Work with dplyr and ggplot

Data Visualization: Session 5

Kieran Healy

Code Horizons, April 2023

Tidyverse components, again

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

Tidyverse components, again

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

Call the package and ...

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

Other tidyverse components

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

Other tidyverse components

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

Other tidyverse components

`forcats`	◁ **Deal with factors**
`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

2. Mapping

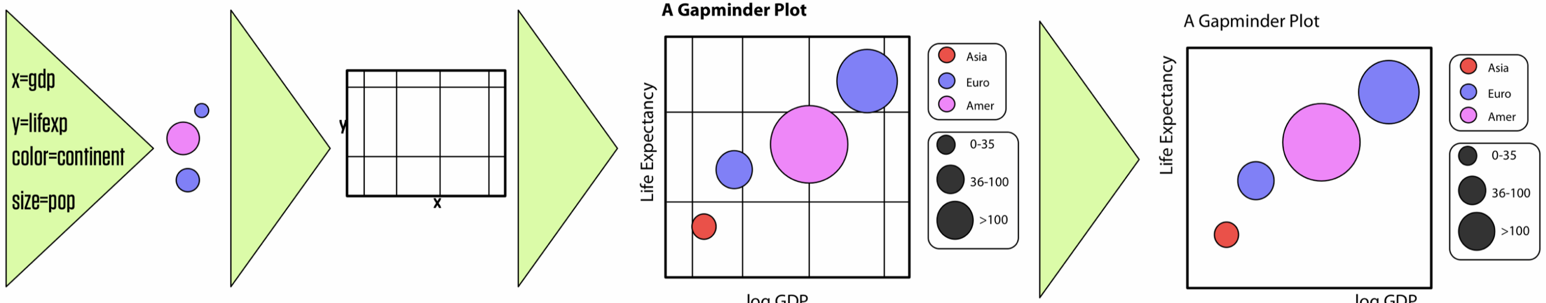
3. Geom

4. Co-Ordinates, Scales

5. Labels & Guides

6. Themes

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



ggplot(data = gapminder,

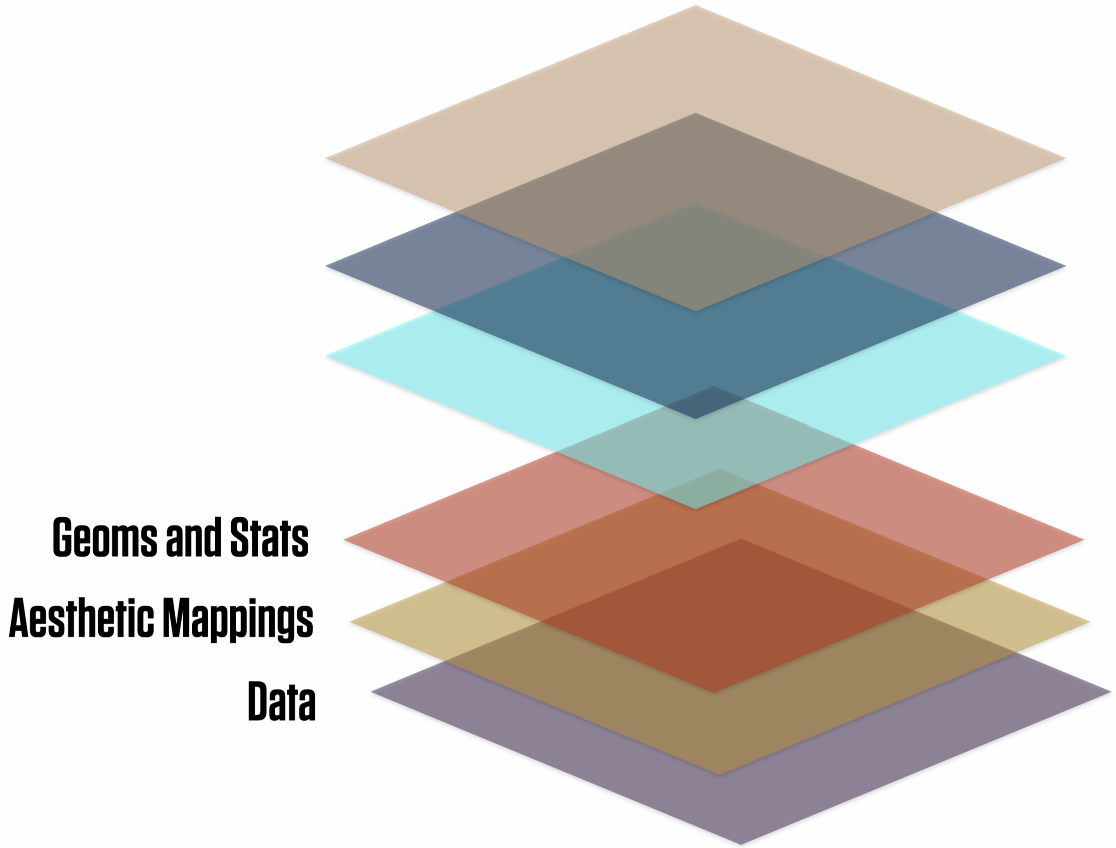
mapping =
aes(x = gdp,
y = lifespan,
color = continent,
size = pop))

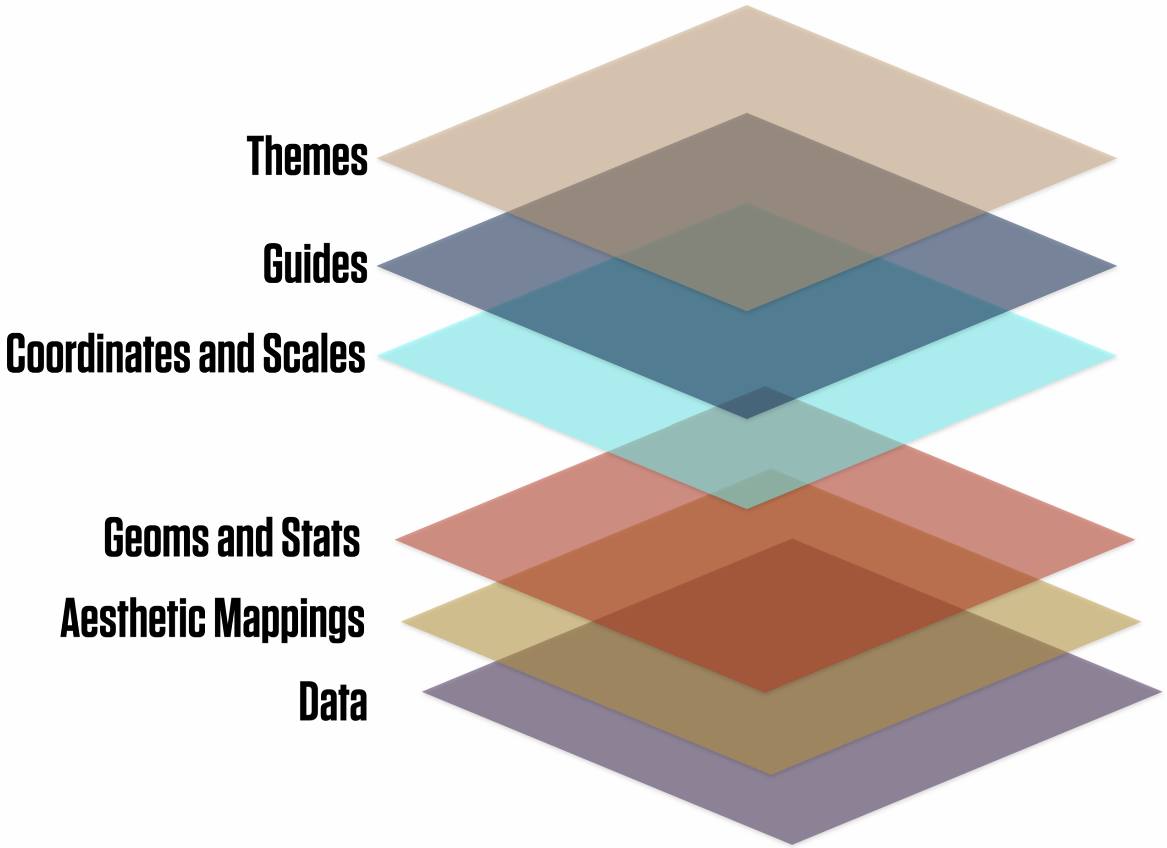
geom_point()

coord_cartesian()
scale_x_log10()

labs()
guides()

theme_minimal()


Geoms and Stats
Aesthetic Mappings
Data


Themes
Guides
Coordinates and Scales
Geoms and Stats
Aesthetic Mappings
Data

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 childs sibs   degree race  sex   region income16
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct>
##  1  2016     1 1            47      3 2      Bache… White Male  New E… $170000…
##  2  2016     2 2            61      0 3      High … White Male  New E… $50000 …
##  3  2016     3 3            72      2 3      Bache… White Male  New E… $75000 …
##  4  2016     4 1            43      4 3      High … White Fema… New E… $170000…
##  5  2016     5 3            55      2 2      Gradu… White Fema… New E… $170000…
##  6  2016     6 2            53      2 2      Junio… White Fema… New E… $60000 …
##  7  2016     7 1            50      2 2      High … White Male  New E… $170000…
##  8  2016     8 3            23      3 6      High … Other Fema… Middl… $30000 …
##  9  2016     9 1            45      3 5      High … Black Male  Middl… $60000 …
## 10  2016    10 3            71      4 1      Junio… White Male  Middl… $60000 …
## # ℹ 2,857 more rows
## # ℹ 21 more variables: relig <fct>, marital <fct>, padeg <fct>, madeg <fct>,
## #   partyid <fct>, polviews <fct>, happy <fct>, partners <fct>, grass <fct>,
## #   zodiac <fct>, pres12 <labelled>, wtssall <dbl>, income_rc <fct>,
## #   agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
## #   bigregion <fct>, partners_rc <fct>, obama <dbl>
```

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

Two-way tables: Row percents

bigregion	Protestant	Catholic	Jewish	None	Other	NA_	Total
Northeast	32.4	33.2	5.5	23.0	5.7	0.2	100.0
Midwest	46.8	24.7	0.4	22.6	4.7	0.7	100.0
South	61.8	15.2	1.0	16.2	4.8	1.0	100.0
West	37.7	24.5	1.6	28.5	7.6	0.2	100.0

Two-way tables: Column percents

bigregion	Protestant	Catholic	Jewish	None	Other	NA_
Northeast	11.5	25.0	52.9	18.1	17.6	5.6
Midwest	23.7	26.5	5.9	25.4	20.8	27.8
South	47.4	24.7	21.6	27.5	31.4	61.1
West	17.4	23.9	19.6	29.1	30.2	5.6
Total	100.0	100.0	100.0	100.0	100.0	100.0

Two-way tables: Full marginals

bigregion	Protestant	Catholic	Jewish	None	Other	NA_
Northeast	5.5	5.7	0.9	3.9	1.0	0.0
Midwest	11.3	6.0	0.1	5.5	1.2	0.2
South	22.7	5.6	0.4	5.9	1.7	0.4
West	8.3	5.4	0.3	6.3	1.7	0.0

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.

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

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

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

Subset either the rows or columns of or table.

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

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

Each action is implemented by a function

Each action is implemented by a function

Group using `group_by()`.

Each action is implemented by a function

Group using `group_by()`.

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

Each action is implemented by 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()`.

Each action is implemented by 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()`.

Example:
The GSS

U.S. General Social Survey data: `gss_sm`

```
gss_sm
```

```
## # A tibble: 2,867 × 32
##     year    id ballot       age childs sibs   degree race  sex   region income16
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct>
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $170000…
##  2  2016     2 2             61      0 3      High … White Male  New E… $50000 …
##  3  2016     3 3             72      2 3      Bache… White Male  New E… $75000 …
##  4  2016     4 1             43      4 3      High … White Fema… New E… $170000…
##  5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170000…
##  6  2016     6 2             53      2 2      Junio… White Fema… New E… $60000 …
##  7  2016     7 1             50      2 2      High … White Male  New E… $170000…
##  8  2016     8 3             23      3 6      High … Other Fema… Middl… $30000 …
##  9  2016     9 1             45      3 5      High … Black Male  Middl… $60000 …
## 10  2016    10 3             71      4 1      Junio… White Male  Middl… $60000 …
## # ℹ 2,857 more rows
## # ℹ 21 more variables: relig <fct>, marital <fct>, padeg <fct>, madeg <fct>,
## #   partyid <fct>, polviews <fct>, happy <fct>, partners <fct>, grass <fct>,
## #   zodiac <fct>, pres12 <labelled>, wtssall <dbl>, income_rc <fct>,
## #   agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
## #   bigregion <fct>, partners_rc <fct>, obama <dbl>
```

Notice again how the tibble already tells us a lot.

Summarizing a Table

Here's what we're going to do:

1. Individual-Level GSS Data on Region and Religion

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

2. Summary Count of Religious Preferences by Census Region

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

3. Percent Religious Preferences by Census Region

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

Summarizing a Table

We're just taking a look at the relevant columns here. We don't need to narrow it like this to do our summary, though.

```
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
```

Count up by *one* column or variable

```r
gss_sm
```

```
## # A tibble: 2,867 × 32
##     year    id ballot       age childs sibs   degree race  sex   region income16
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct>
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $170000…
##  2  2016     2 2             61      0 3      High … White Male  New E… $50000 …
##  3  2016     3 3             72      2 3      Bache… White Male  New E… $75000 …
##  4  2016     4 1             43      4 3      High … White Fema… New E… $170000…
##  5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170000…
##  6  2016     6 2             53      2 2      Junio… White Fema… New E… $60000 …
##  7  2016     7 1             50      2 2      High … White Male  New E… $170000…
##  8  2016     8 3             23      3 6      High … Other Fema… Middl… $30000 …
##  9  2016     9 1             45      3 5      High … Black Male  Middl… $60000 …
## 10  2016    10 3             71      4 1      Junio… White Male  Middl… $60000 …
## # ℹ 2,857 more rows
## # ℹ 21 more variables: relig <fct>, marital <fct>, padeg <fct>, madeg <fct>,
## #   partyid <fct>, polviews <fct>, happy <fct>, partners <fct>, grass <fct>,
## #   zodiac <fct>, pres12 <labelled>, wtssall <dbl>, income_rc <fct>,
## #   agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
## #   bigregion <fct>, partners_rc <fct>, obama <dbl>
```

Count up by *one* column or variable

```
gss_sm ▷
  group_by(bigregion)   #<<
```

```
## # A tibble: 2,867 × 32
## # Groups:   bigregion [4]
##     year    id ballot       age childs sibs   degree race  sex   region income16
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct>
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $170000…
##  2  2016     2 2             61      0 3      High … White Male  New E… $50000 …
##  3  2016     3 3             72      2 3      Bache… White Male  New E… $75000 …
##  4  2016     4 1             43      4 3      High … White Fema… New E… $170000…
##  5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170000…
##  6  2016     6 2             53      2 2      Junio… White Fema… New E… $60000 …
##  7  2016     7 1             50      2 2      High … White Male  New E… $170000…
##  8  2016     8 3             23      3 6      High … Other Fema… Middl… $30000 …
##  9  2016     9 1             45      3 5      High … Black Male  Middl… $60000 …
## 10  2016    10 3             71      4 1      Junio… White Male  Middl… $60000 …
## # ℹ 2,857 more rows
## # ℹ 21 more variables: relig <fct>, marital <fct>, padeg <fct>, madeg <fct>,
## #   partyid <fct>, polviews <fct>, happy <fct>, partners <fct>, grass <fct>,
## #   zodiac <fct>, pres12 <labelled>, wtssall <dbl>, income_rc <fct>,
## #   agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
## #   bigregion <fct>, partners_rc <fct>, obama <dbl>
```

Count up by *one* column or variable

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

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

Grouping changes the *logical* structure of the tibble. It tells you what subsets of rows the next mutate or summary operation will be carried out within.

Summarize by region and religion

```r
gss_sm
```

```
## # A tibble: 2,867 × 32
##     year    id ballot       age childs sibs   degree race  sex   region income16
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct>
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $170000…
##  2  2016     2 2             61      0 3      High … White Male  New E… $50000 …
##  3  2016     3 3             72      2 3      Bache… White Male  New E… $75000 …
##  4  2016     4 1             43      4 3      High … White Fema… New E… $170000…
##  5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170000…
##  6  2016     6 2             53      2 2      Junio… White Fema… New E… $60000 …
##  7  2016     7 1             50      2 2      High … White Male  New E… $170000…
##  8  2016     8 3             23      3 6      High … Other Fema… Middl… $30000 …
##  9  2016     9 1             45      3 5      High … Black Male  Middl… $60000 …
## 10  2016    10 3             71      4 1      Junio… White Male  Middl… $60000 …
## # ℹ 2,857 more rows
## # ℹ 21 more variables: relig <fct>, marital <fct>, padeg <fct>, madeg <fct>,
## #   partyid <fct>, polviews <fct>, happy <fct>, partners <fct>, grass <fct>,
## #   zodiac <fct>, pres12 <labelled>, wtssall <dbl>, income_rc <fct>,
## #   agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
## #   bigregion <fct>, partners_rc <fct>, obama <dbl>
```

Summarize by region and religion

```r
gss_sm |>
  group_by(bigregion, religion)
```

```
## # A tibble: 2,867 × 32
## # Groups:   bigregion, religion [24]
##     year    id ballot       age childs sibs   degree race  sex   region income16
##    <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct>
##  1  2016     1 1             47      3 2      Bache… White Male  New E… $170000…
##  2  2016     2 2             61      0 3      High … White Male  New E… $50000 …
##  3  2016     3 3             72      2 3      Bache… White Male  New E… $75000 …
##  4  2016     4 1             43      4 3      High … White Fema… New E… $170000…
##  5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170000…
##  6  2016     6 2             53      2 2      Junio… White Fema… New E… $60000 …
##  7  2016     7 1             50      2 2      High … White Male  New E… $170000…
##  8  2016     8 3             23      3 6      High … Other Fema… Middl… $30000 …
##  9  2016     9 1             45      3 5      High … Black Male  Middl… $60000 …
## 10  2016    10 3             71      4 1      Junio… White Male  Middl… $60000 …
## # ℹ 2,857 more rows
## # ℹ 21 more variables: relig <fct>, marital <fct>, padeg <fct>, madeg <fct>,
## #   partyid <fct>, polviews <fct>, happy <fct>, partners <fct>, grass <fct>,
## #   zodiac <fct>, pres12 <labelled>, wtssall <dbl>, income_rc <fct>,
## #   agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
## #   bigregion <fct>, partners_rc <fct>, obama <dbl>
```

Summarize by region and religion

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

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

Summarize by region and religion

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

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

Summarize by region and religion

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

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

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 over, or explicitly ungrouped with `ungroup()`.

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 over, or explicitly ungrouped with `ungroup()`.

Summary calculations are done on the innermost group, which then "disappears". (Notice how `religion` is no longer a group in the output, but `bigregion` is.)

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` to calculate `pct`, even though we are creating them both in the same `mutate()` expression.

Convenience functions

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

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

Do it yourself with `n()`

```r
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
```

*The result is **grouped**.*

Three options for counting up rows

Do it yourself with `n()`

```
gss_sm ▷
  group_by(bigregion, religion) ▷
  summarize(n = n())
```

```
## # A tibble: 24 × 3
## # Groups:   bigregion [4]
##    bigregion religion       n
##    <fct>     <fct>      <int>
##  1 Northeast Protestant   158
##  2 Northeast Catholic     162
##  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 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
```

*The result is **grouped**.*

Three options for counting up rows

Do it yourself with `n()`

```r
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
```

*The result is **grouped**.*

Use `tally()`

```r
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
```

*The result is **grouped**.*

use `count()`

```r
gss_sm ▷
  count(bigregion, religion)
```

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

*One step; the result is **not grouped**.*

Pipelined tables can be quickly checked

```
## Calculate pct religion within region?
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?

Pipelined tables can be quickly checked

```r
## Calculate pct religion within region?
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?

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

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

No! What has gone wrong here?

Pipelined tables can be quickly checked

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

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

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

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

With `count()`, the `pct` values in this case are the marginals for the whole table.

Pipelined tables can be quickly checked

```r
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.

```r
rel_by_region |>
  summarize(total = sum(pct))
```

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

With `count()`, the `pct` values in this case are the marginals for the whole table.

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

```r
# 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.
```

`group_by()` and `tally()` both return a grouped result. We get some rounding error because we used `round()` after summing originally.

Two lessons

Check your tables!

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

Two lessons

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.

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!

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.

