06 — Extend your Vocabulary

Kieran Healy

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Extend your `ggplot` vocabulary

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

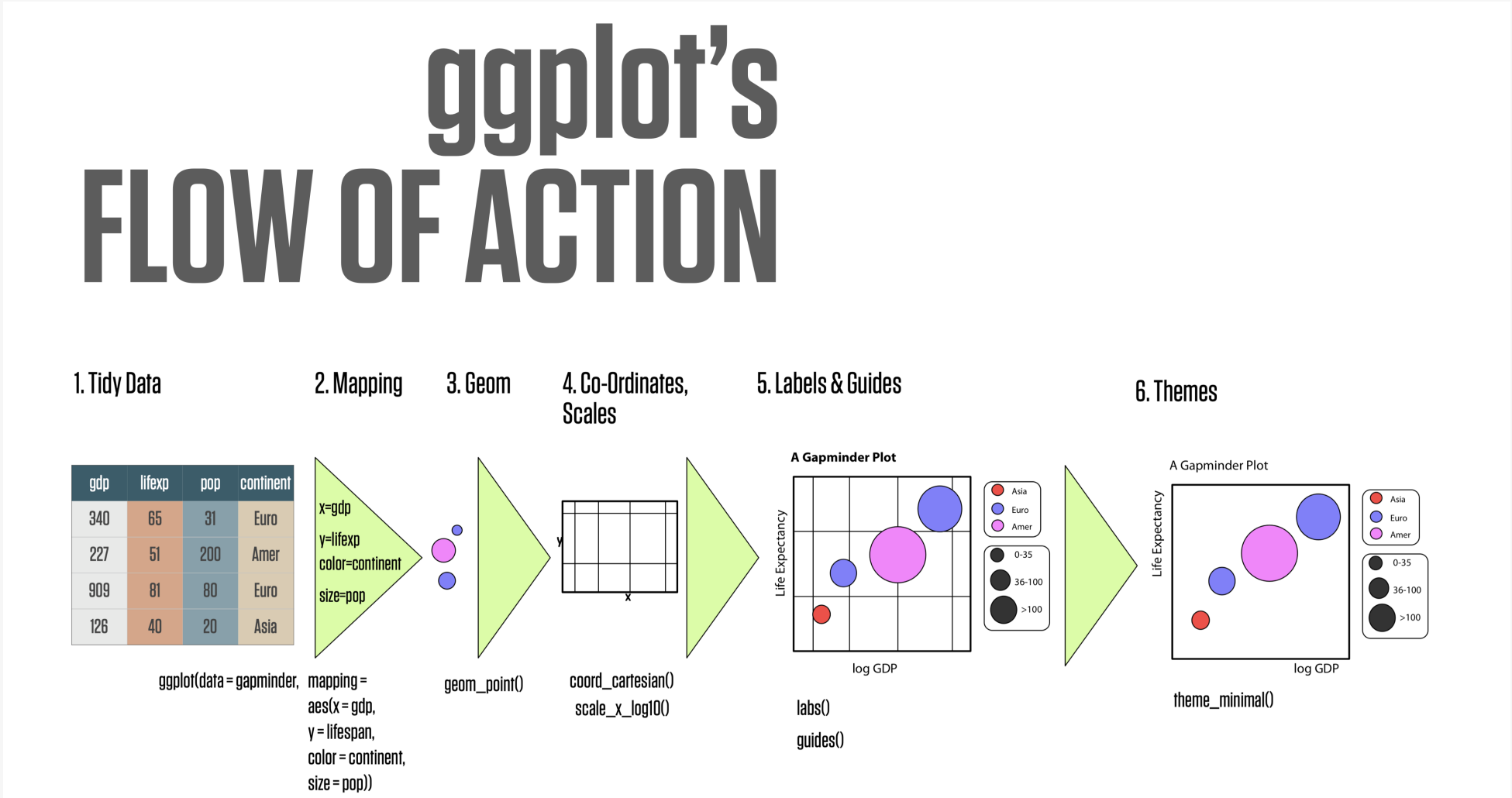
Load the package and ...

