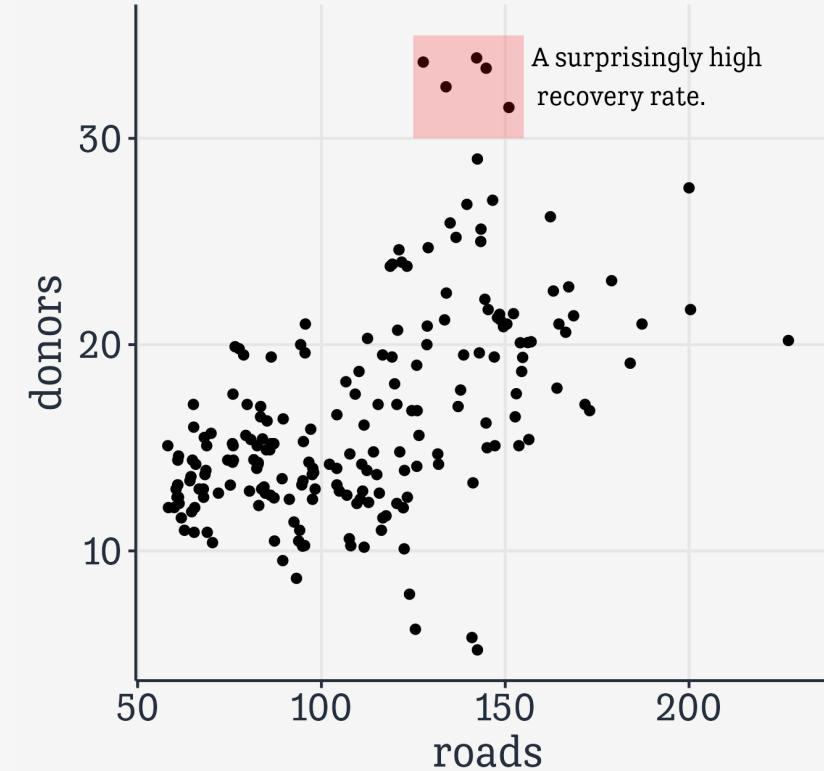
annotate() can imitate geoms

```
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\nrecovery 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>()

Naming conventions

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scale_<MAPPING>_<KIND>()

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()

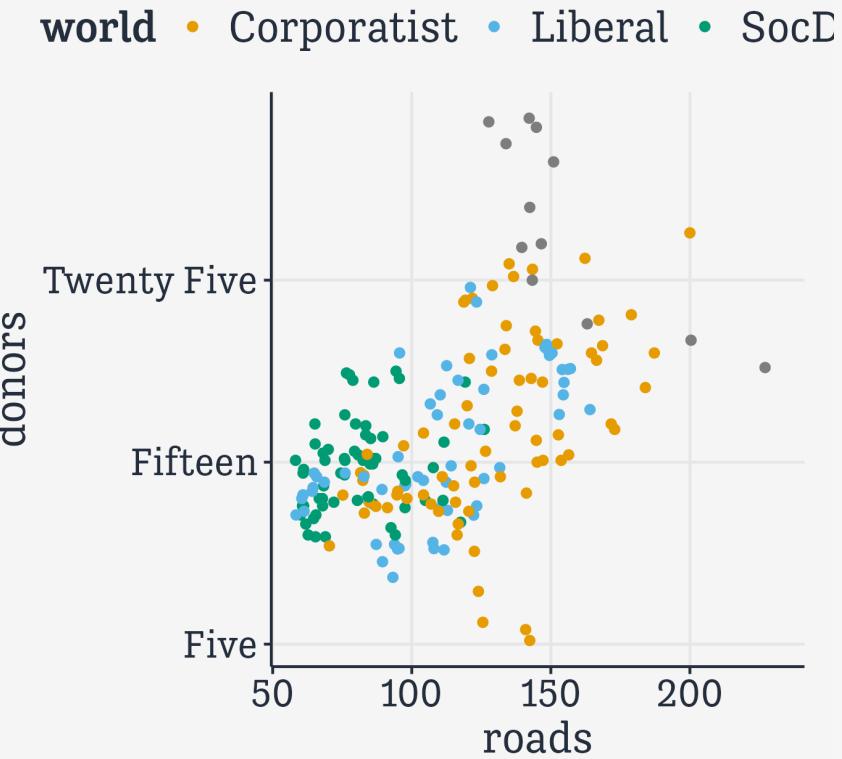
scale_fill_gradient2()

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 ...

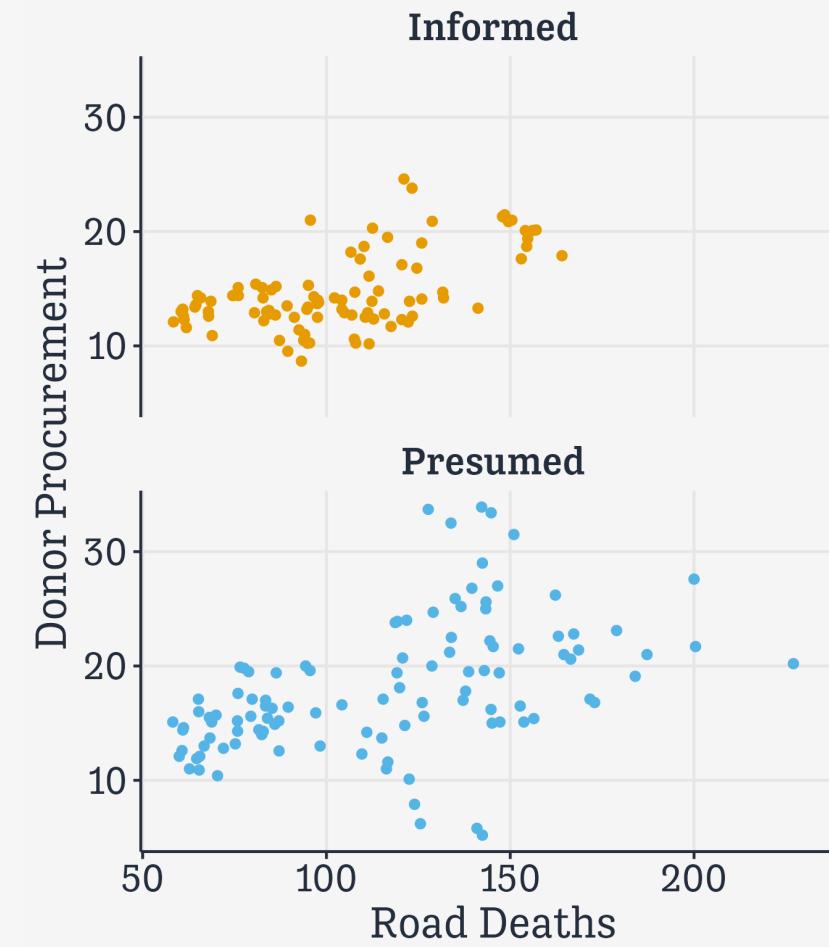
```
organdata >  
  ggplot(mapping = aes(x = roads,  
                        y = donors,  
                        color = world)) +  
  geom_point() +  
  scale_color_discrete(labels =  
    c("Corporatist",  
     "Liberal",  
     "Social Democratic",  
     "Unclassified")) +  
  labs(x = "Road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