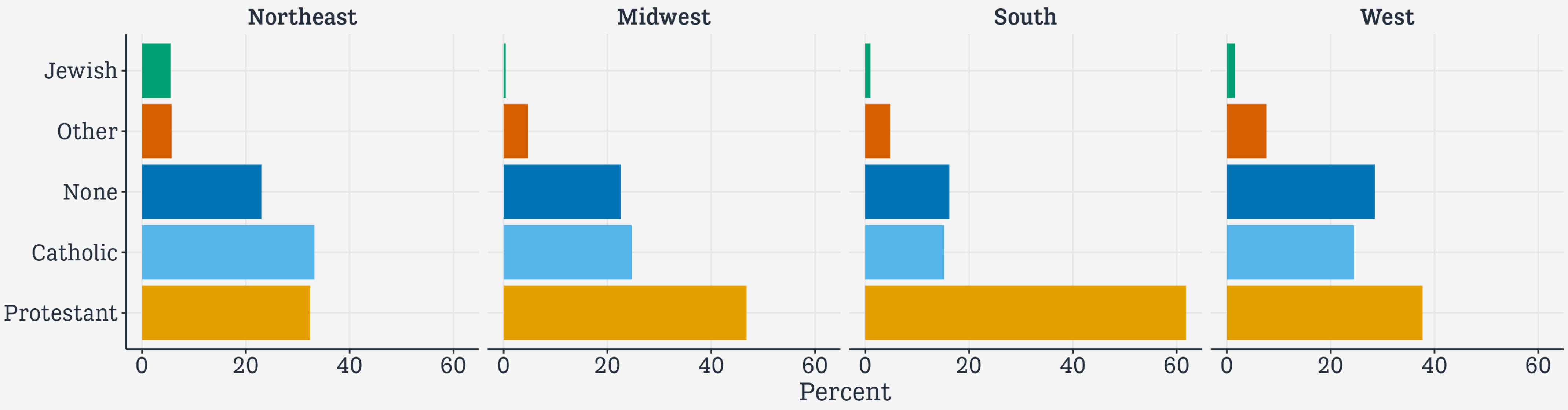
Pass your pipeline on to a table

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

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

Pass your pipeline on to a graph

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



Use `dplyr` pipelines to create summary tables. Then send your clean tables to `ggplot`.

Facets are often better than Guides

Let's put that table in an object

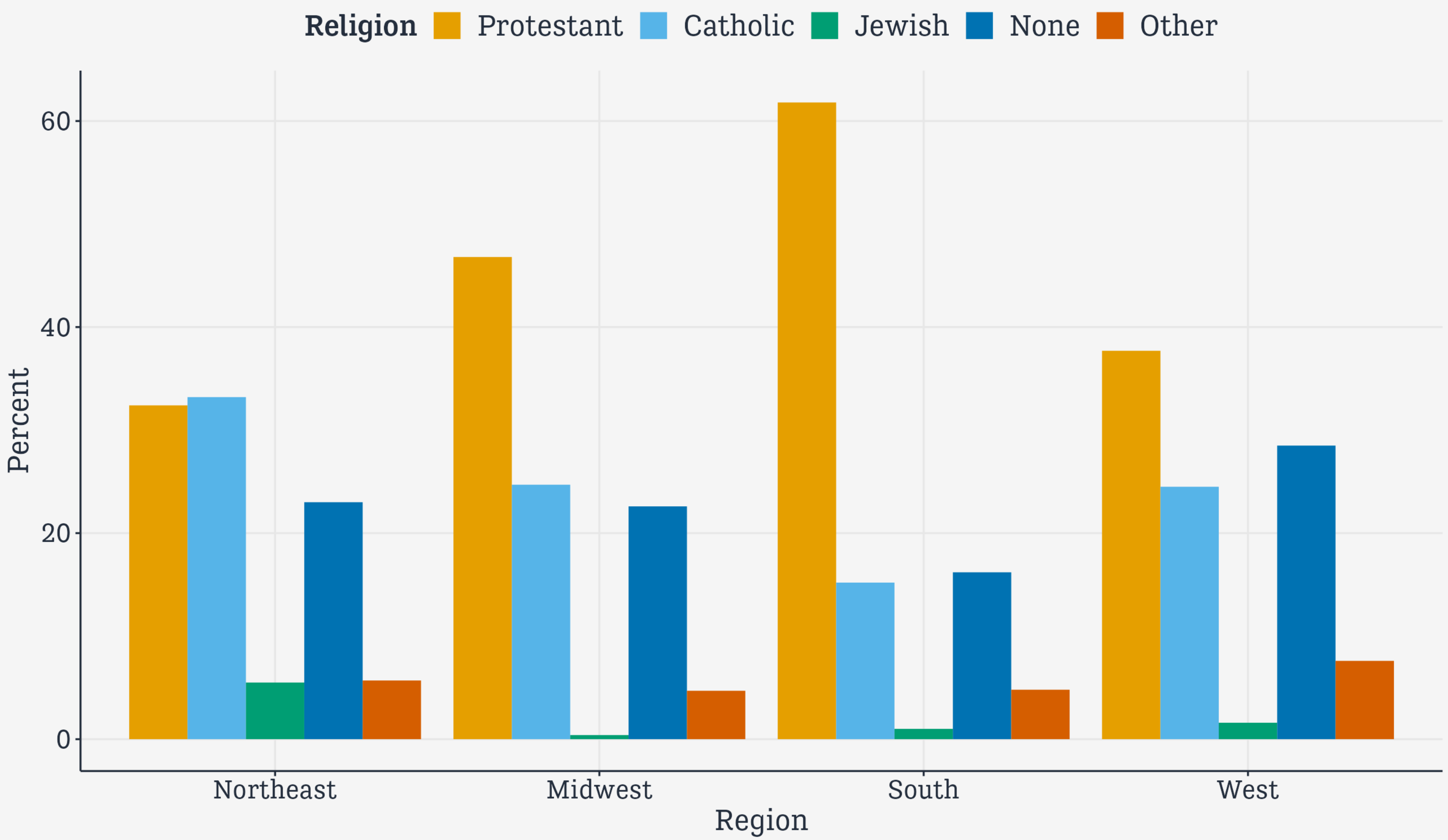
```r
rel_by_region <- gss_sm |>
  group_by(bigregion, religion) |>
  tally() |>
  mutate(pct = round((n/sum(n))*100, 1)) |>
  drop_na()


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
```

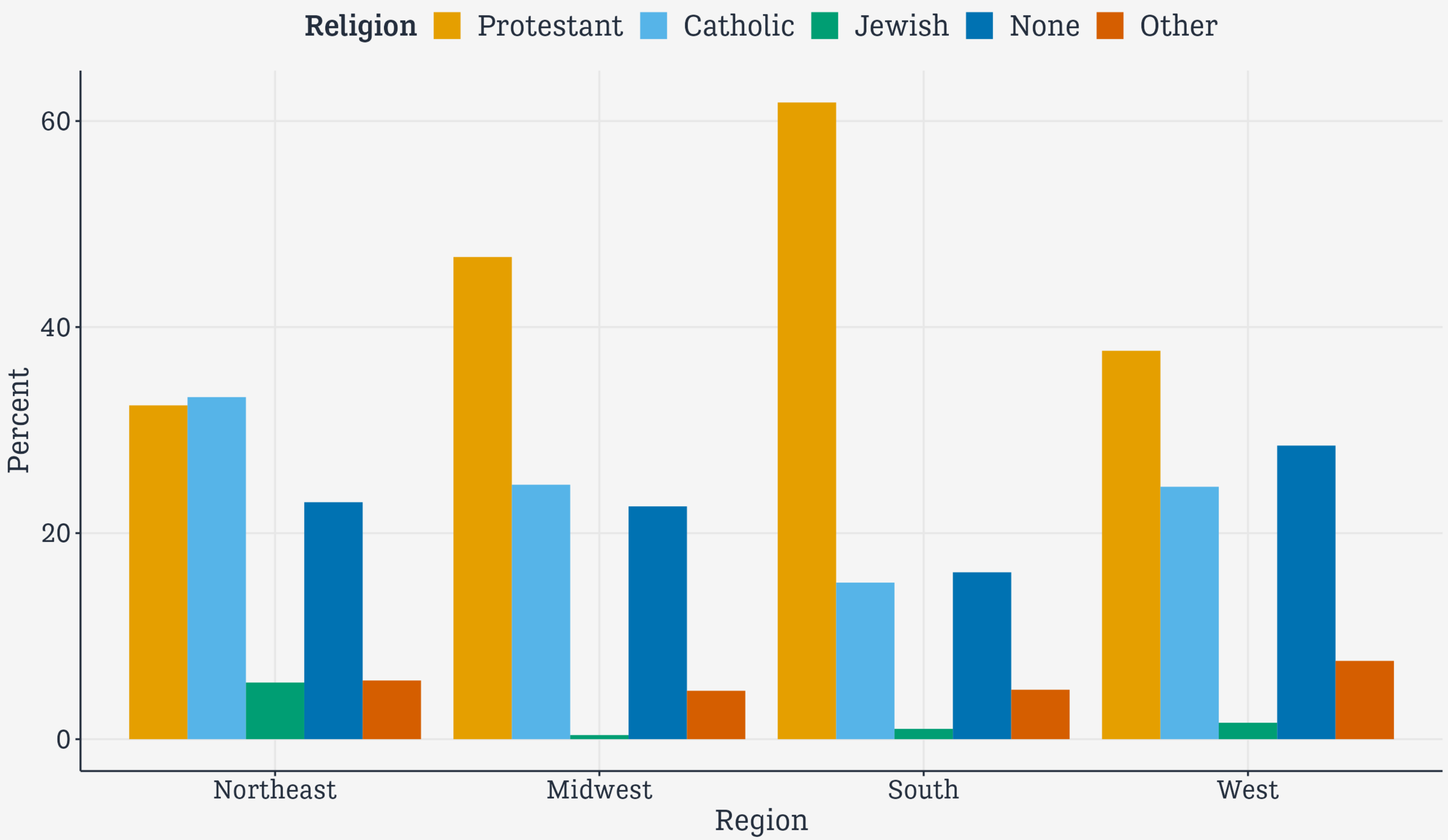
We might write ...

```r
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!



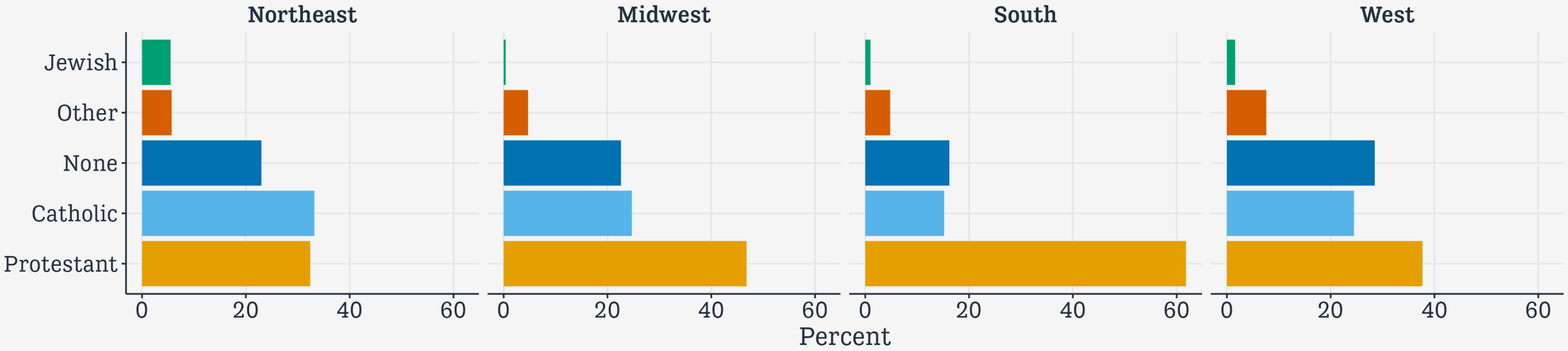
Try faceting instead

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

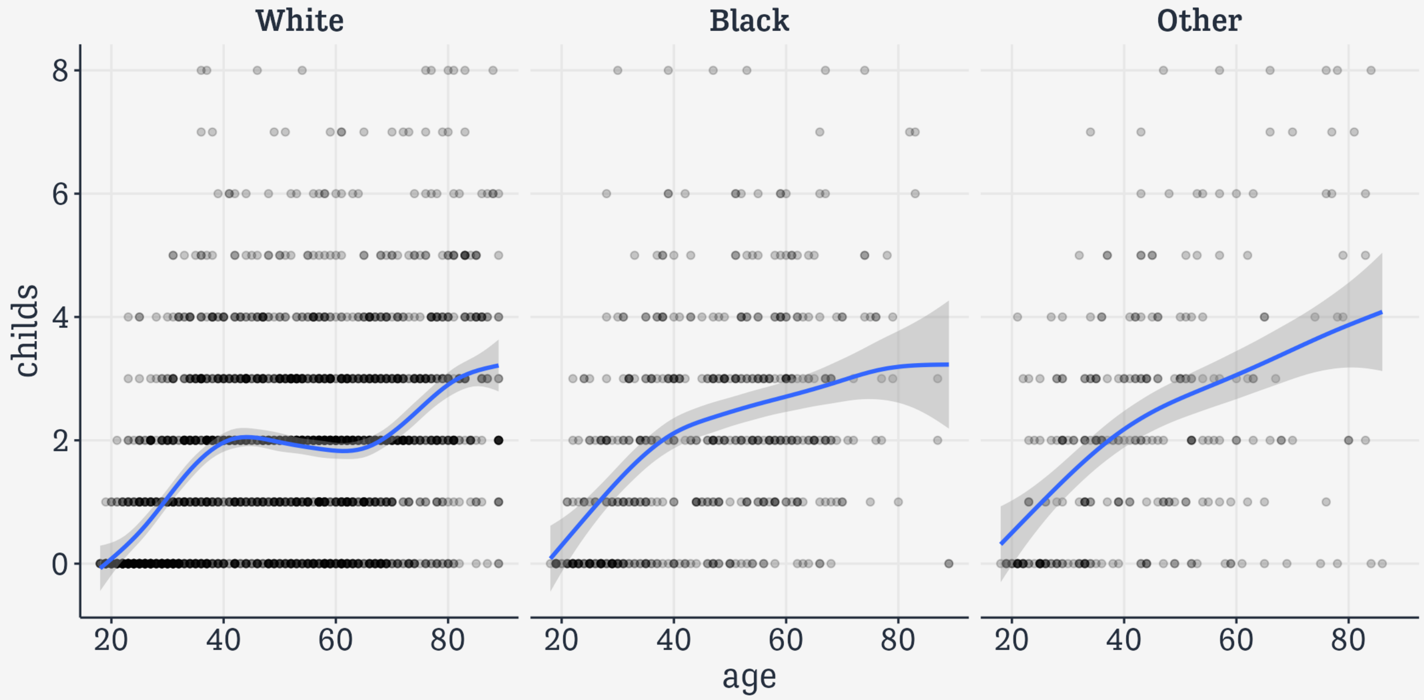
Try faceting variables instead of mapping them to color or shape.

Try to minimize the need for guides and legends.

Two kinds of facet

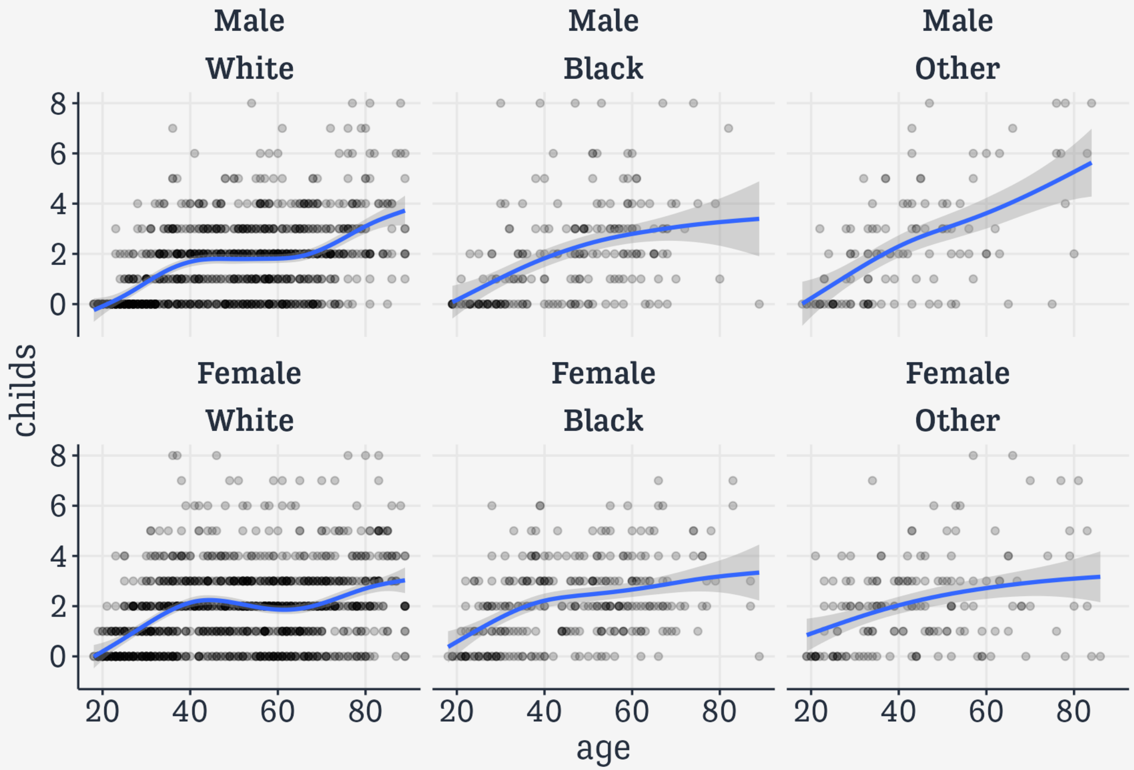
Facet Children vs Age, by Race

```r
p <-  ggplot(data = gss_sm,
             mapping = aes(x = age, y = childs))

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



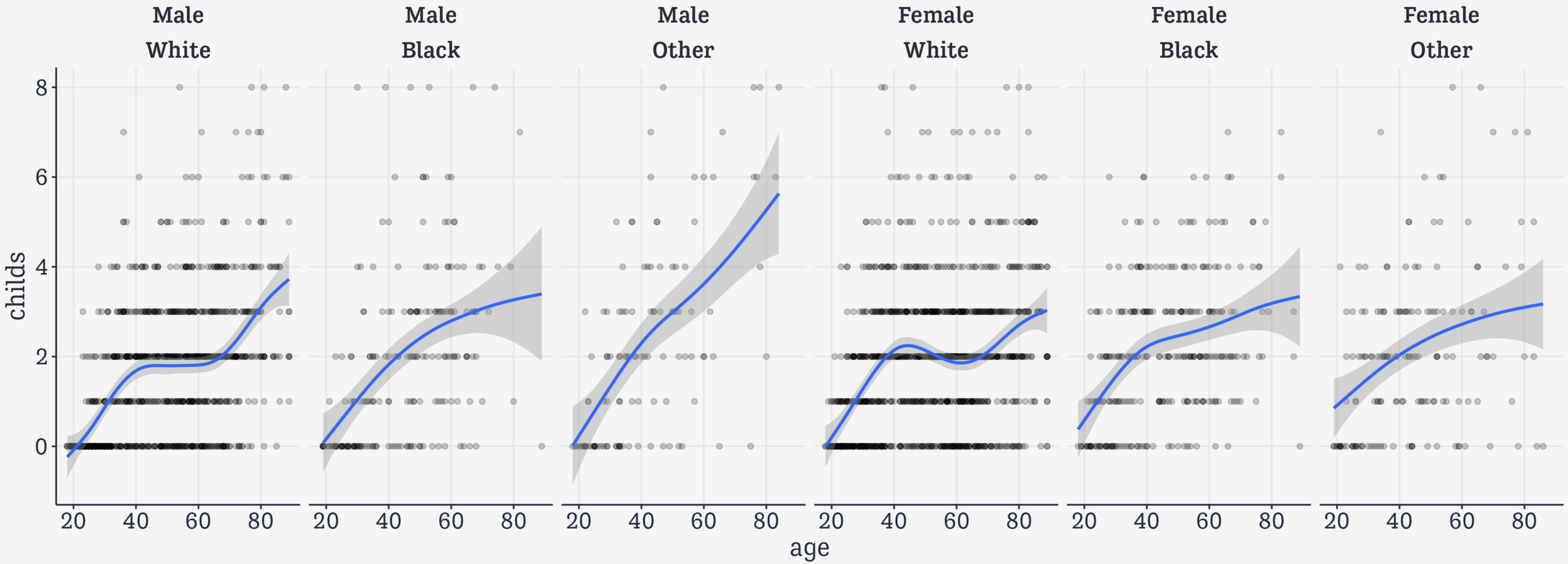
We can facet by more than one variable

```
p <-  ggplot(data = gss_sm,
             mapping = aes(x = age, y = childs))

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



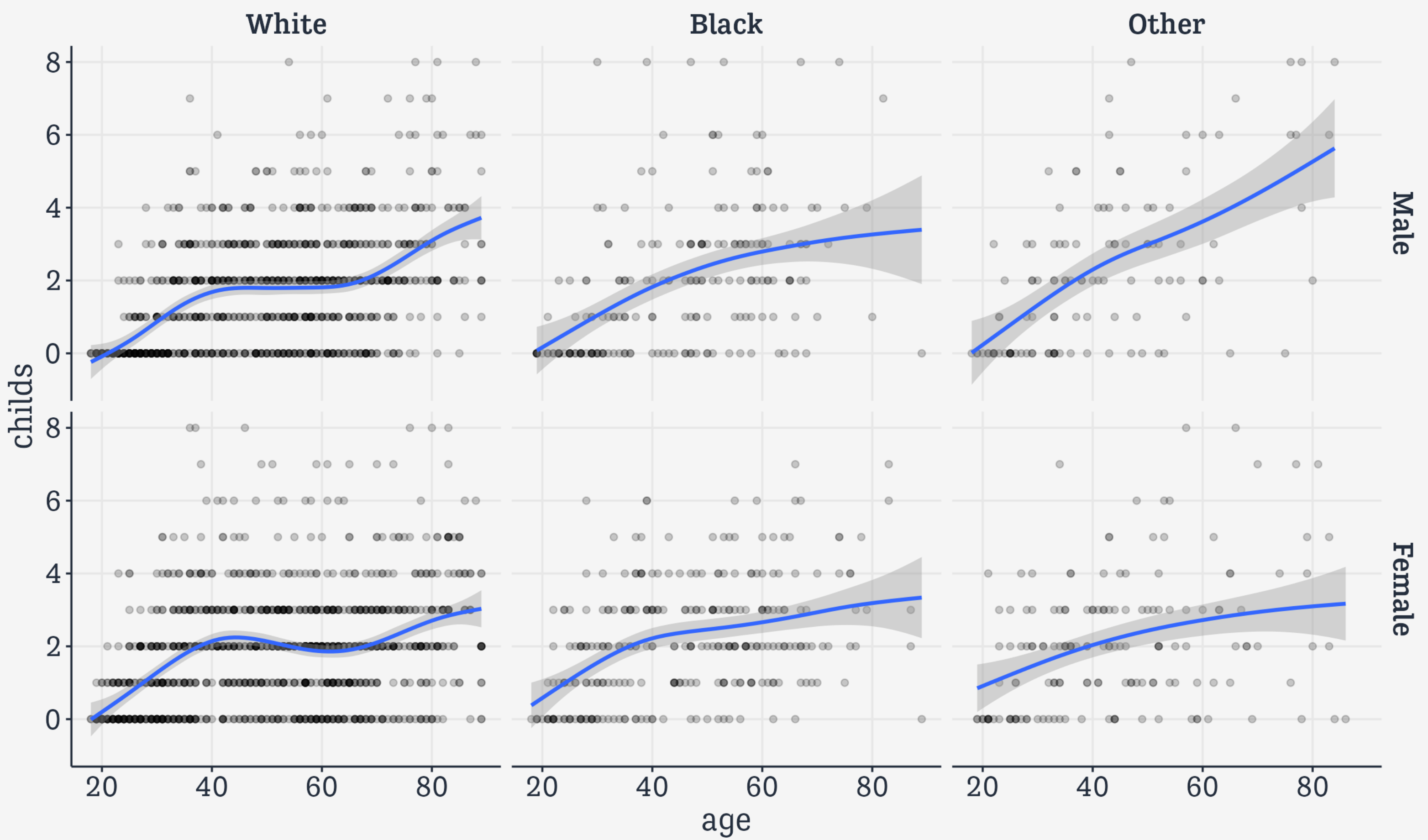
We can arrange facet_wrap() quite freely