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

Other tidyverse components

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

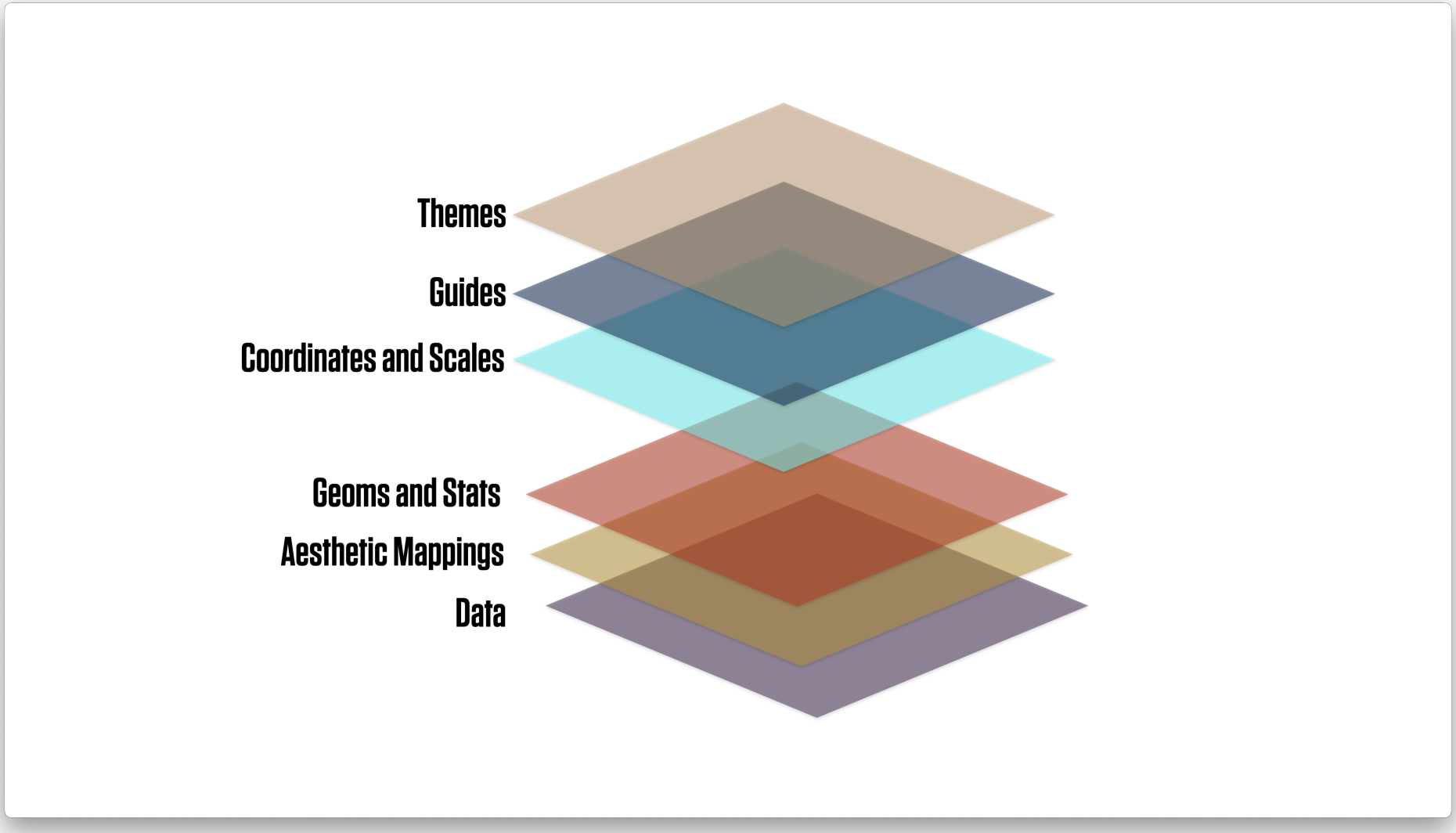
Not all of these are attached when we do `library(tidyverse)`



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.

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.

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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).