- Corporatist • Liberal • Social Democratic



The `guides()` function

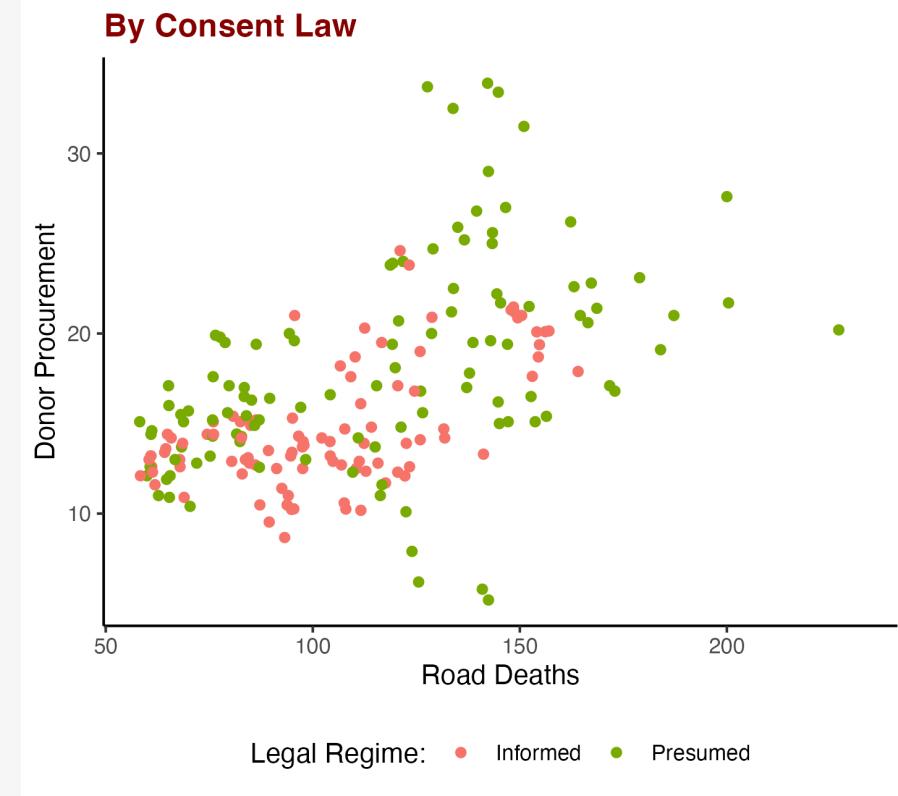
```
organdata %>  
  ggplot(mapping = aes(x = roads,  
                        y = donors,  
                        color = consent_law)) +  
  
  geom_point() +  
  facet_wrap(~ consent_law, ncol = 1) +  
  guides(color = "none") +  
  labs(x = "Road Deaths",  
       y = "Donor Procurement")
```



Controls overall properties of the guide labels. Common use: turning it off. We'll learn about that.

The **theme()** function

```
## 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 = "darkred",
                                   face = "bold"))
```



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