```
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)
```



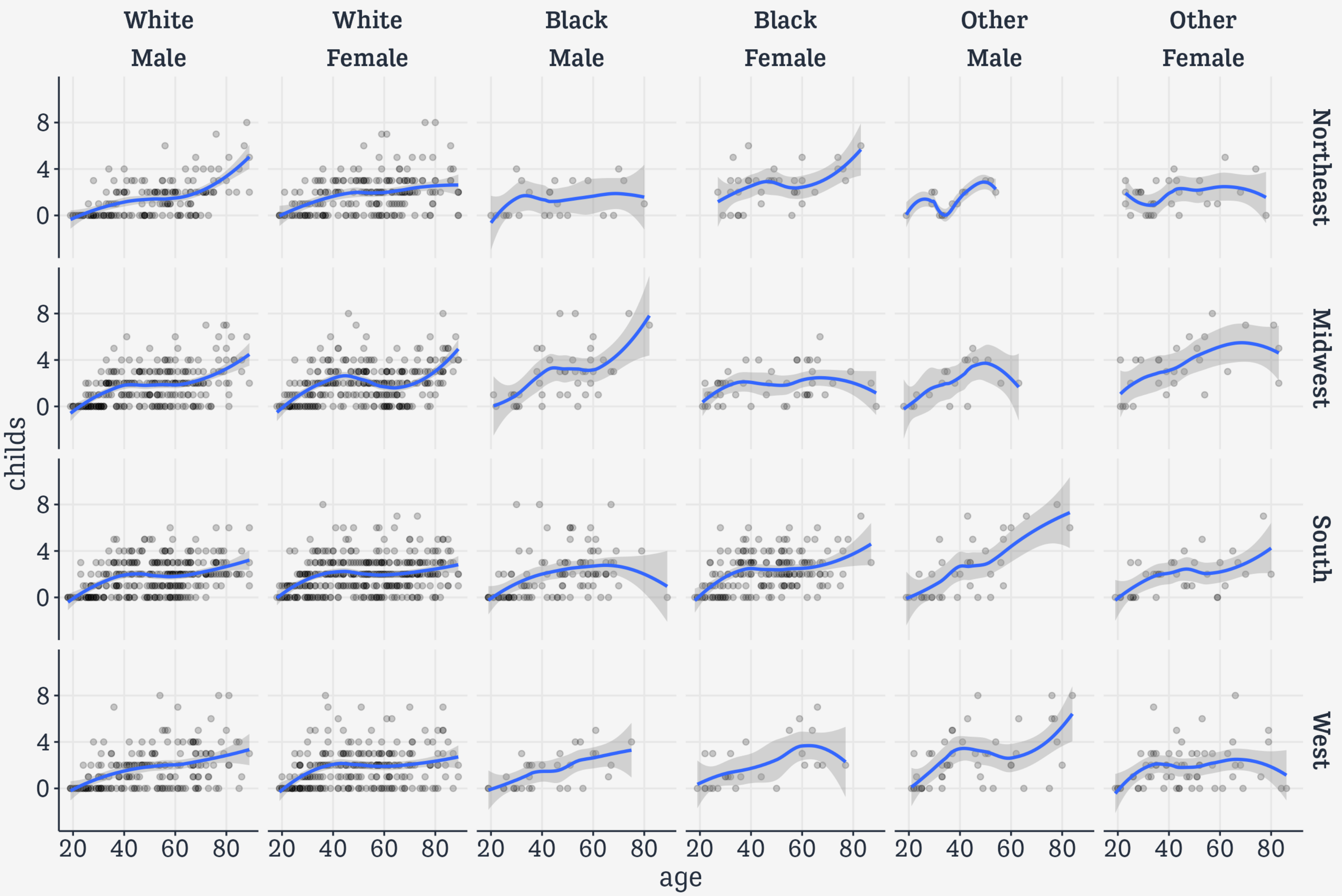
facet_grid() is more like a true crosstab

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



Both can be exended to multi-way views

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



White Male
White Female
Black Male
Black Female
Other Male
Other Female
Northeast
Midwest
South
West
childs
age
0
4
8
20
40
60
80

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()
```

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
```

Extend your `ggplot` vocabulary

We'll move forward in three ways

Learn more geoms

`geom_point()`, `geom_line()`, `geom_col()`, `geom_histogram()`, `geom_density()`, `geom_jitter()`, `geom_boxplot()`, `geom_pointrange()`,...

We'll move forward in three ways

Learn more geoms

`geom_point()`, `geom_line()`, `geom_col()`, `geom_histogram()`, `geom_density()`, `geom_jitter()`, `geom_boxplot()`, `geom_pointrange()`,...

Learn more about scales, guides, and themes

Functions that control the details of representing data and styling our plots.

We'll move forward in three ways

Learn more geoms

`geom_point()`, `geom_line()`, `geom_col()`, `geom_histogram()`, `geom_density()`, `geom_jitter()`, `geom_boxplot()`, `geom_pointrange()`,...

Learn more about scales, guides, and themes

Functions that control the details of representing data and styling our plots.

Learn more about extensions to ggplot

Packages that enhance `ggplot`'s capabilities, usually by adding support for new kinds of plot (i.e., new geoms), or new functionality (e.g., the `scales` package).

Some data on Organ Donation

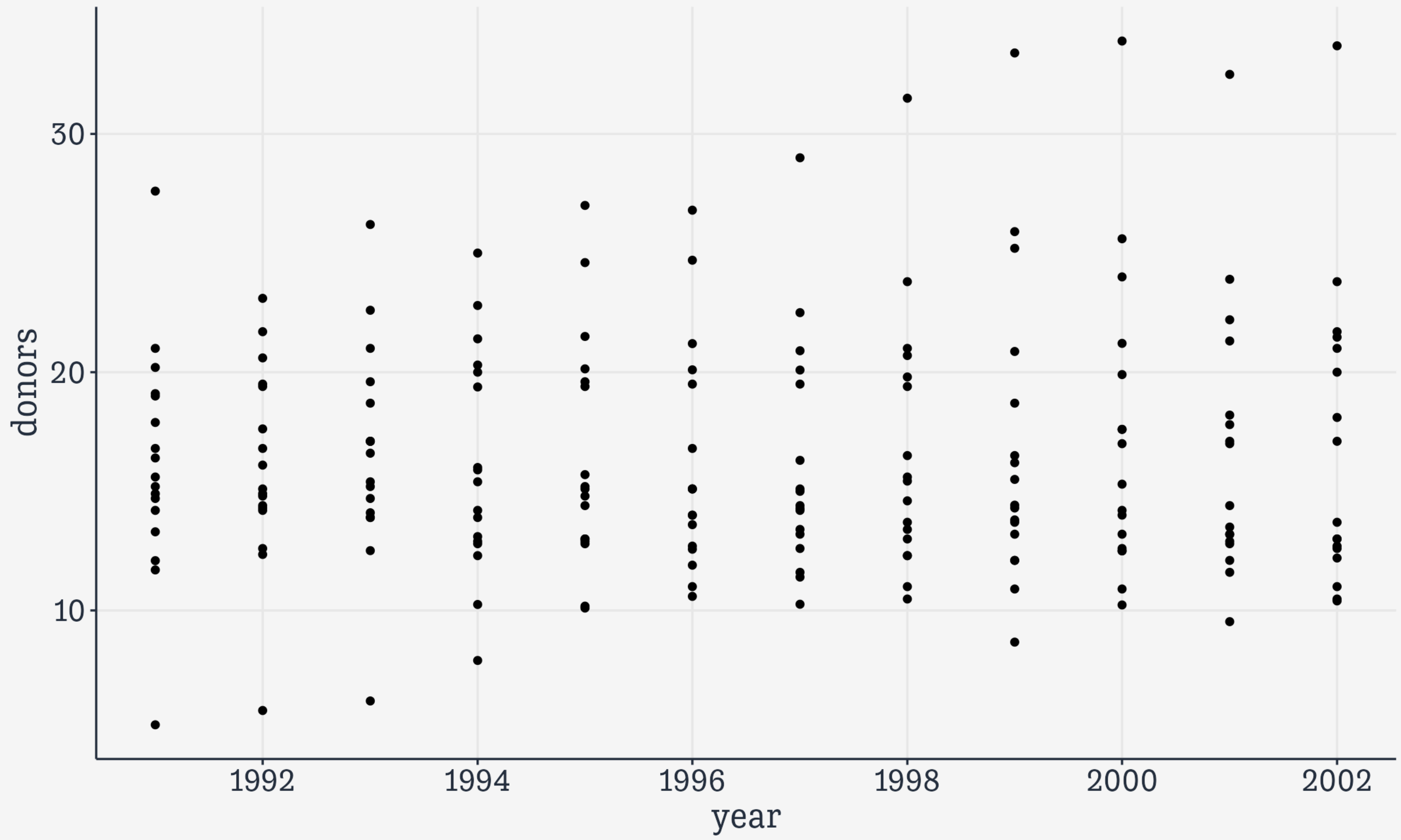
`organdata` is in the `socviz` package