Example and extension: Organ Donation data

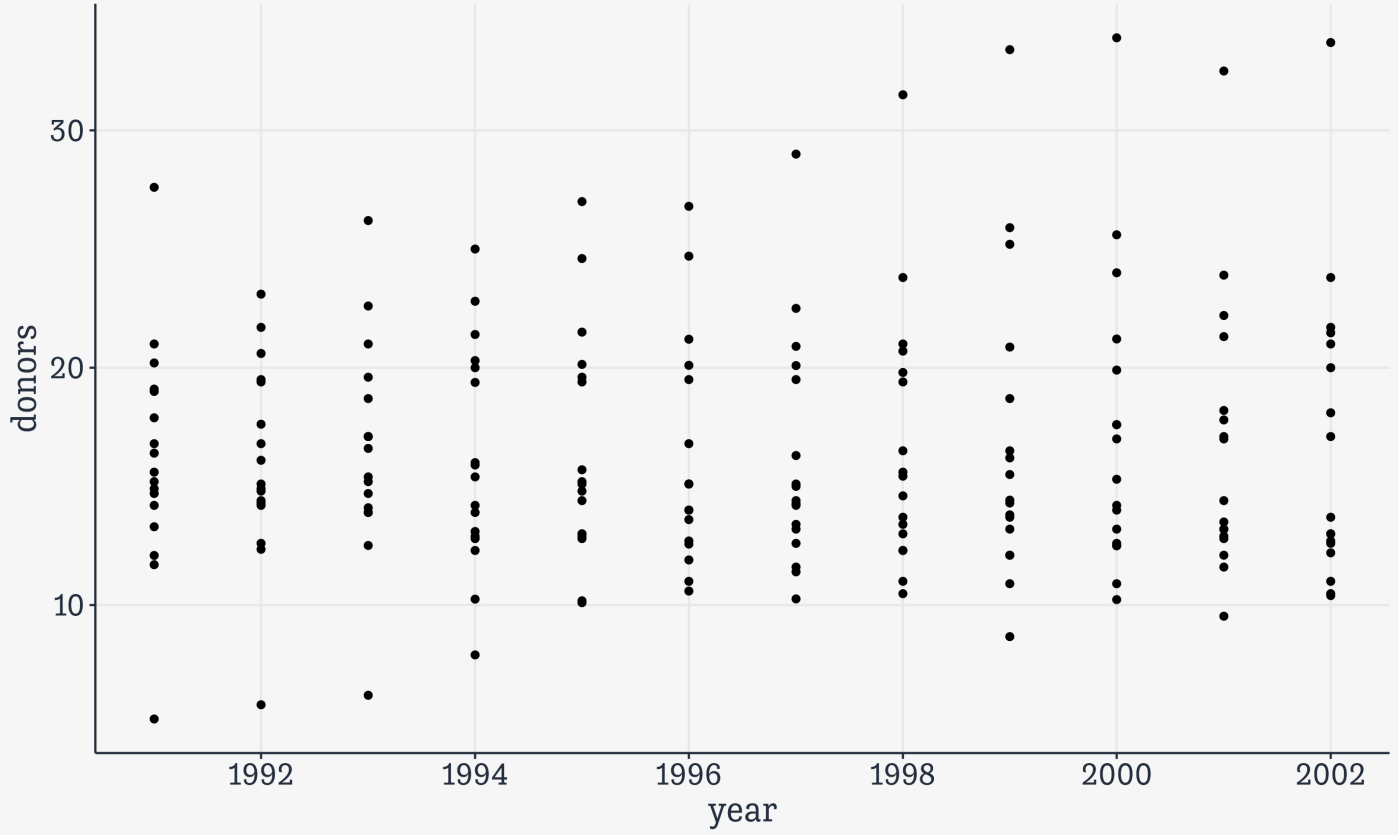
`organdata` is in the `socviz` package

```
organdata
```