```r
organdata
```

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

First looks

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

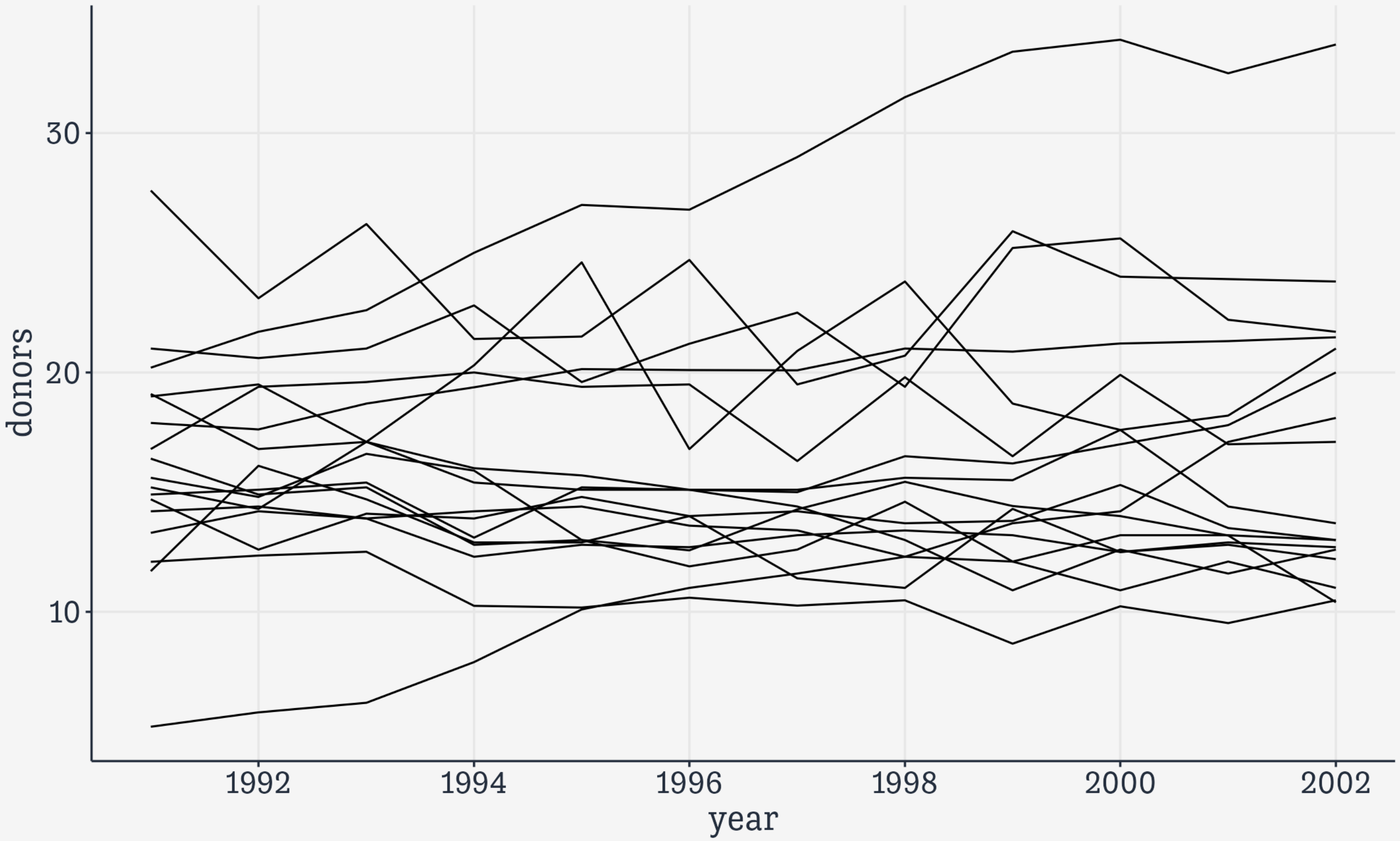


First looks

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

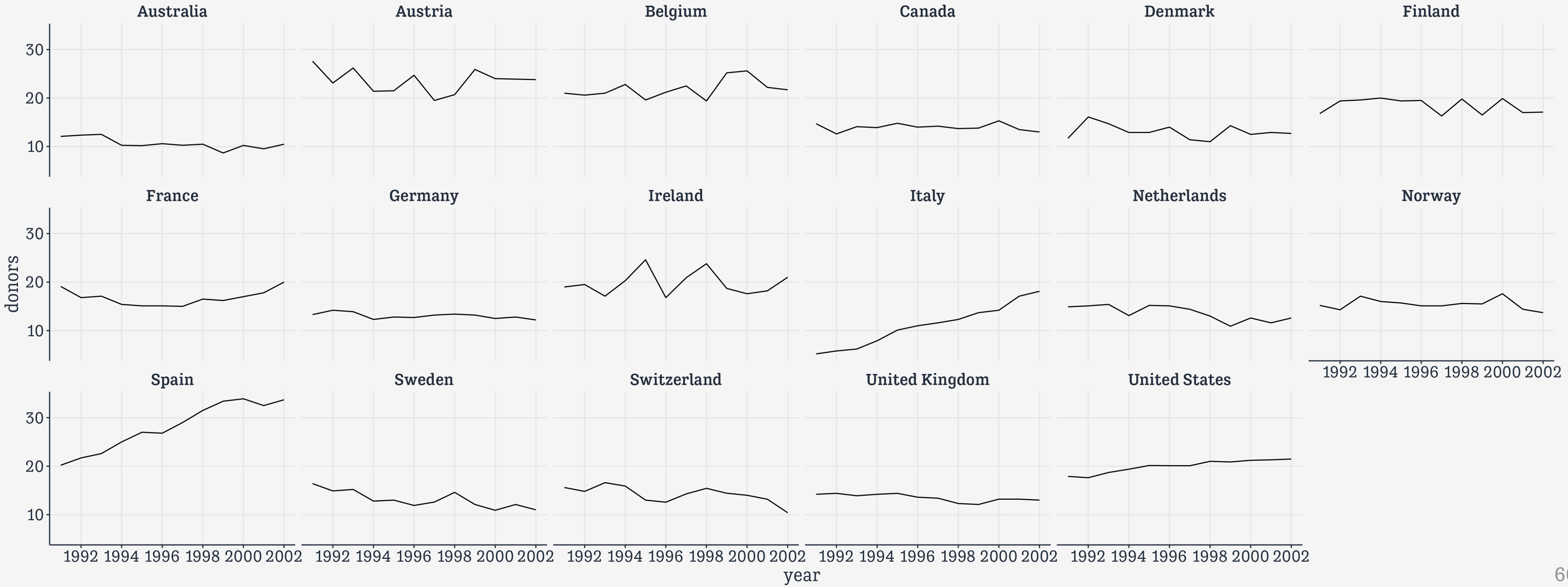
First looks

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



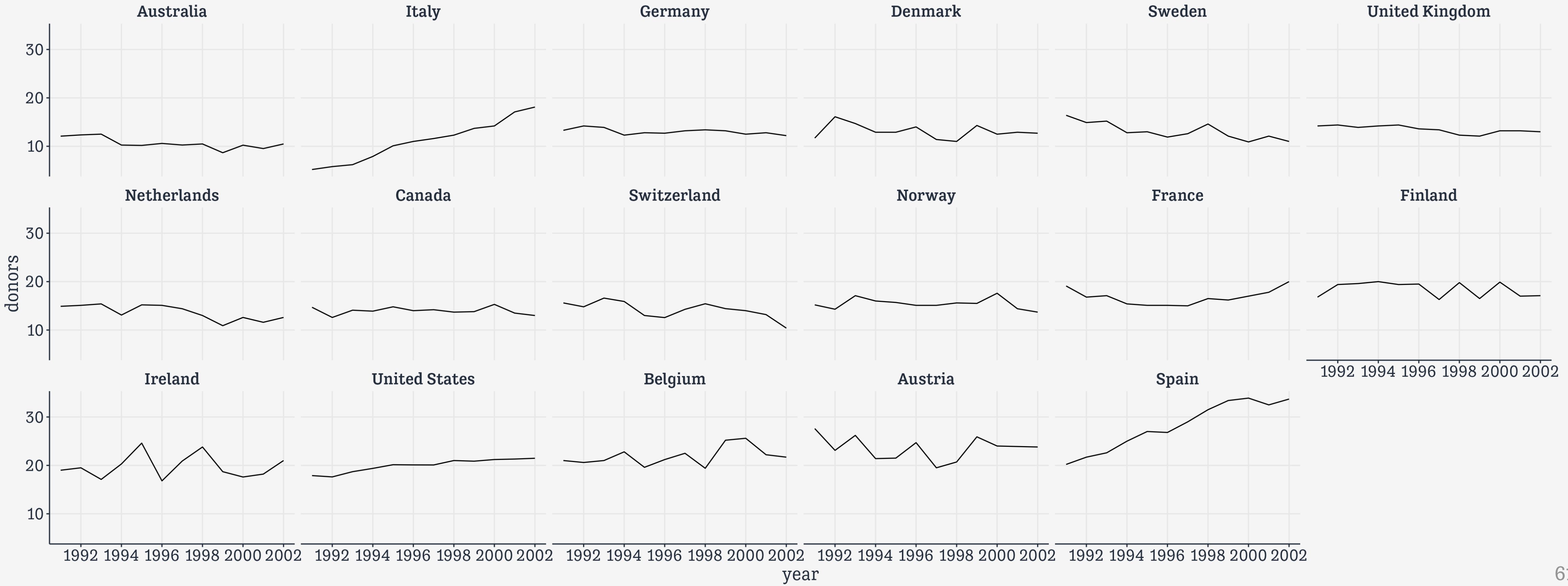
First looks

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



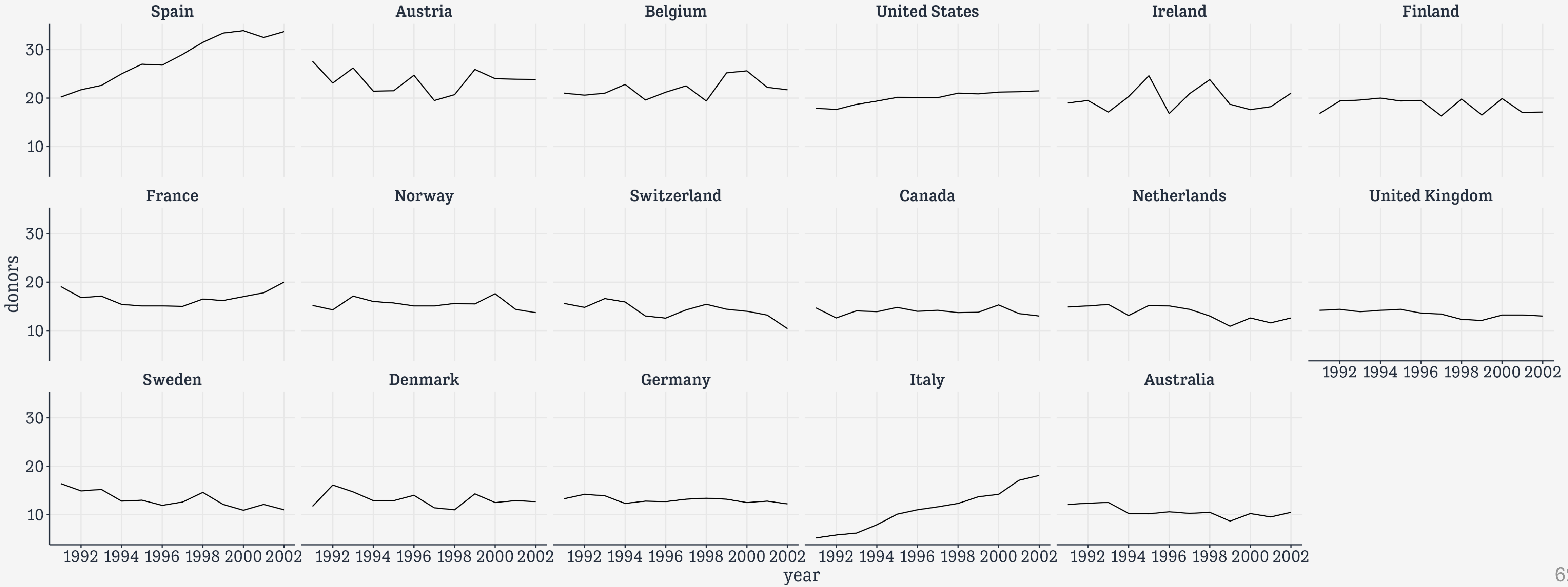
First looks

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



First looks

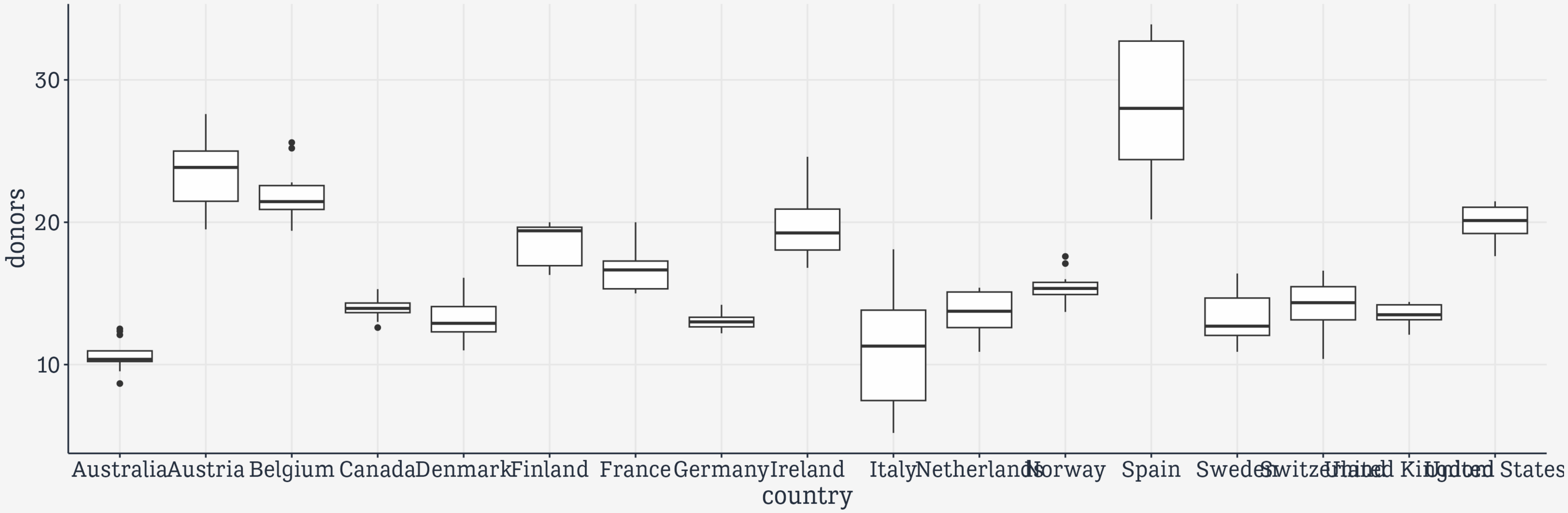
```r
p <- ggplot(data = organdata,
            mapping = aes(x = year, y = donors))
p + geom_line() +
  facet_wrap(~ reorder(country, -donors, na.rm = TRUE), nrow = 3)
```



Showing continuous measures by category

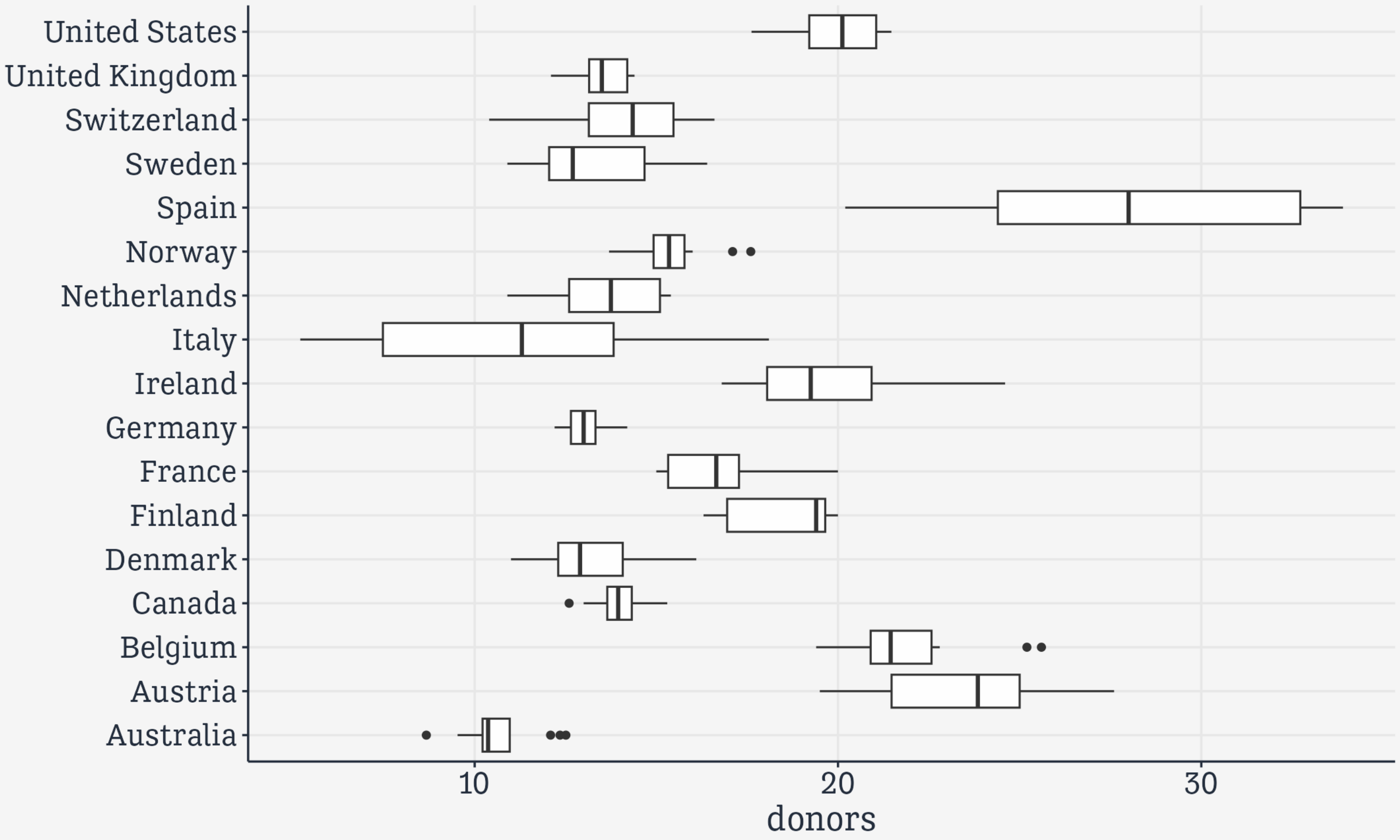
Boxplots: `geom_boxplot()`

```
## Pipeline the data directly; then it's implicitly the first argument to `ggplot()`
organdata ▷
  ggplot(mapping = aes(x = country, y = donors)) +
  geom_boxplot()
```



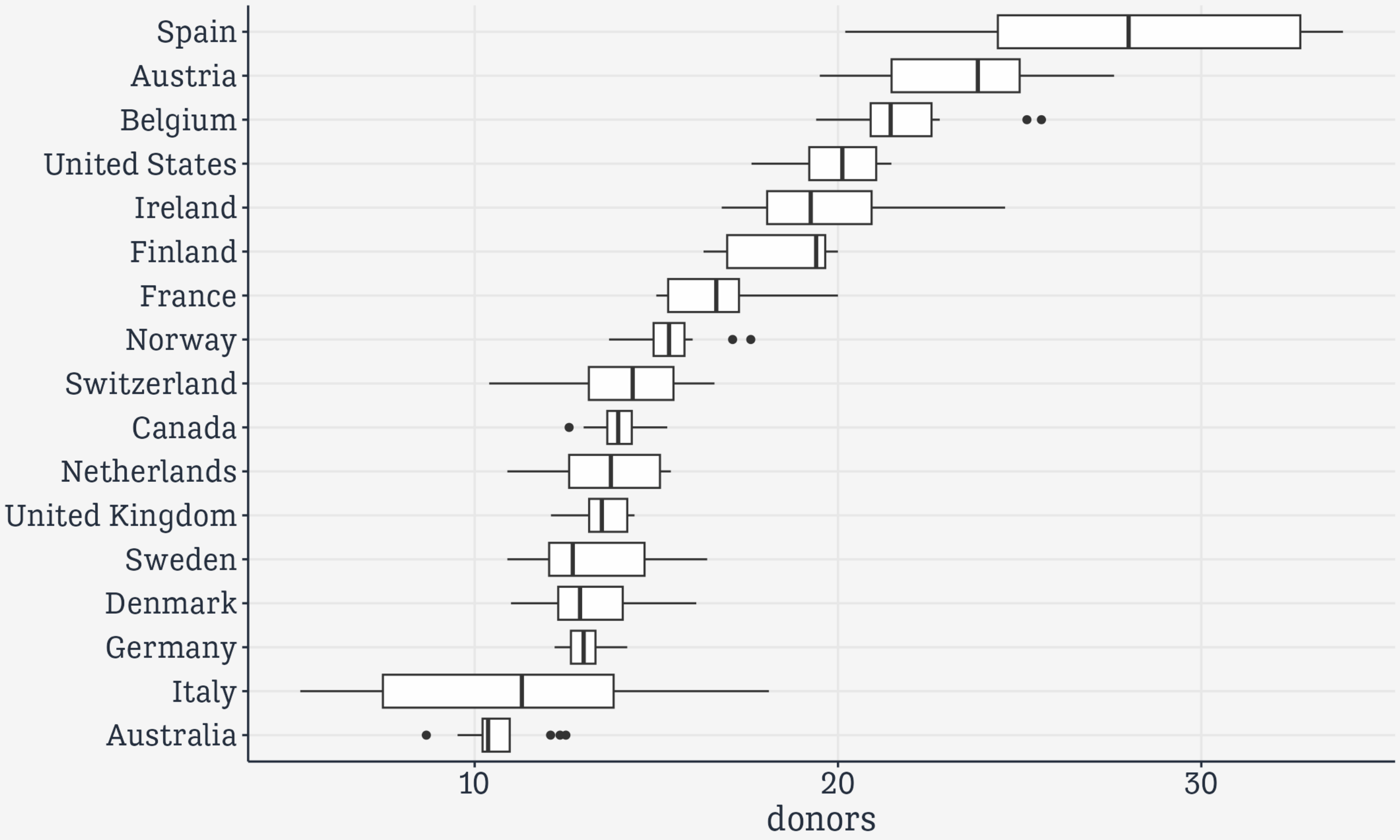
Put categories on the y-axis!

```
organdata |>
  ggplot(mapping = aes(x = donors, y = country)) +
  geom_boxplot() +
  labs(y = NULL)
```



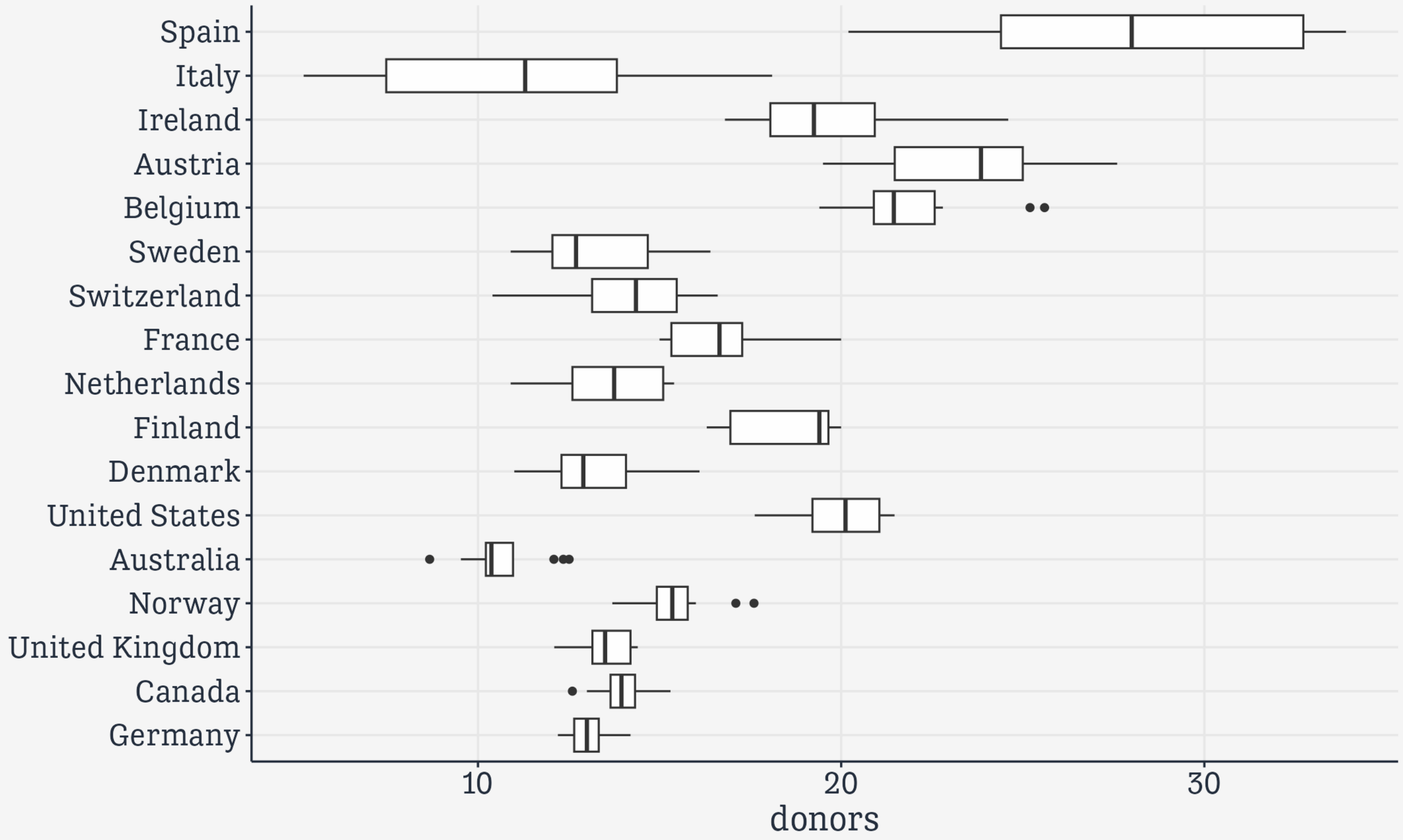
Reorder y by the mean of x

```r
organdata ▷
  ggplot(mapping = aes(x = donors, y = reorder(country, donors, na.rm = TRUE))) +
  geom_boxplot() +
  labs(y = NULL)
```



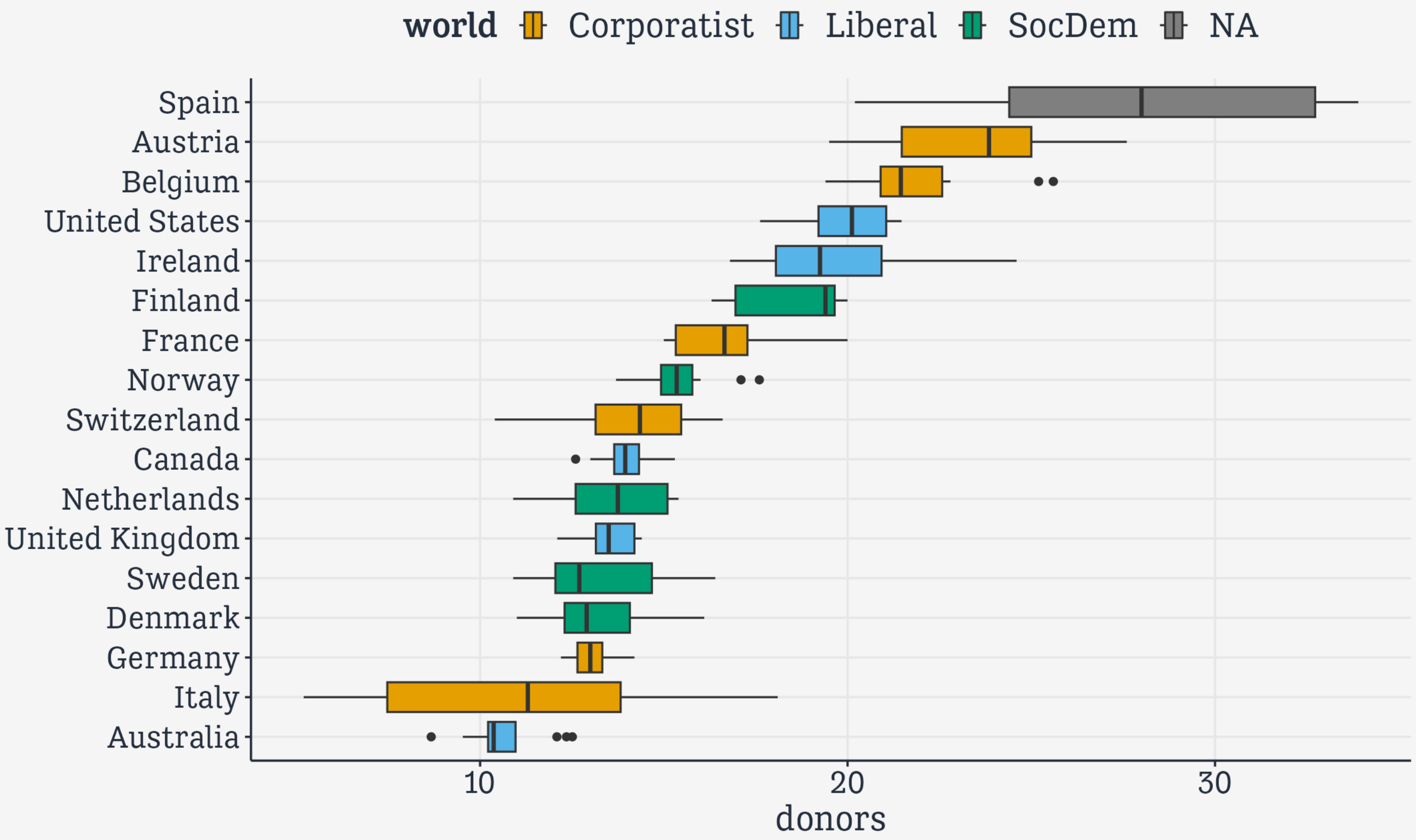
(Reorder y by any statistic you like)

```
organdata ▷
  ggplot(mapping = aes(x = donors, y = reorder(country, donors, sd, na.rm = TRUE)) +
  geom_boxplot() +
  labs(y = NULL)
```



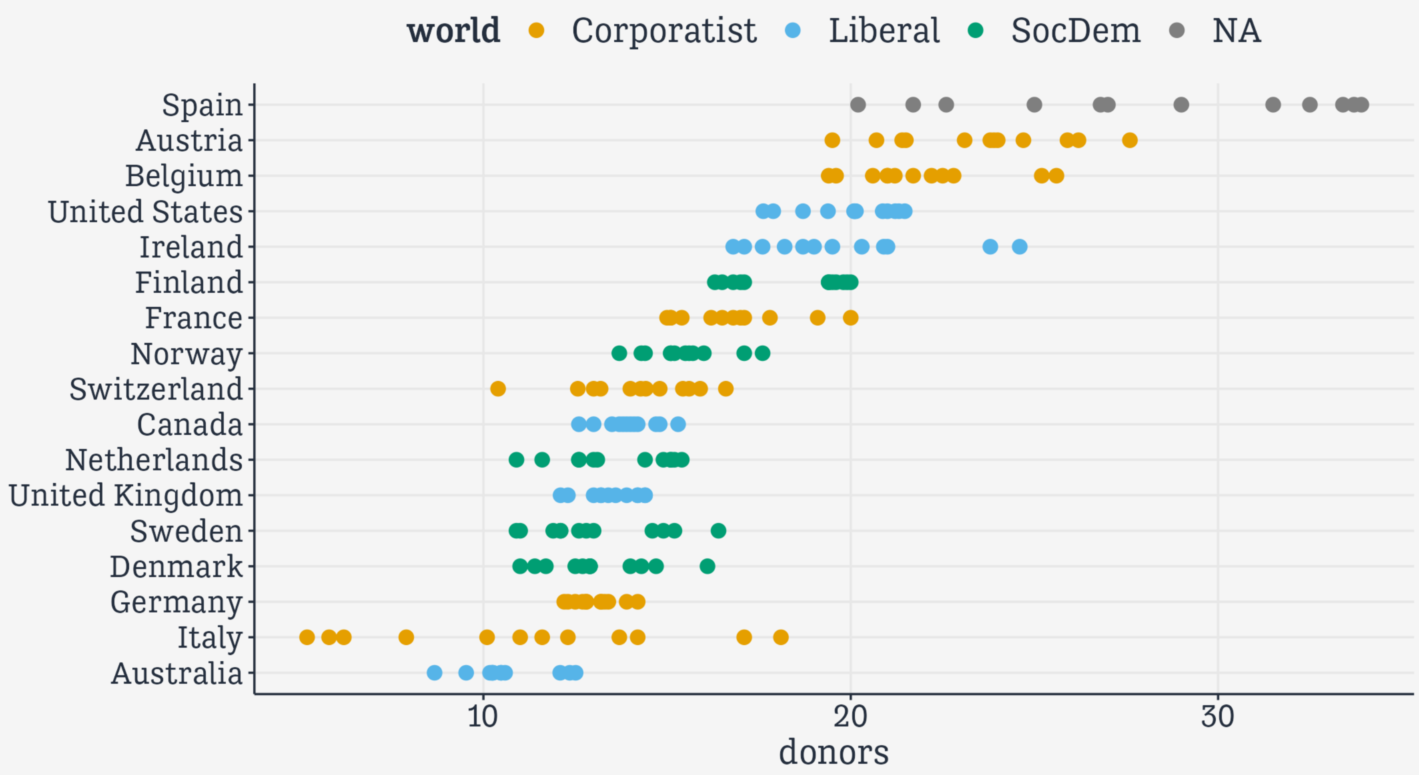
geom_boxplot() knows color and fill

```
organdata ▷
  ggplot(mapping = aes(x = donors, y = reorder(country, donors, na.rm = TRUE), fill = world)) +
  geom_boxplot() +
  labs(y = NULL)
```



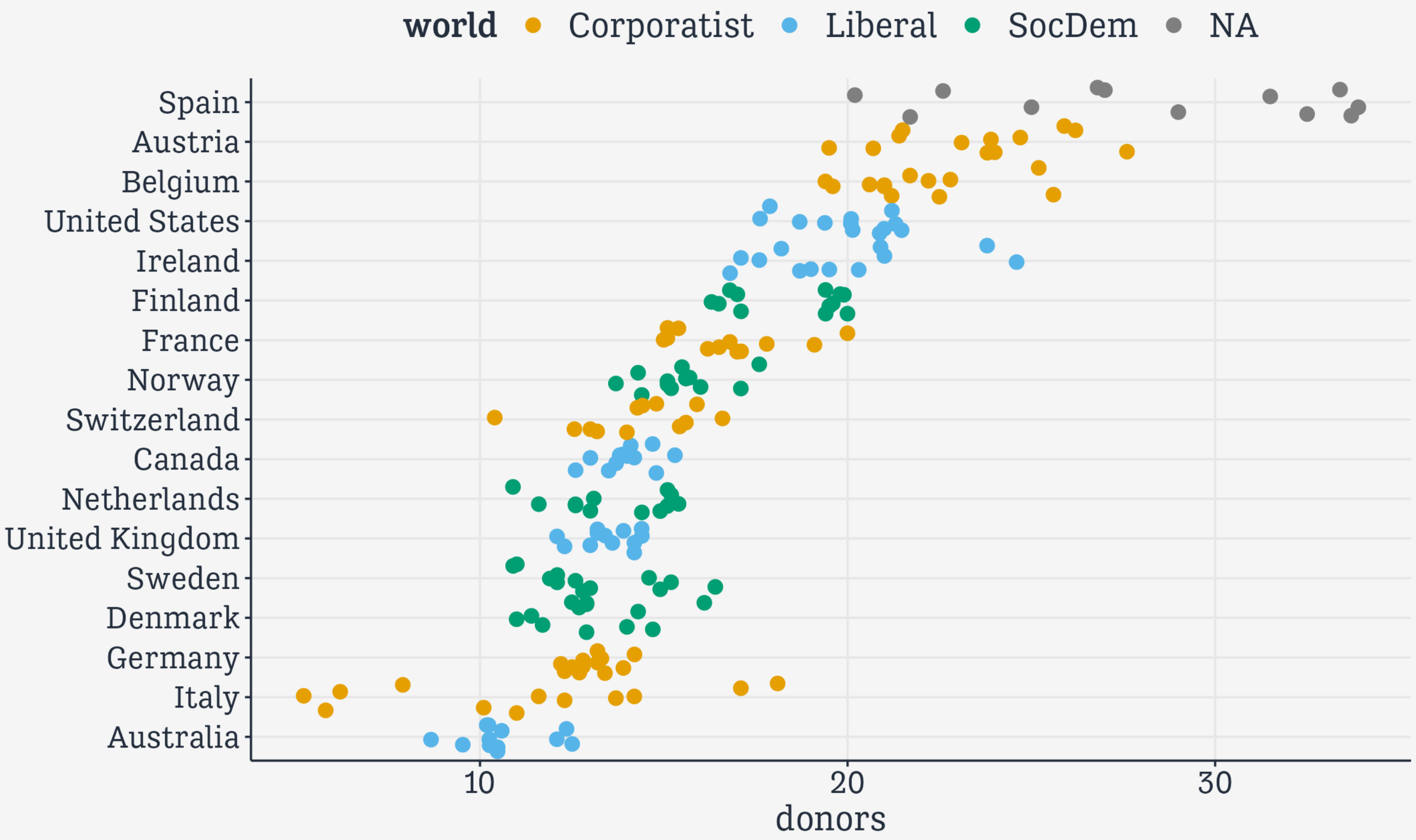
These strategies are quite general

```r
organdata ▷
  ggplot(mapping = aes(x = donors, y = reorder(country, donors, na.rm = TRUE), color = world)) +
  geom_point(size = rel(3)) +
  labs(y = NULL)
```



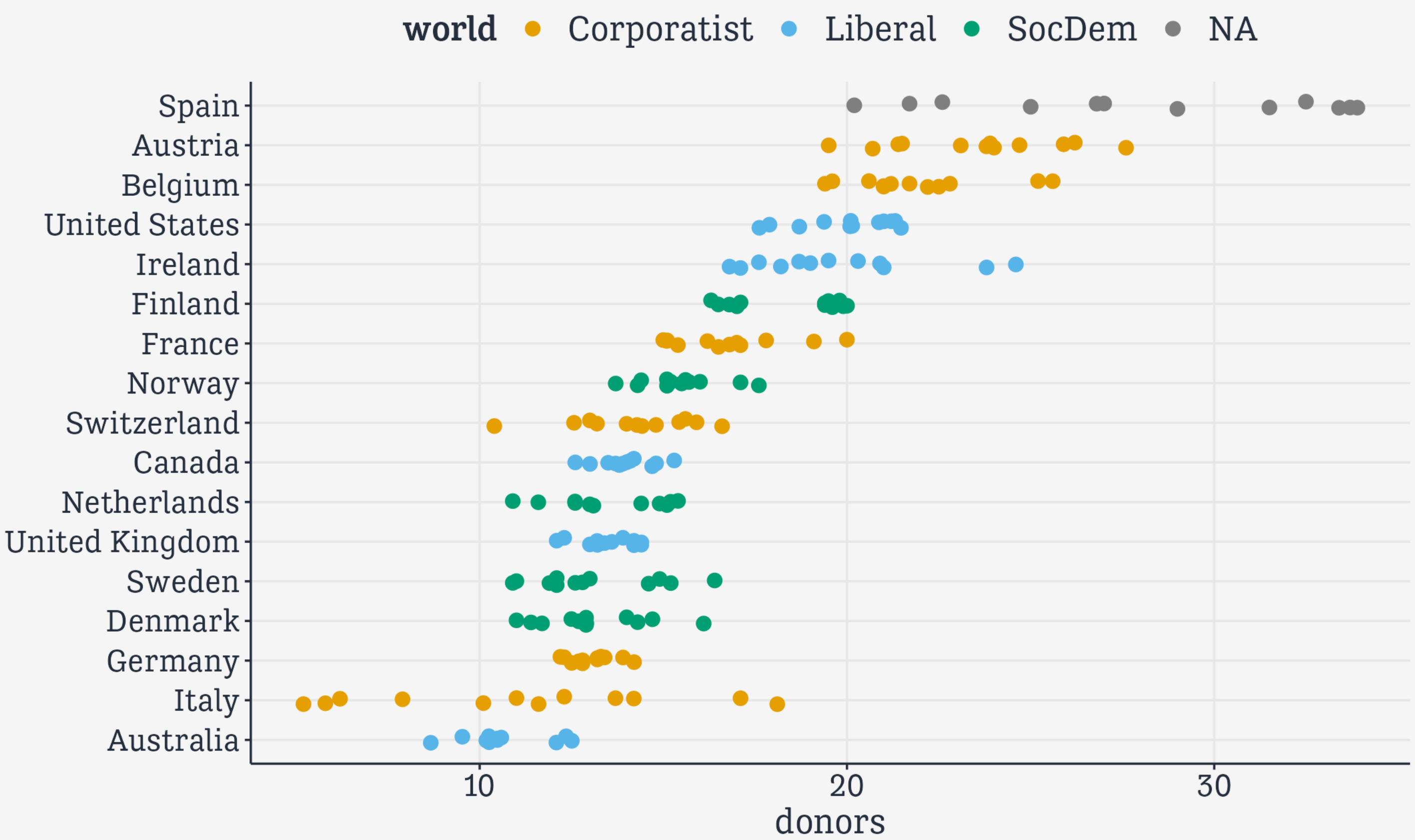
geom-jitter() can help with overplotting

```r
organdata |>
  ggplot(mapping = aes(x = donors, y = reorder(country, donors, na.rm = TRUE), color = world)) +
  geom_jitter(size = rel(3)) +
  labs(y = NULL)
```



Adjust with a `position` argument

```r
organdata |>
  ggplot(mapping = aes(x = donors, y = reorder(country, donors, na.rm = TRUE),
                       color = world)) +
  geom_jitter(size = rel(3), position = position_jitter(height = 0.1)) +
  labs(y = NULL)
```



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

```r
by_country <- organdata |>
  group_by(consent_law, country) |>
    summarize(across(where(is.numeric),
                     list(mean = mean,
                          sd = sd),
                      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

```r
by_country <- organdata |>
  group_by(consent_law, country) |>
    summarize(across(where(is.numeric),
                     list(mean = mean,
                          sd = sd),
                      na.rm = TRUE),
              .groups = "drop")
head(by_country)
```

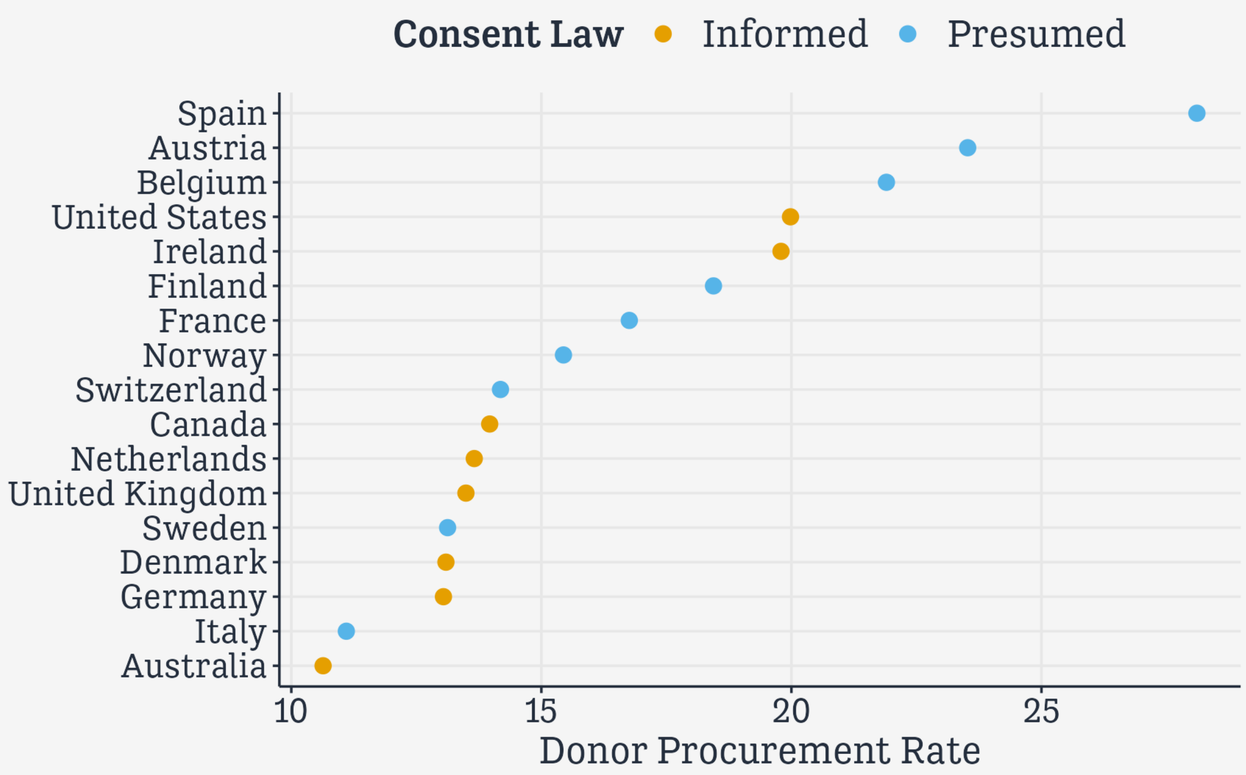
```
## # A tibble: 6 × 28
##   consent_law country     donors_mean donors_sd pop_mean pop_sd pop_dens_mean
##   <chr>       <chr>             <dbl>     <dbl>    <dbl>  <dbl>         <dbl>
## 1 Informed    Australia          10.6     1.14    18318.  831.          0.237
## 2 Informed    Canada             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")
```

Plot our summary data

```r
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?

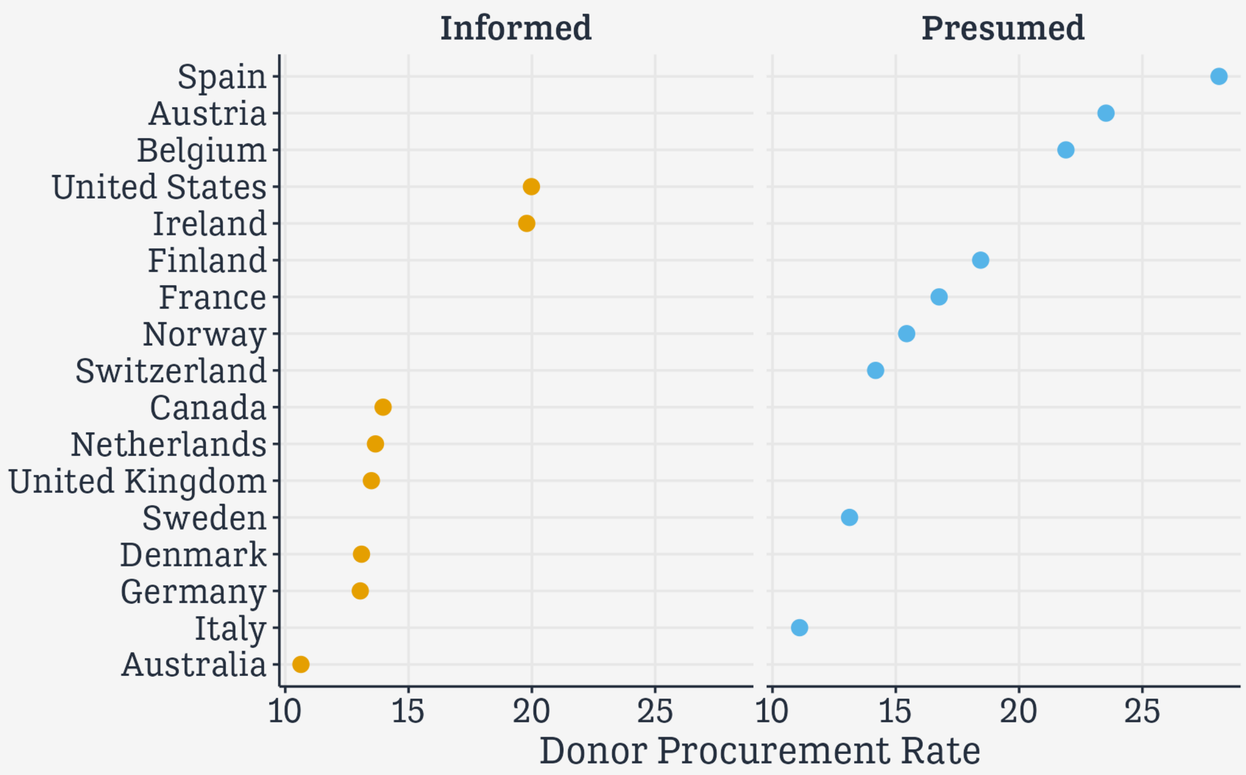
```
by_country ▷
  ggplot(mapping =
           aes(x = donors_mean,
               y = reorder(country, donors_mean),
               color = consent_law)) +
  geom_point(size=3) +
  guides(color = "none") +
  facet_wrap(~ consent_law) +
  labs(x = "Donor Procurement Rate",
       y = NULL,
       color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

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

What about faceting it instead?

```r
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")
```

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



What about faceting it instead?