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

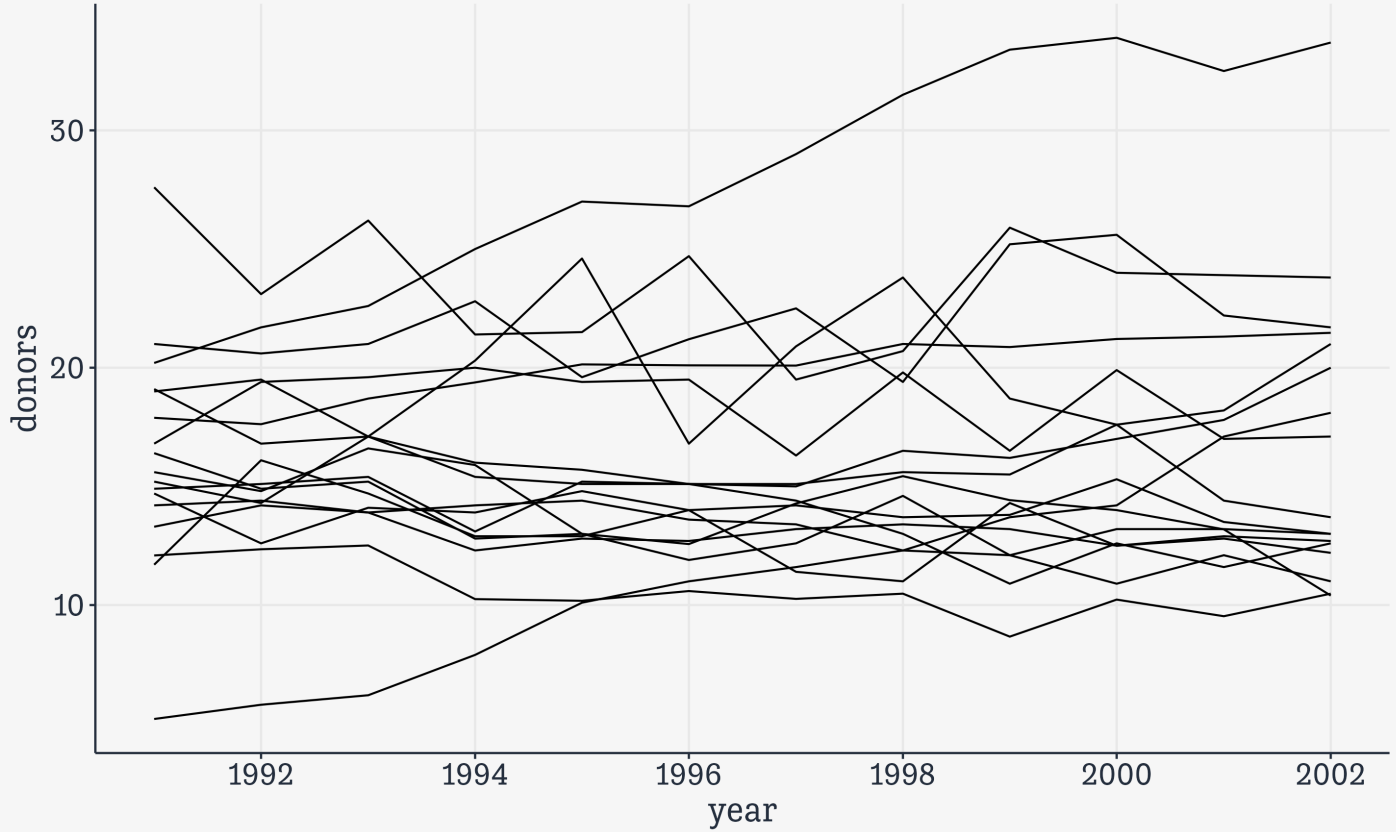


First look

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