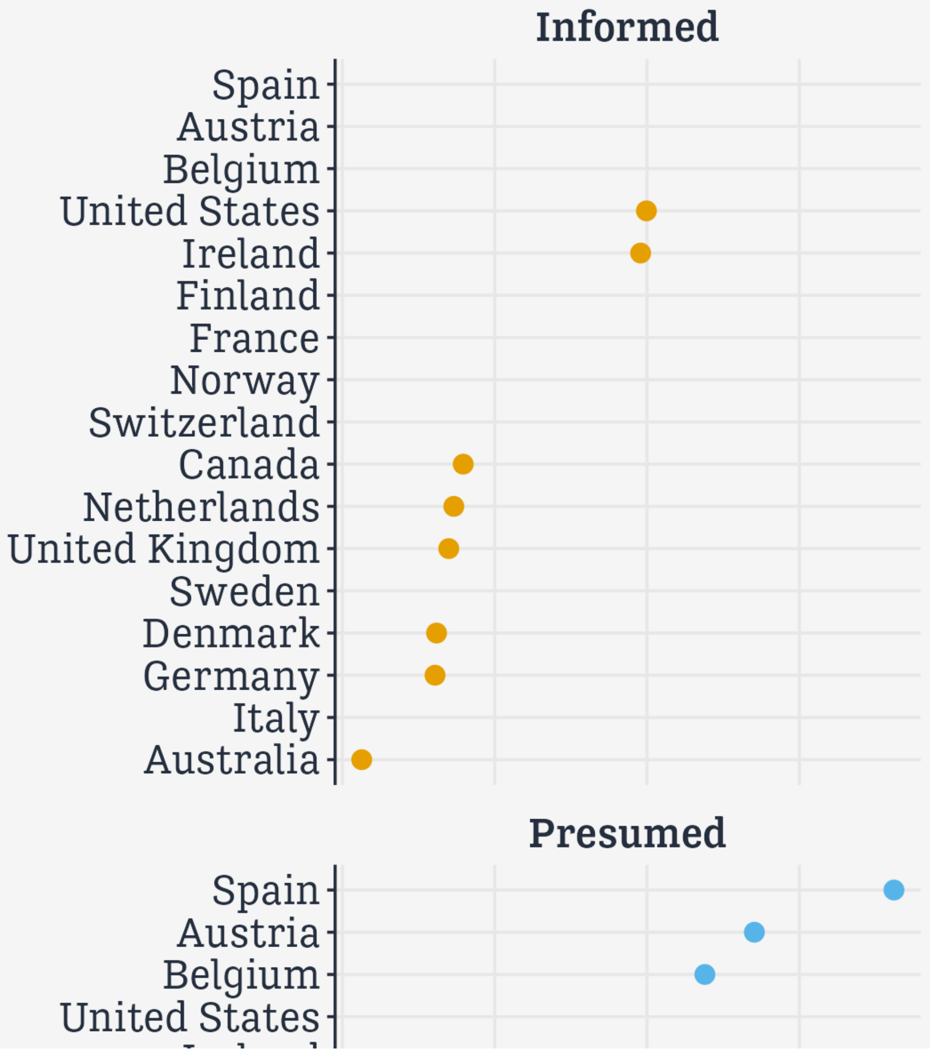
```
by_country |>
  ggplot(mapping =
           aes(x = donors_mean,
               y = reorder(country, donors_mean),
               color = consent_law)) +
  geom_point(size=3) +
  guides(color = "none") +
  facet_wrap(~ consent_law, ncol = 1) +
  labs(x = "Donor Procurement Rate",
       y = NULL,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

Restricting to one column doesn't fix it.

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")
```

Restricting to one column doesn't fix it.



Allow the y-scale to vary

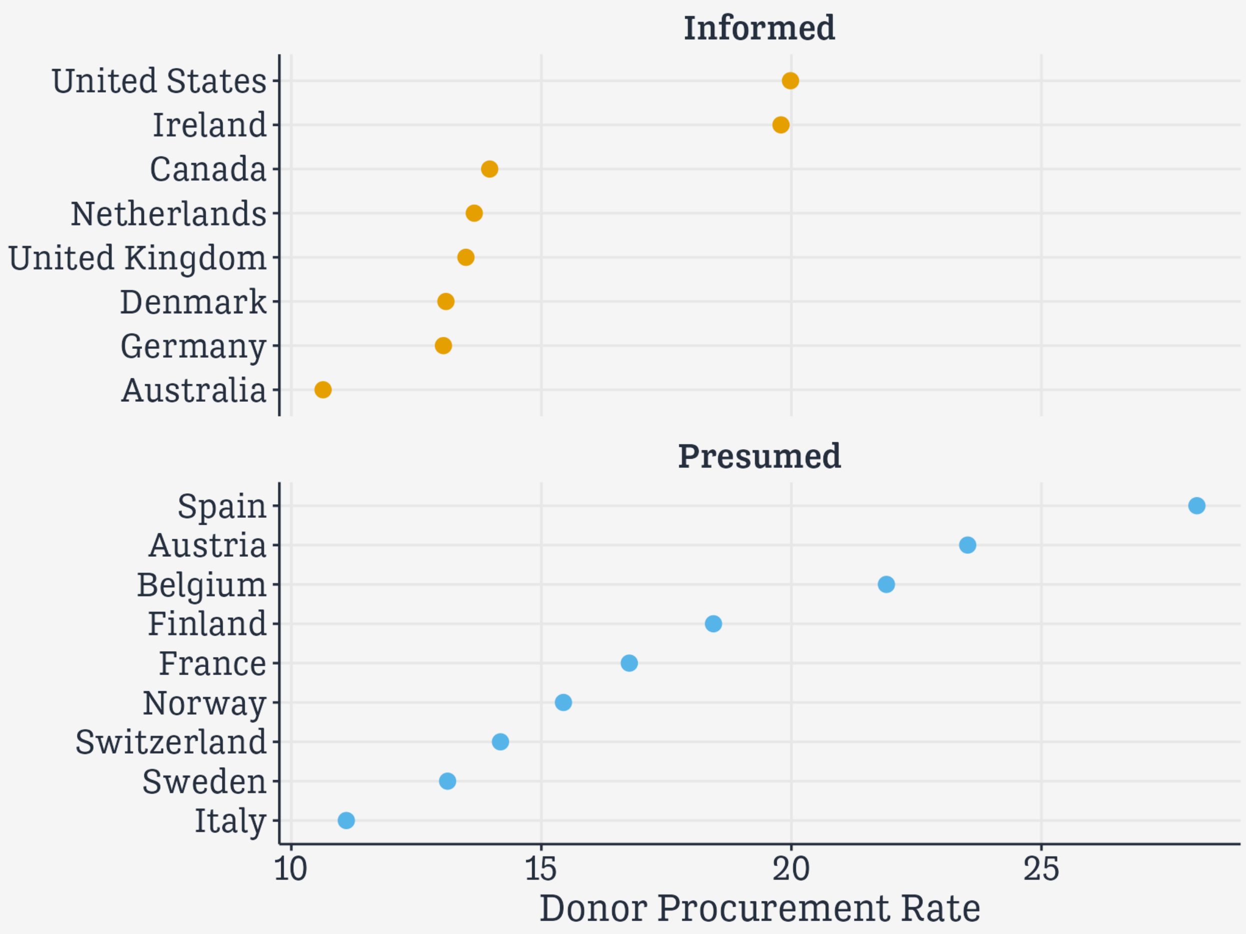
```
by_country |>
  ggplot(mapping =
           aes(x = donors_mean,
               y = reorder(country, donors_mean),
               color = consent_law)) +
  geom_point(size=3) +
  guides(color = "none") +
  facet_wrap(~ consent_law,
             ncol = 1,
             scales = "free_y") +
  labs(x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

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.

Allow the y-scale to vary

```
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")
```

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.

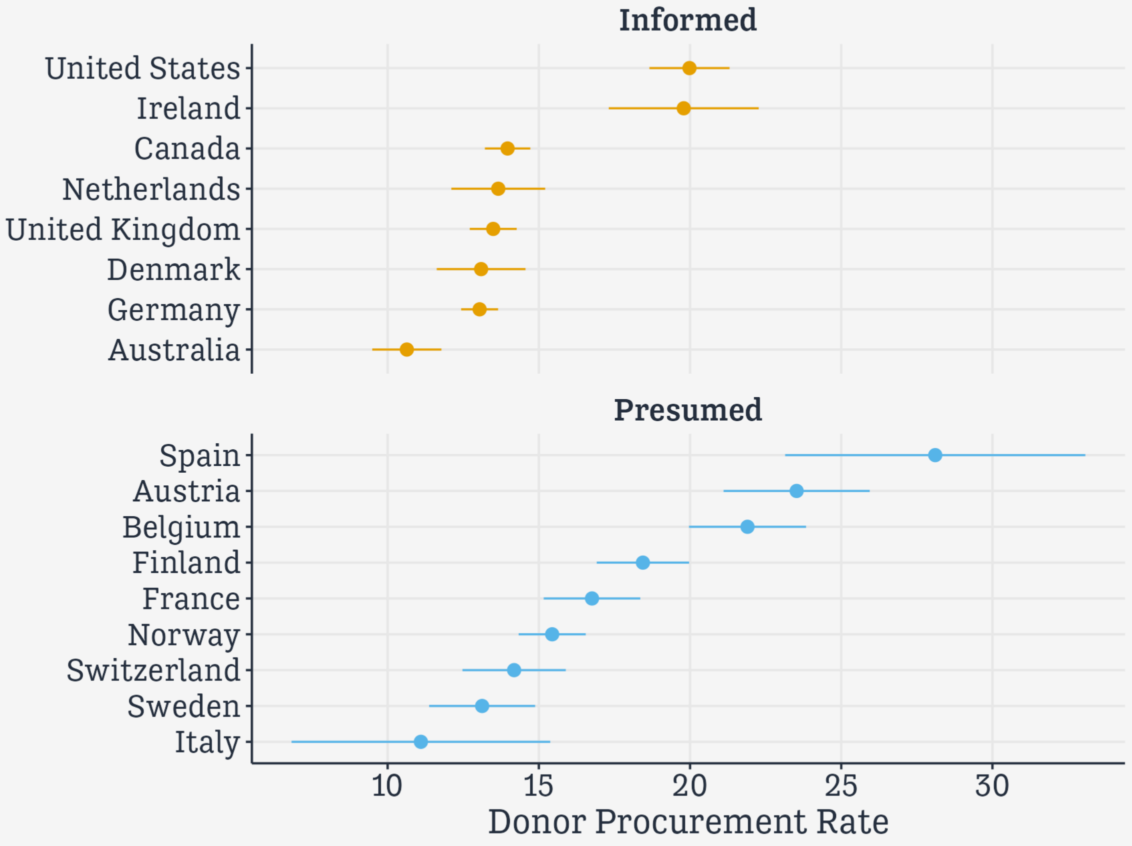


Again, these methods are general

```r
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")
```

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")
```



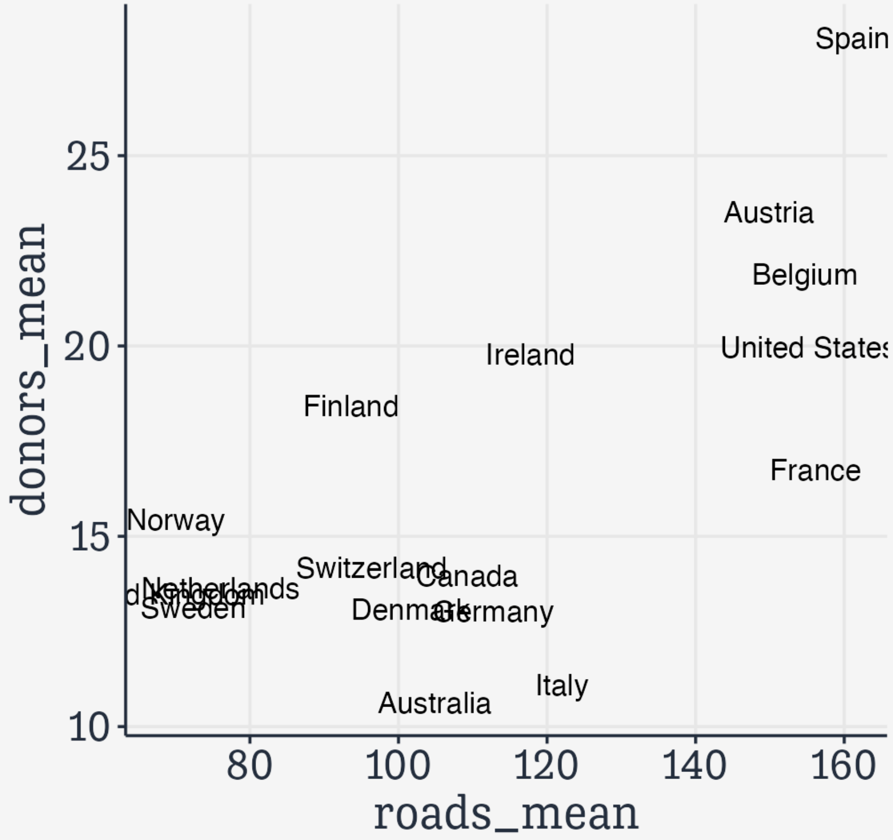
Plot text directly

`geom_text()` for basic labels

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

`geom_text()` for basic labels

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

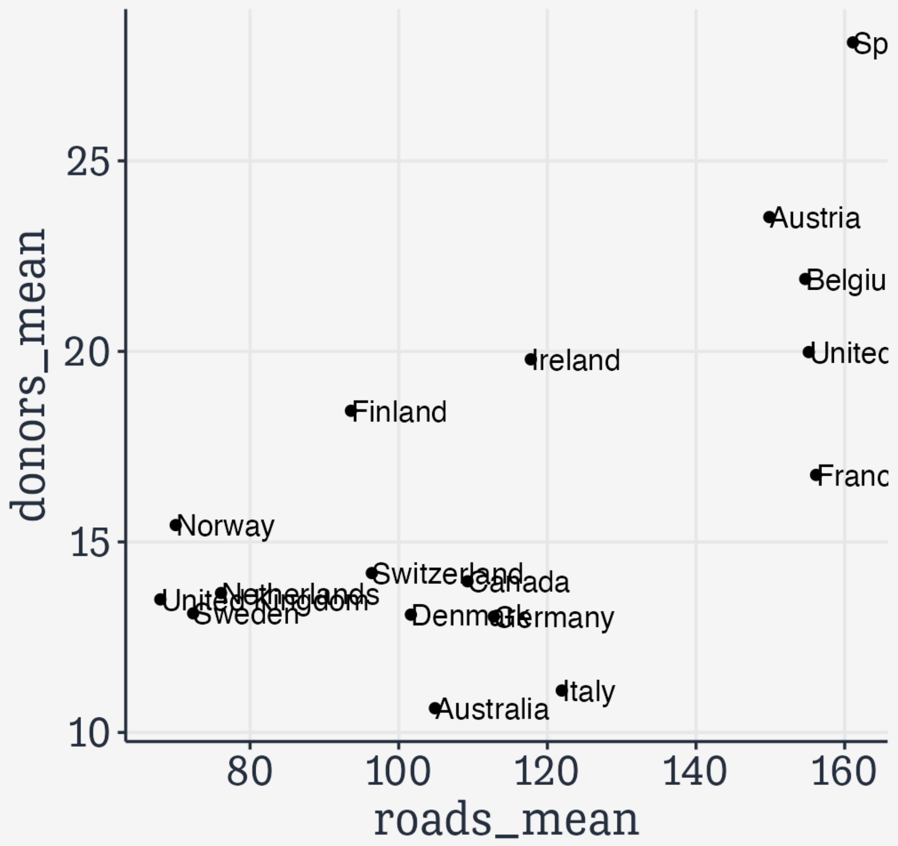


It's not very flexible

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

It's not very flexible

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

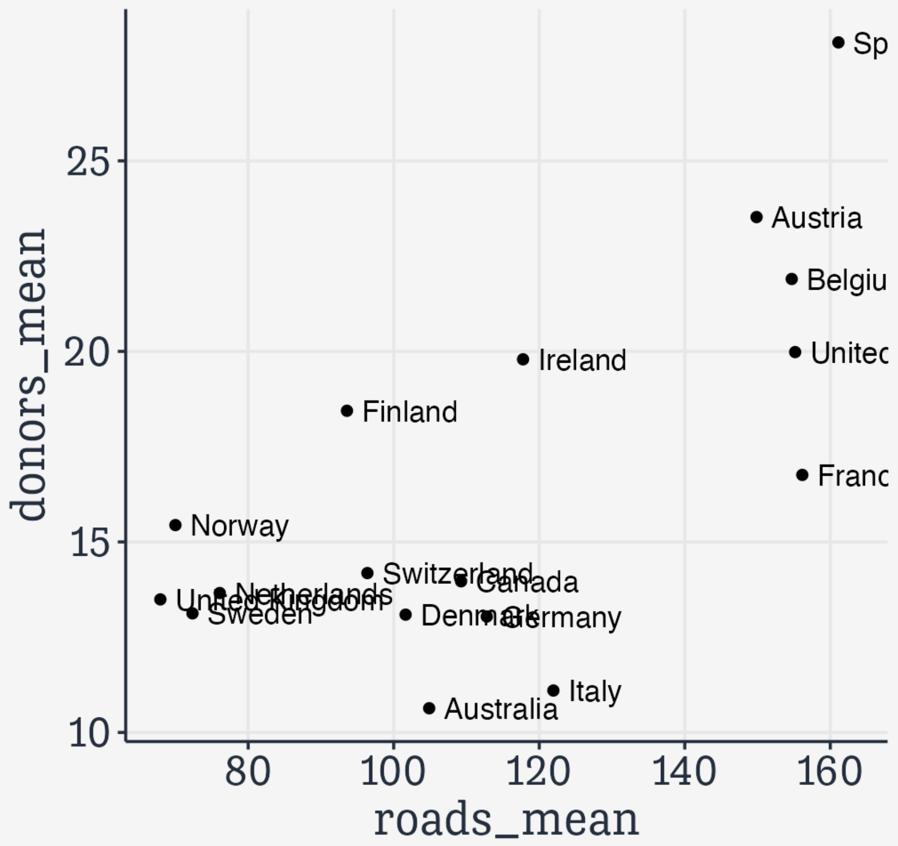


There are tricks, but they're limited

```
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)
```

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()`

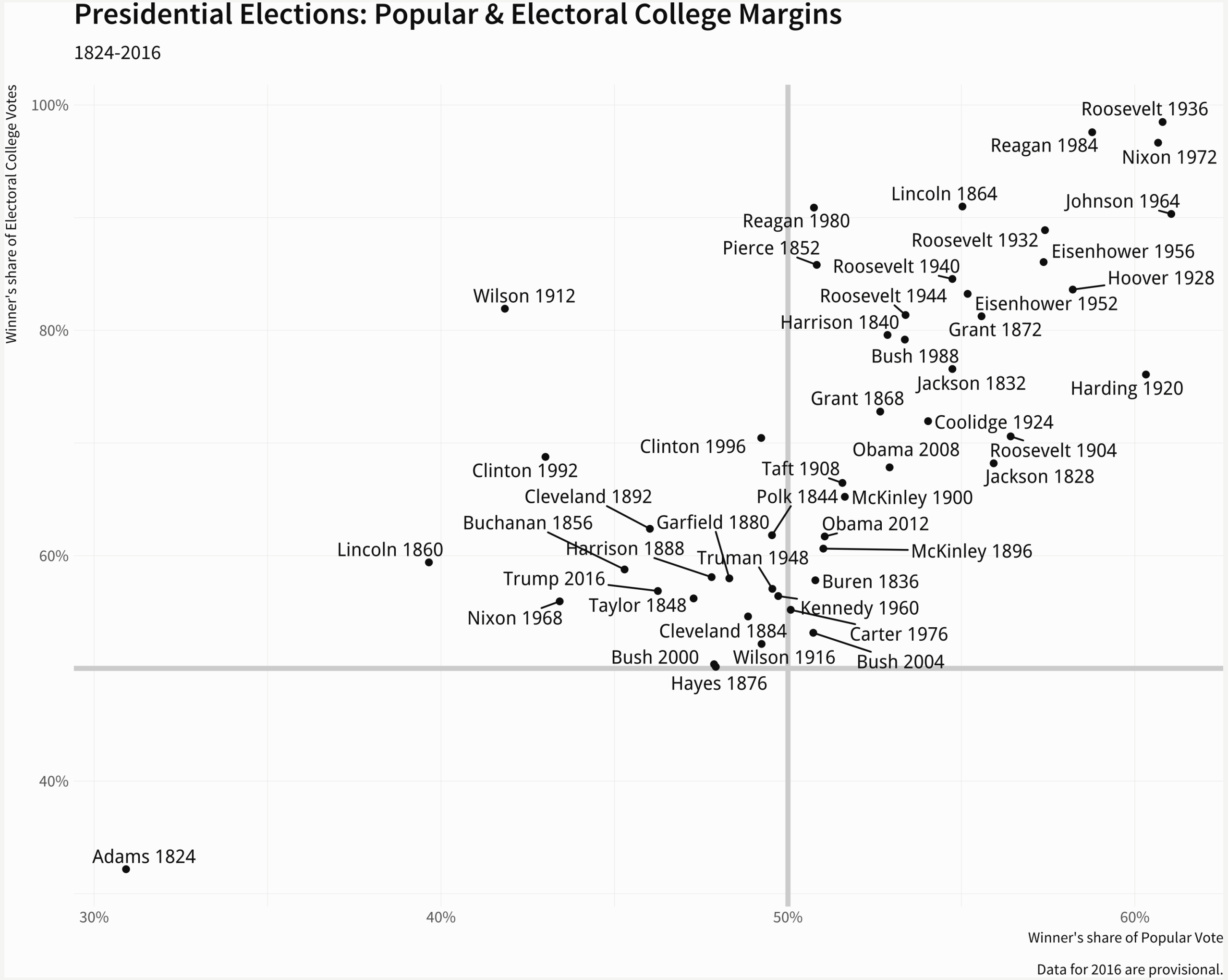
U.S. Historic Presidential Elections

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 Quinc… D.-R.      0.322       0.309        -0.104  1.13e5
##  2       11  1828 Andrew Jac… Dem.       0.682       0.559         0.122  6.43e5
##  3       12  1832 Andrew Jac… Dem.       0.766       0.547         0.178  7.03e5
##  4       13  1836 Martin Van… Dem.       0.578       0.508         0.142  7.63e5
##  5       14  1840 William He… 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 Ta… Whig       0.562       0.473         0.0479 1.36e6
##  8       17  1852 Franklin P… Dem.       0.858       0.508         0.0695 1.61e6
##  9       18  1856 James Buch… Dem.       0.588       0.453         0.122  1.84e6
## 10       19  1860 Abraham Li… 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



Keep things neat

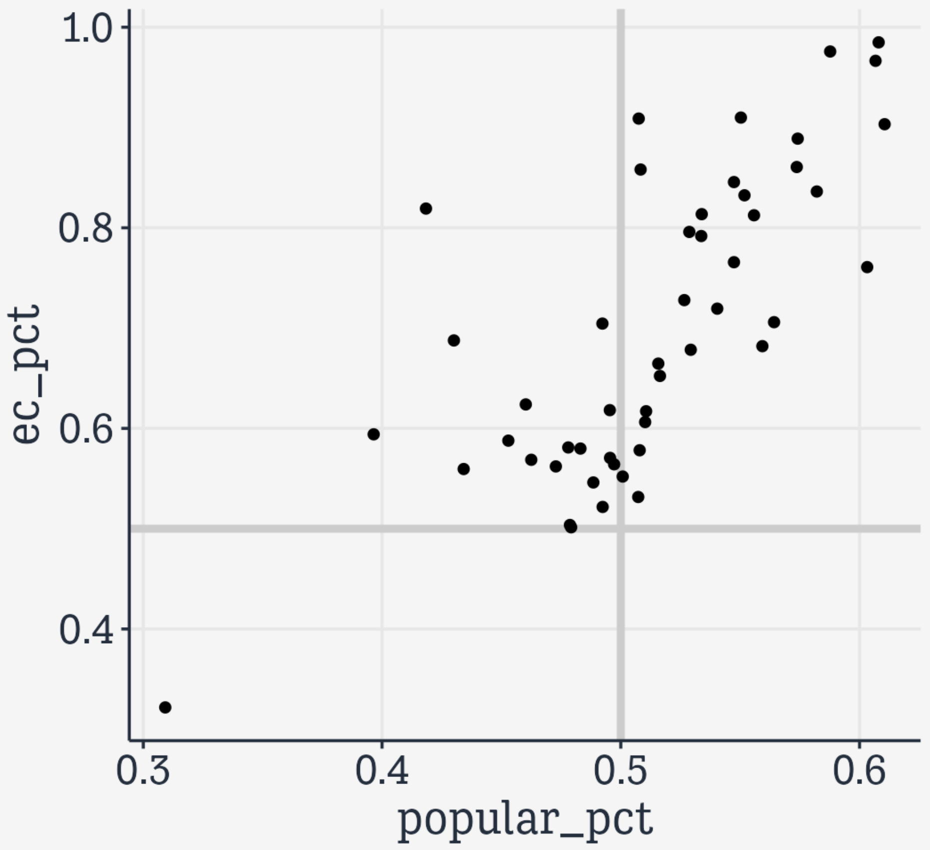
```r
## The packages we'll use in addition to ggplot
library(ggrepel)
library(scales)

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

```r
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()
```

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

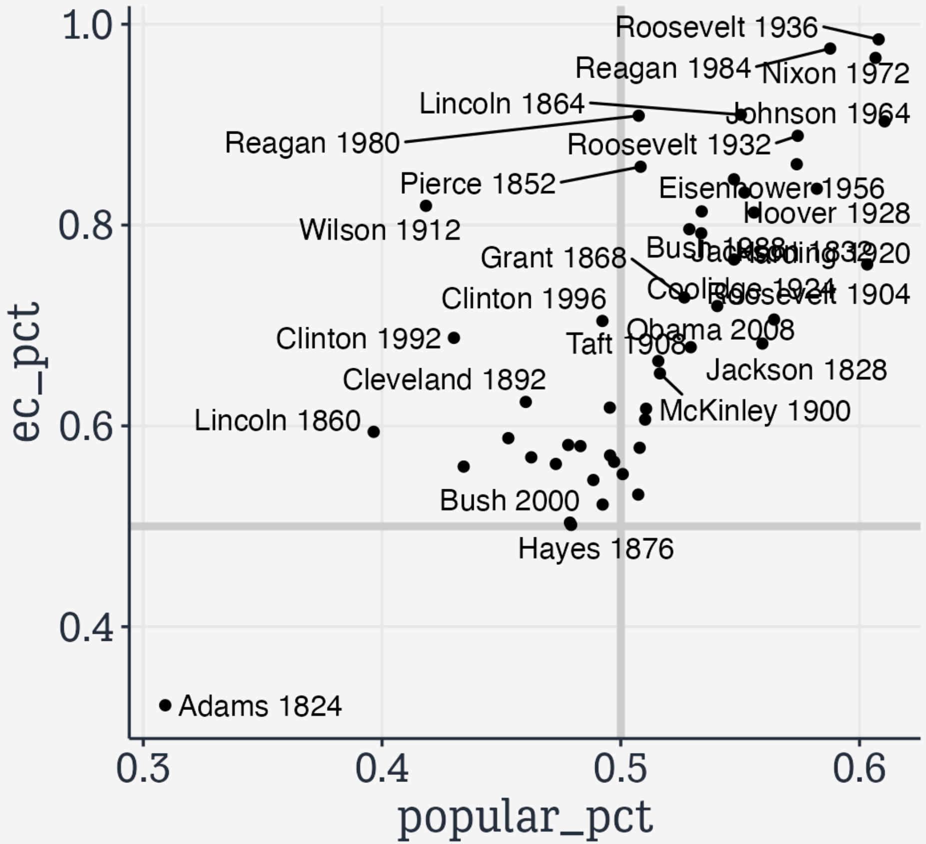
```r
p <- ggplot(data = elections_historic,
            mapping = aes(x = popular_pct,
                          y = ec_pct,
                          label = winner_label))

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()
```

This looks messy 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.

Add the labels

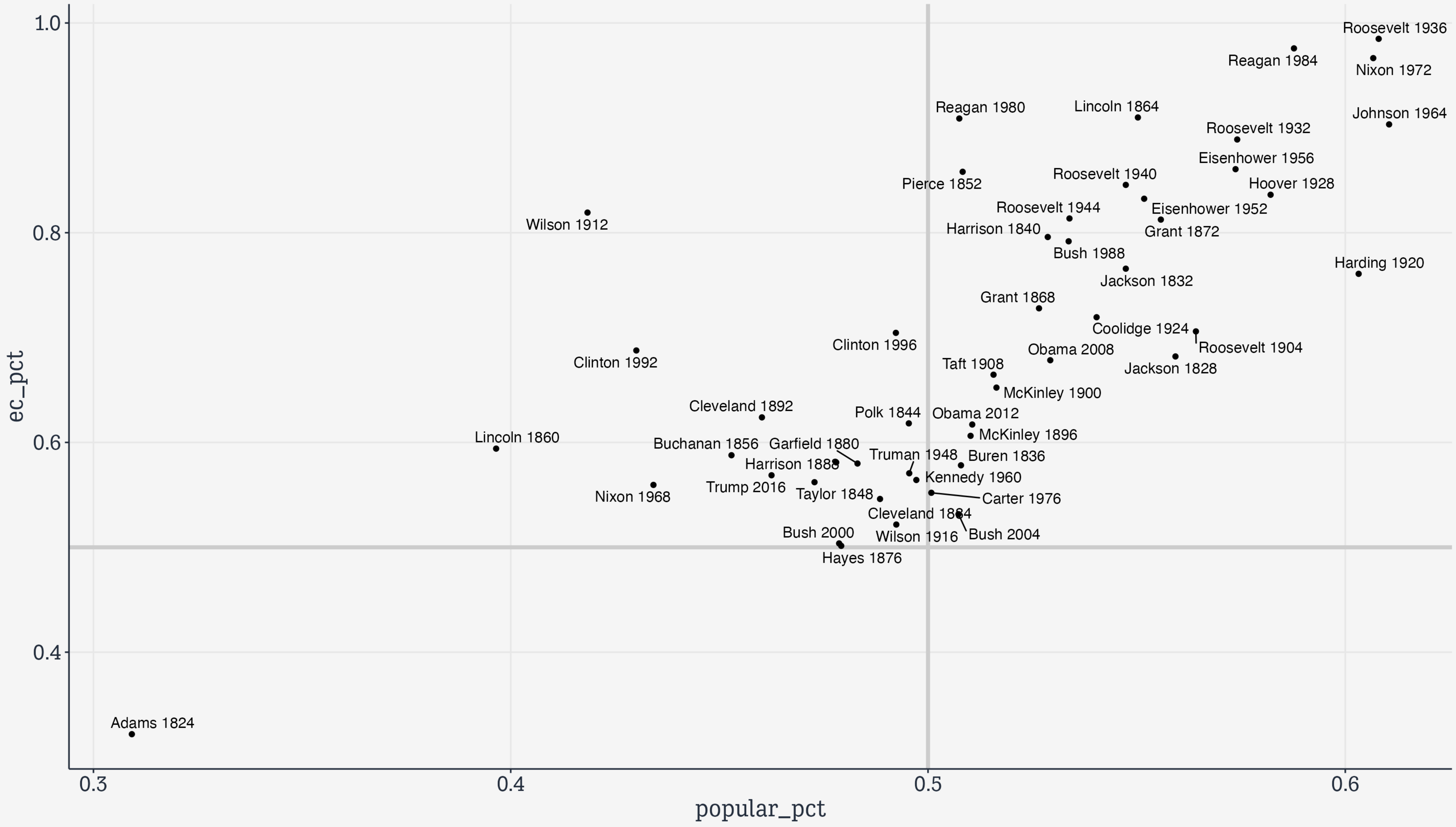
```r
p <- ggplot(data = elections_historic,
            mapping = aes(x = popular_pct,
                          y = ec_pct,
                          label = winner_label))

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()
```

This looks messy 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.



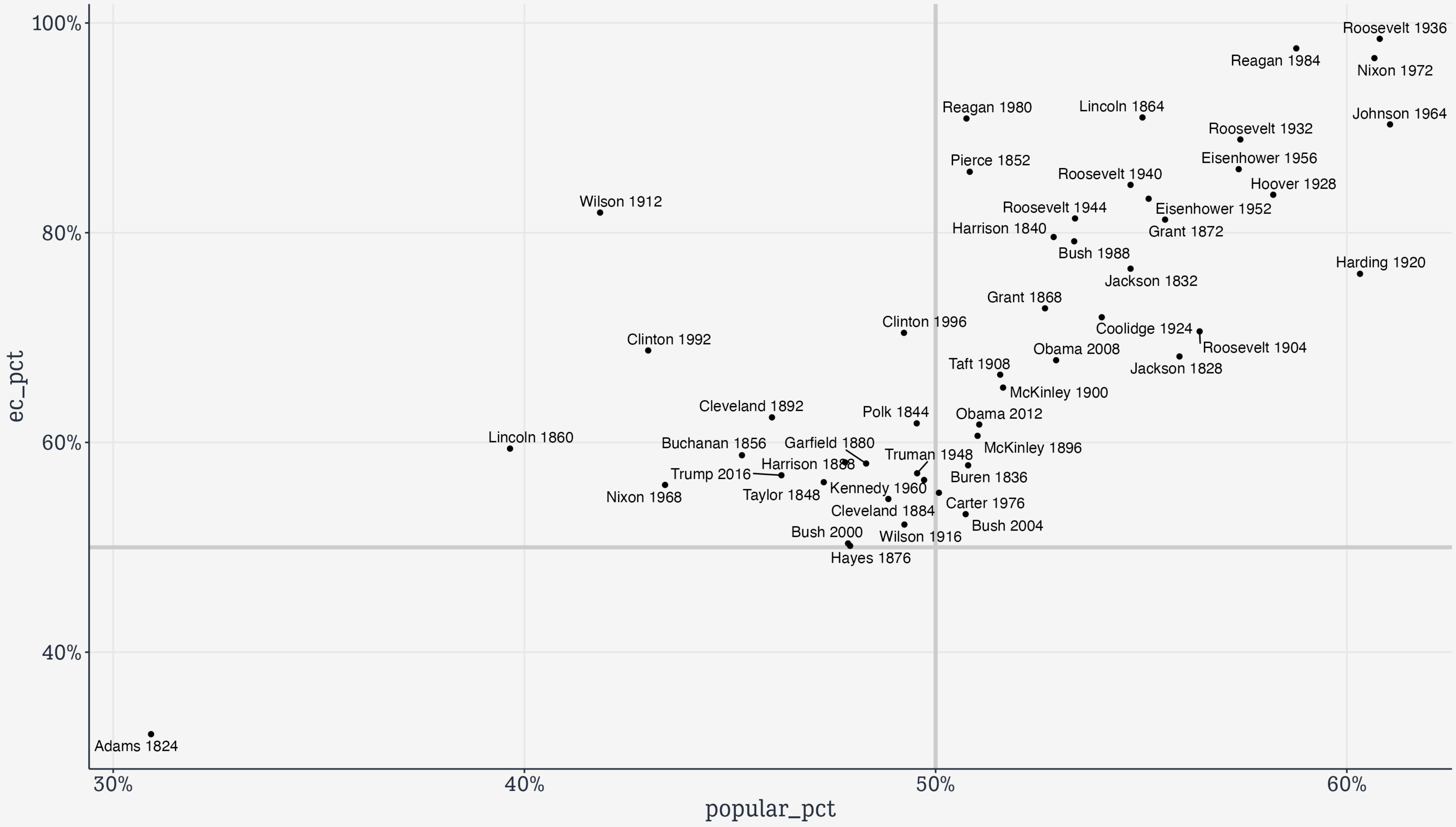
The labeling is with respect to the plot size

```
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()
```


ec_pct
popular_pct
1.0
0.8
0.6
0.4
0.3
0.4
0.5
0.6
Roosevelt 1936
Reagan 1984
Nixon 1972
Reagan 1980
Lincoln 1864
Johnson 1964
Roosevelt 1932
Eisenhower 1956
Pierce 1852
Roosevelt 1940
Hoover 1928
Wilson 1912
Roosevelt 1944
Eisenhower 1952
Harrison 1840
Grant 1872
Bush 1988
Harding 1920
Jackson 1832
Grant 1868
Coolidge 1924
Clinton 1996
Roosevelt 1904
Clinton 1992
Obama 2008
Taft 1908
Jackson 1828
McKinley 1900
Cleveland 1892
Polk 1844
Obama 2012
Lincoln 1860
McKinley 1896
Buchanan 1856
Garfield 1880
Truman 1948
Buren 1836
Harrison 1888
Kennedy 1960
Trump 2016
Nixon 1968
Taylor 1848
Carter 1976
Cleveland 1884
Bush 2000
Wilson 1916
Bush 2004
Hayes 1876
Adams 1824

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())
```

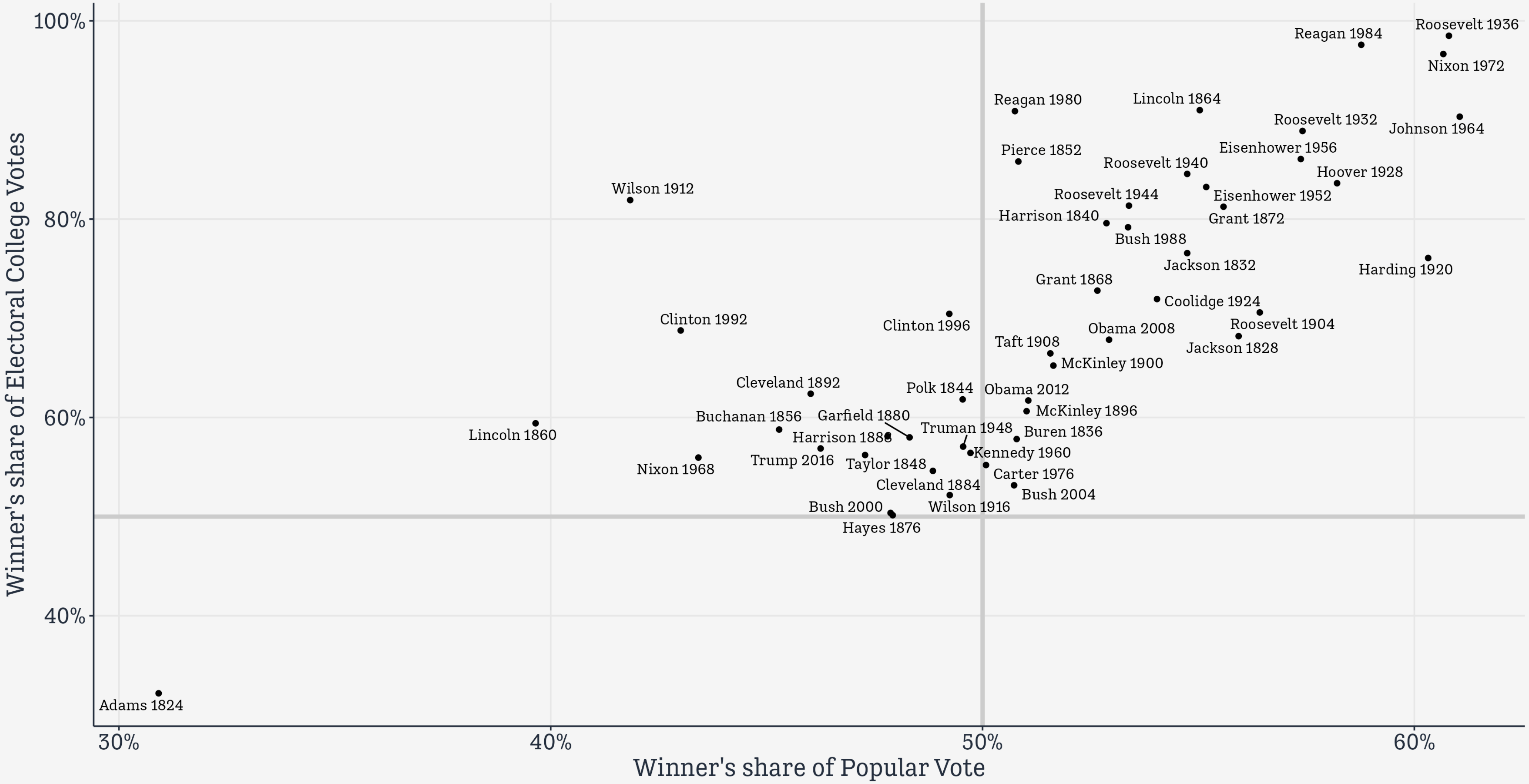

ec_pct
popular_pct
100%
80%
60%
40%
30%
40%
50%
60%
Roosevelt 1936
Reagan 1984
Nixon 1972
Reagan 1980
Lincoln 1864
Johnson 1964
Roosevelt 1932
Pierce 1852
Eisenhower 1956
Roosevelt 1940
Hoover 1928
Wilson 1912
Roosevelt 1944
Eisenhower 1952
Harrison 1840
Grant 1872
Bush 1988
Harding 1920
Jackson 1832
Grant 1868
Clinton 1996
Coolidge 1924
Clinton 1992
Roosevelt 1904
Obama 2008
Taft 1908
Jackson 1828
McKinley 1900
Cleveland 1892
Polk 1844
Obama 2012
Lincoln 1860
Buchanan 1856
Garfield 1880
McKinley 1896
Truman 1948
Harrison 1888
Trump 2016
Buren 1836
Kennedy 1960
Nixon 1968
Taylor 1848
Carter 1976
Cleveland 1884
Bush 2004
Bush 2000
Wilson 1916
Hayes 1876
Adams 1824

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.