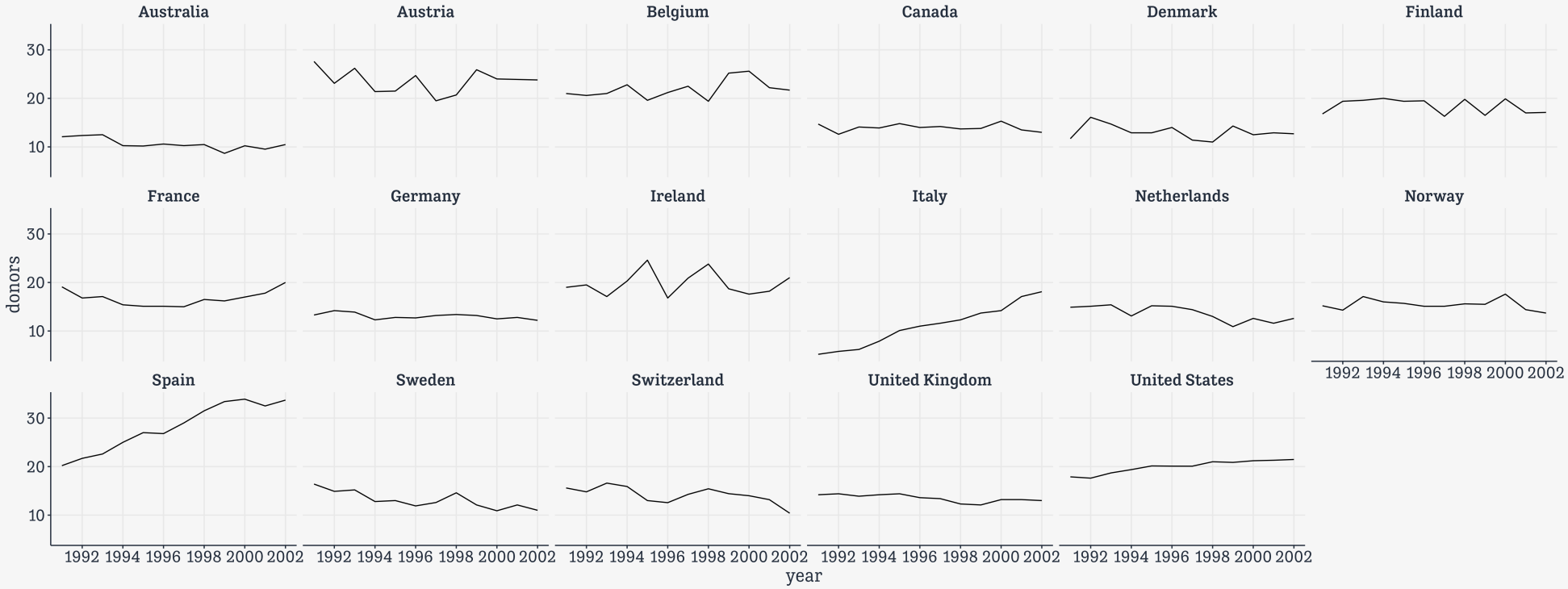
First look

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



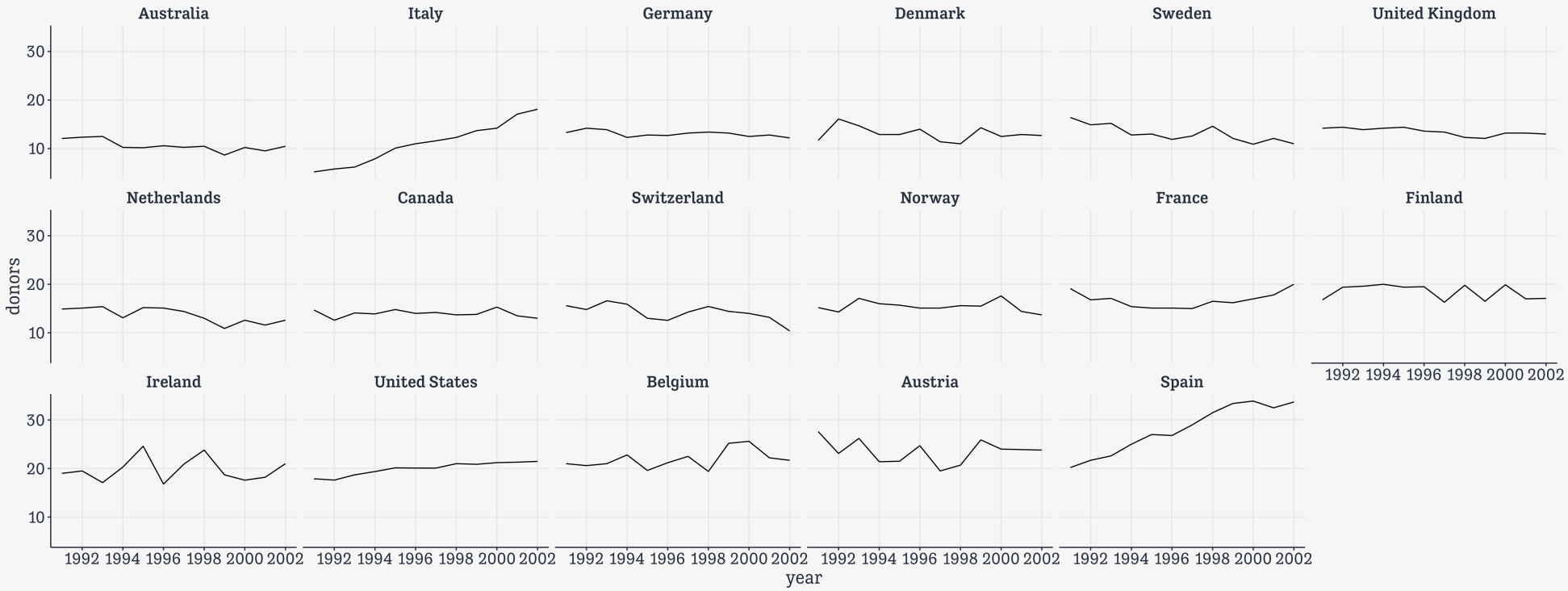
First look