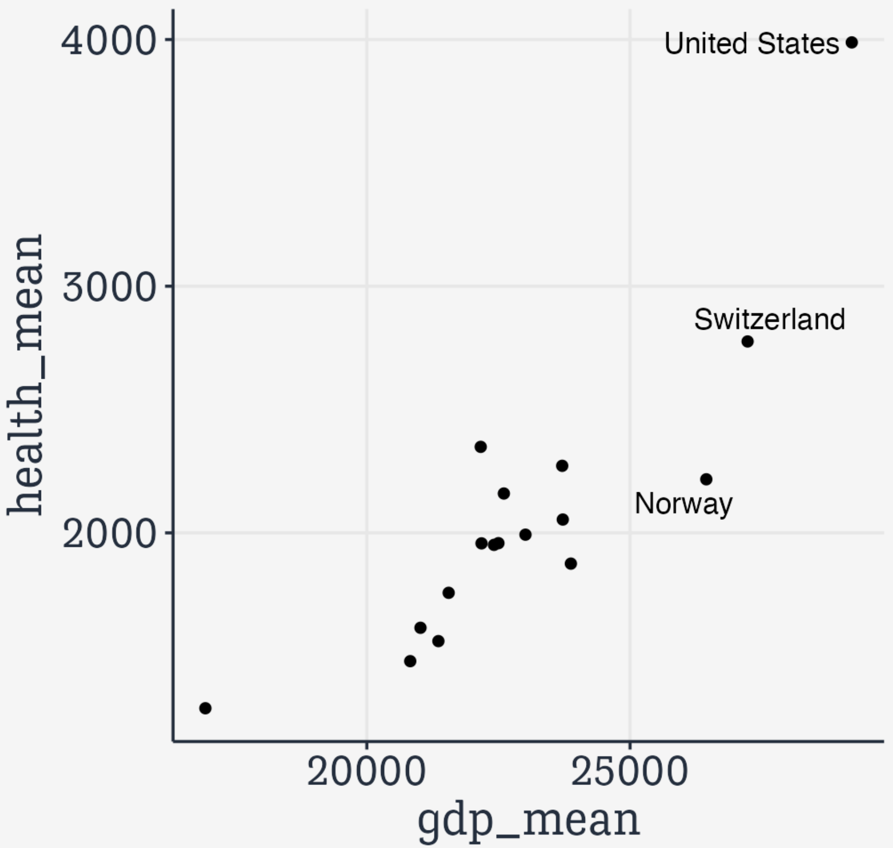
Labeling points of interest

Option 1: On the fly inside `ggplot`

```
by_country ▷
  ggplot(mapping = aes(x = gdp_mean,
                       y = health_mean)) +
  geom_point() +
  geom_text_repel(data = subset(by_country, gdp_mean > 25000),
                  mapping = aes(label = country))
```

Option 1: On the fly inside `ggplot`

```r
by_country |>
  ggplot(mapping = aes(x = gdp_mean,
                       y = health_mean)) +
  geom_point() +
  geom_text_repel(data = subset(by_country, gdp_mean > 25000),
                  mapping = aes(label = country))
```



Option 1: On the fly inside ggplot

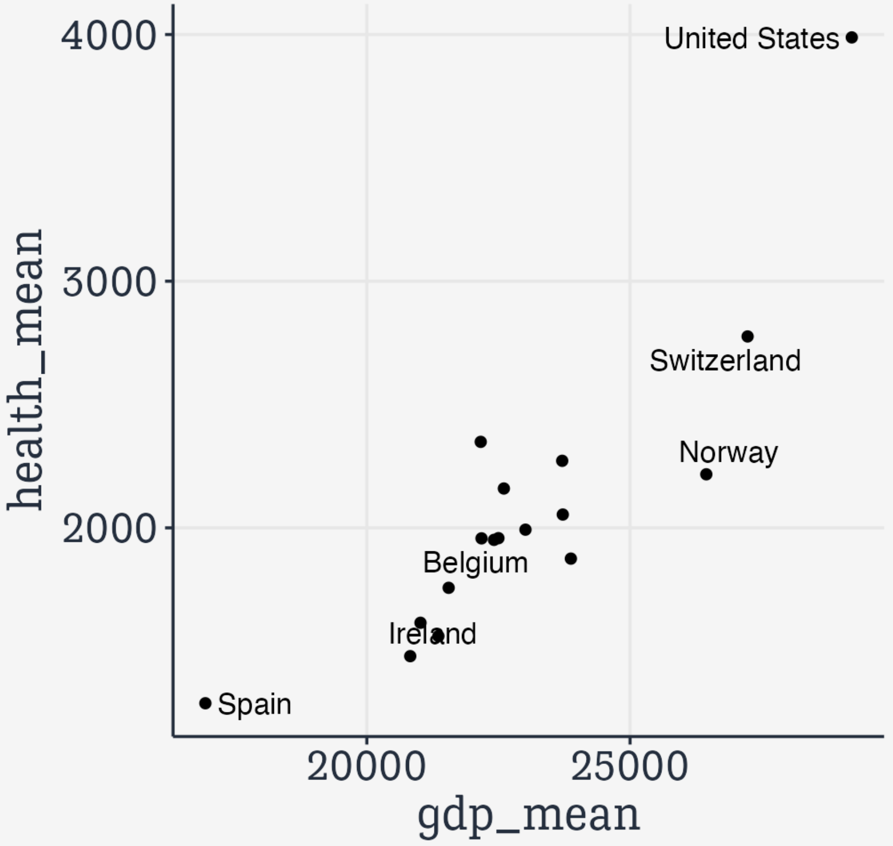
```
by_country |>
  ggplot(mapping = aes(x = gdp_mean,
                       y = health_mean)) +
  geom_point() +
  geom_text_repel(data = subset(by_country,
                                gdp_mean > 25000 |
                                  health_mean < 1500 |
                                  country %in% "Belgium"),
                  mapping = aes(label = country))
```

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

Option 1: On the fly inside `ggplot`

```r
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))
```

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



Option 2: Use dplyr to subset 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` to subset first

```r
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` to subset first

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

This makes things a little neater.

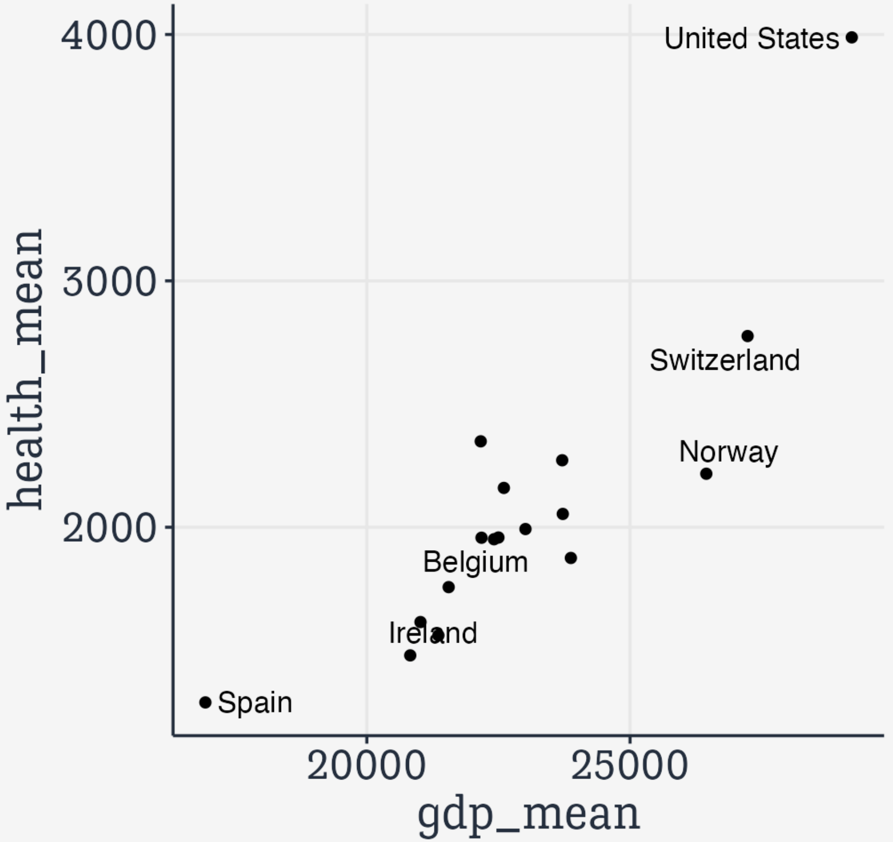
As you can see, a `geom` can be fully "autonomous". Each one can have its own `mapping` call *and* its own `data` source. This can be very useful when building up plots overlaying several sources or subsets of data.

Option 2: Use `dplyr` to subset first

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

This makes things a little neater.

As you can see, 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.



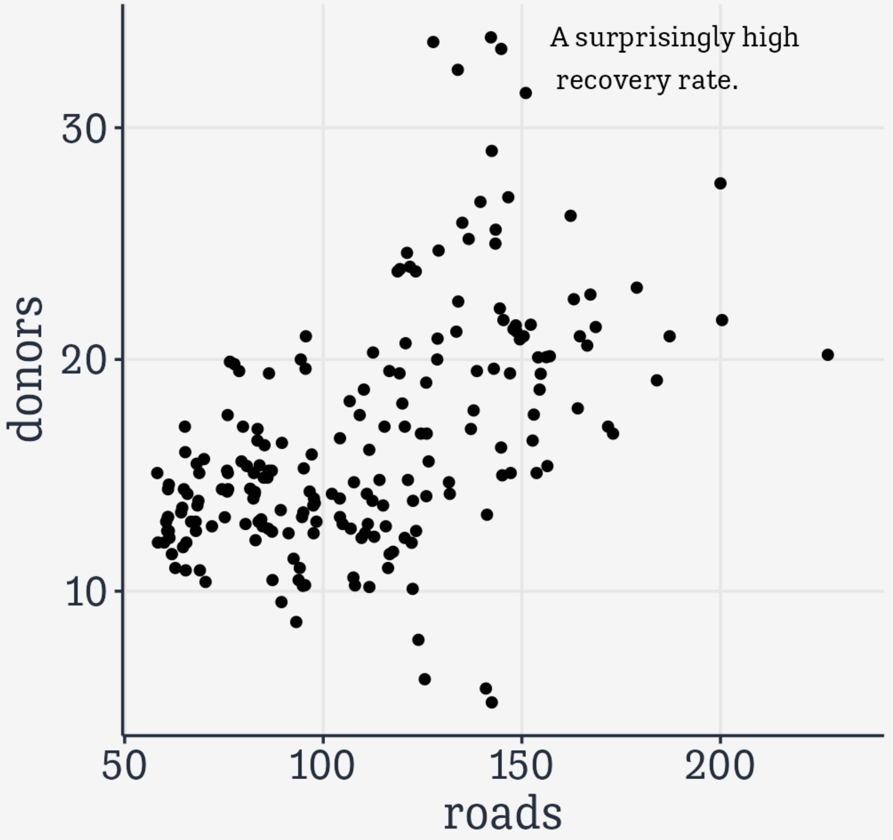
Write and draw inside the plot area

`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 = "text",
           family = "Tenso Slide",
           x = 157,
           y = 33,
           label = "A surprisingly high \n recovery rate.",
           hjust = 0)
```

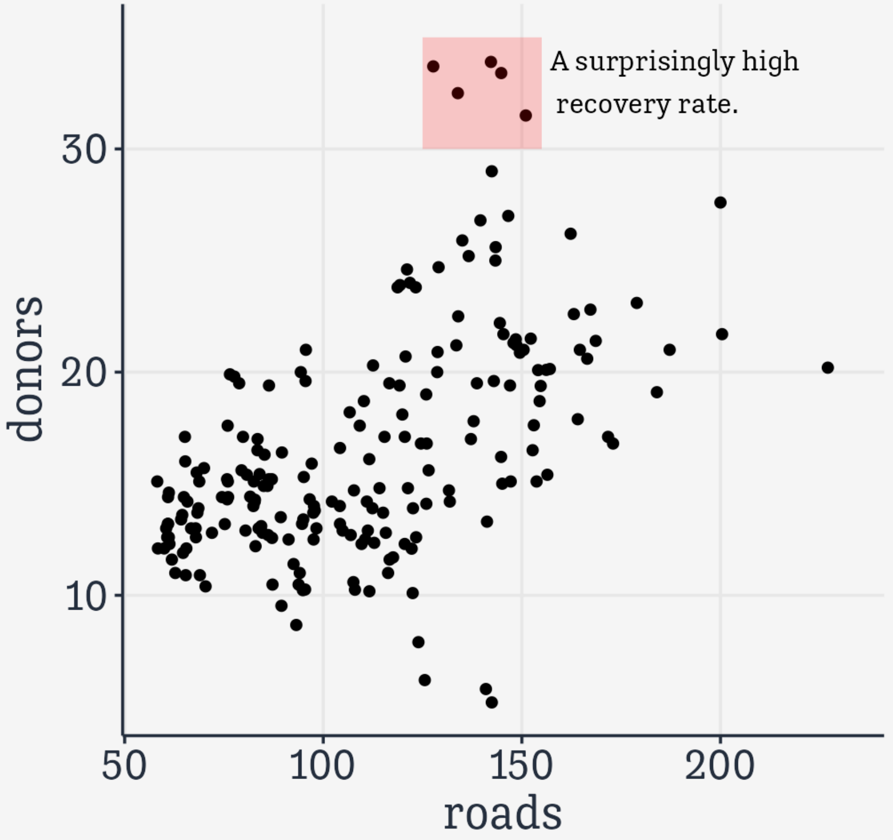


annotate() can imitate geoms

```
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)
```

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, 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>()`

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 for scale functions

```
scale_mapping_kind()

scale_x_continuous()
scale_y_continous()
scale_x_discrete()
scale_y_discrete()
scale_x_log10()
scale_x_sqrt()
```

Naming conventions for scale functions

```
scale_mapping_kind()
```

```
scale_color_discrete()
scale_color_gradient()
scale_color_gradient2()
scale_color_brewer()
scale_fill_discrete()
scale_fill_gradient()
scale_fill_gradient2()
scale_fill_brewer()
```

Scale functions in practice

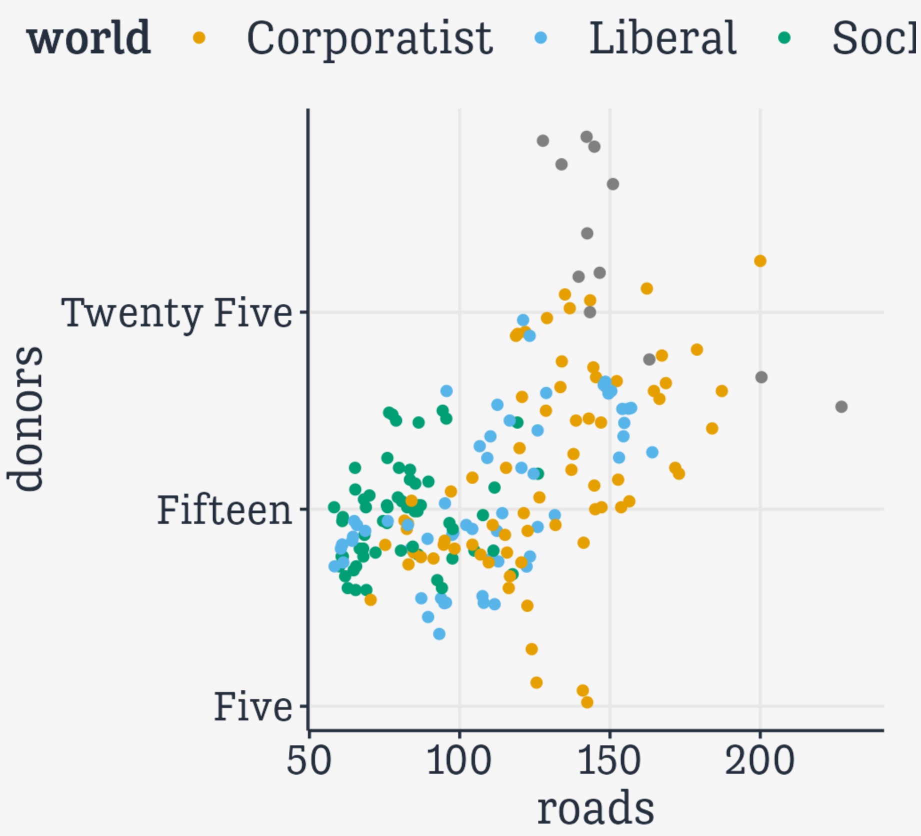
Scale functions take arguments appropriate to their mapping and kind

```
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"))
```

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"))
```

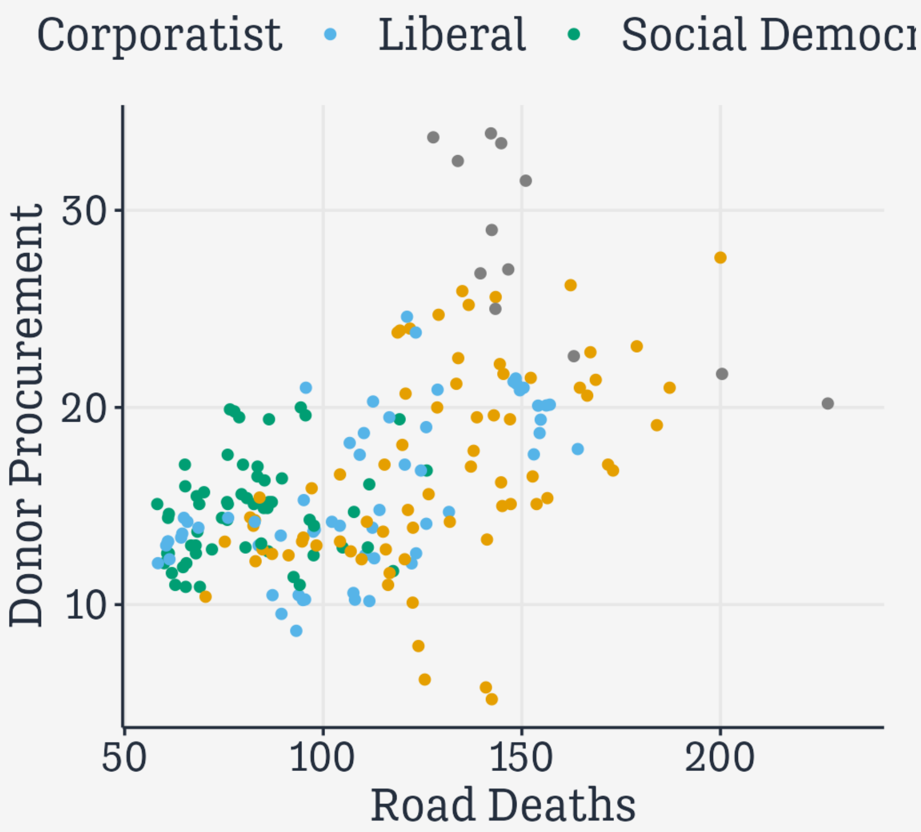


More usefully ...

```r
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")
```

More usefully …

```r
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

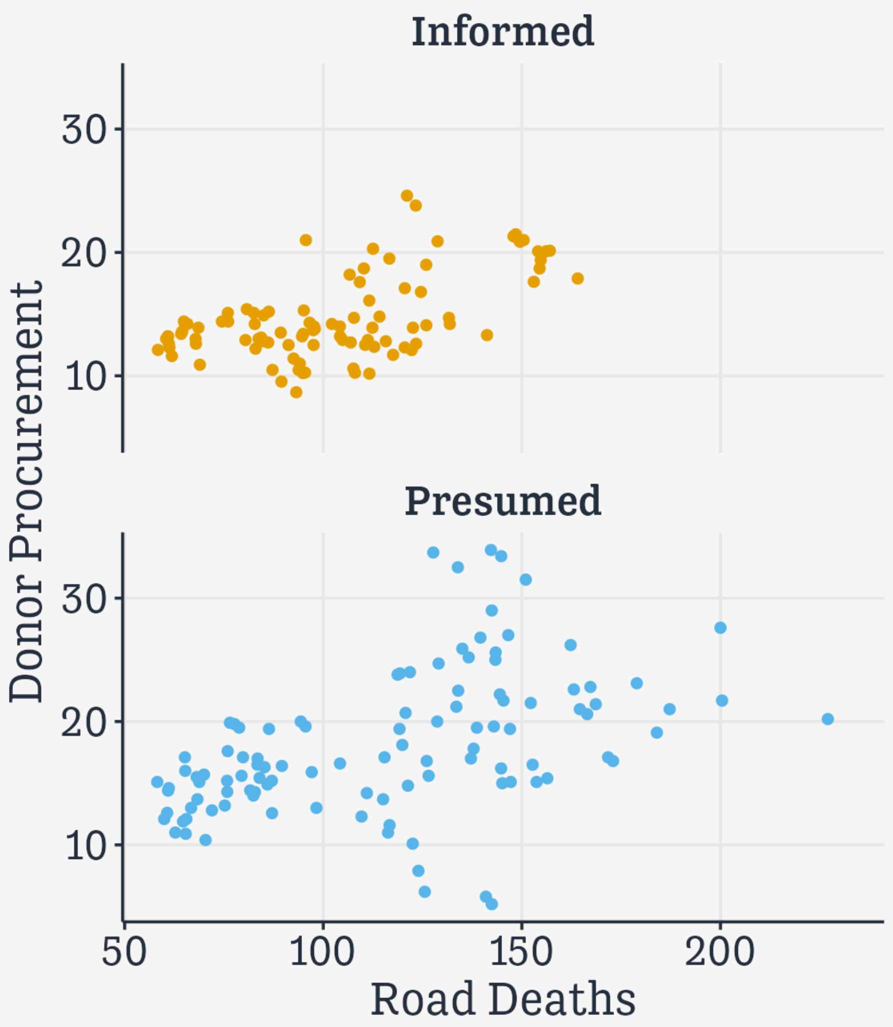
```
organdata ▷
  ggplot(mapping = aes(x = roads,
                       y = donors,
                       color = consent_law)) +
  geom_point() +
  facet_wrap(~ consent_law, ncol = 1) +
  guides(color = "none") +
  labs(x = "Road Deaths",
       y = "Donor Procurement")
```

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

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")
```

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



The `theme()` function

```r
## 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 are *not* directly representing your data. Often the first thing people want to adjust; but logically it's the *last* thing. Again, more detail soon!

The `theme()` function

```r
## 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 are *not* directly representing your data. Often the first thing people want to adjust; but logically it's the *last* thing. Again, more detail soon!