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



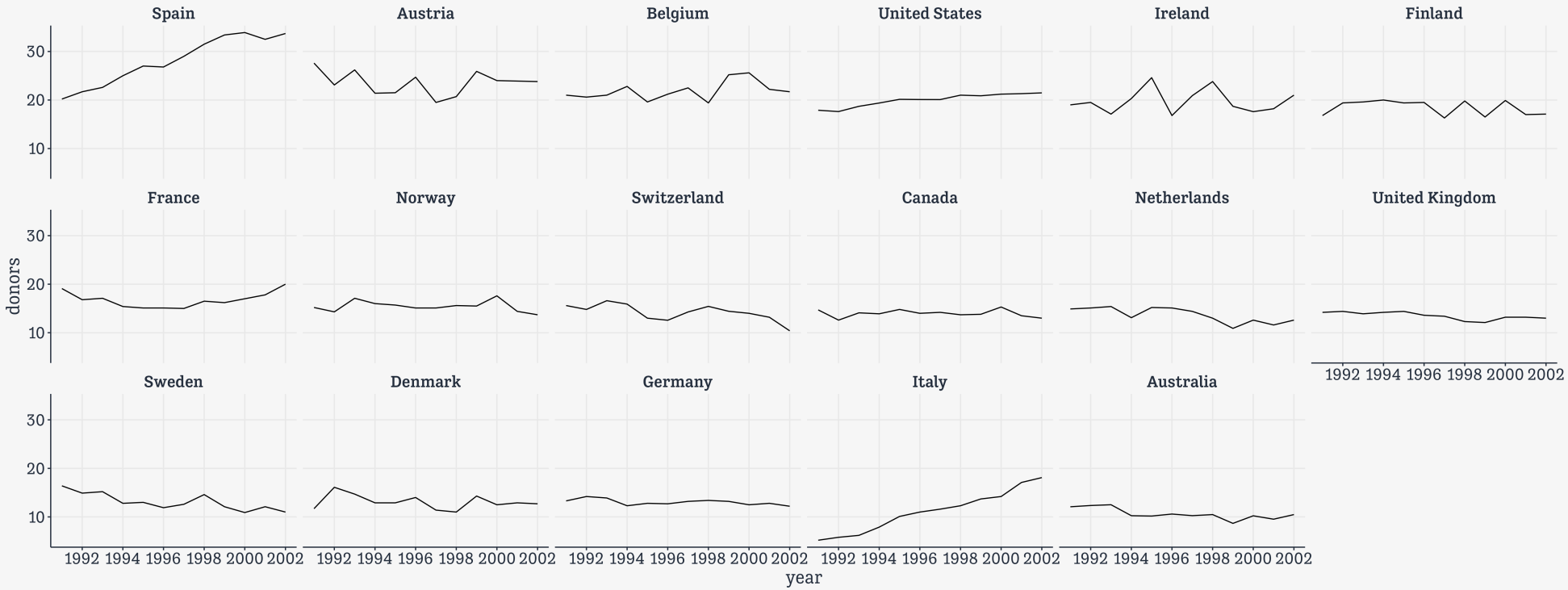
First look

```
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

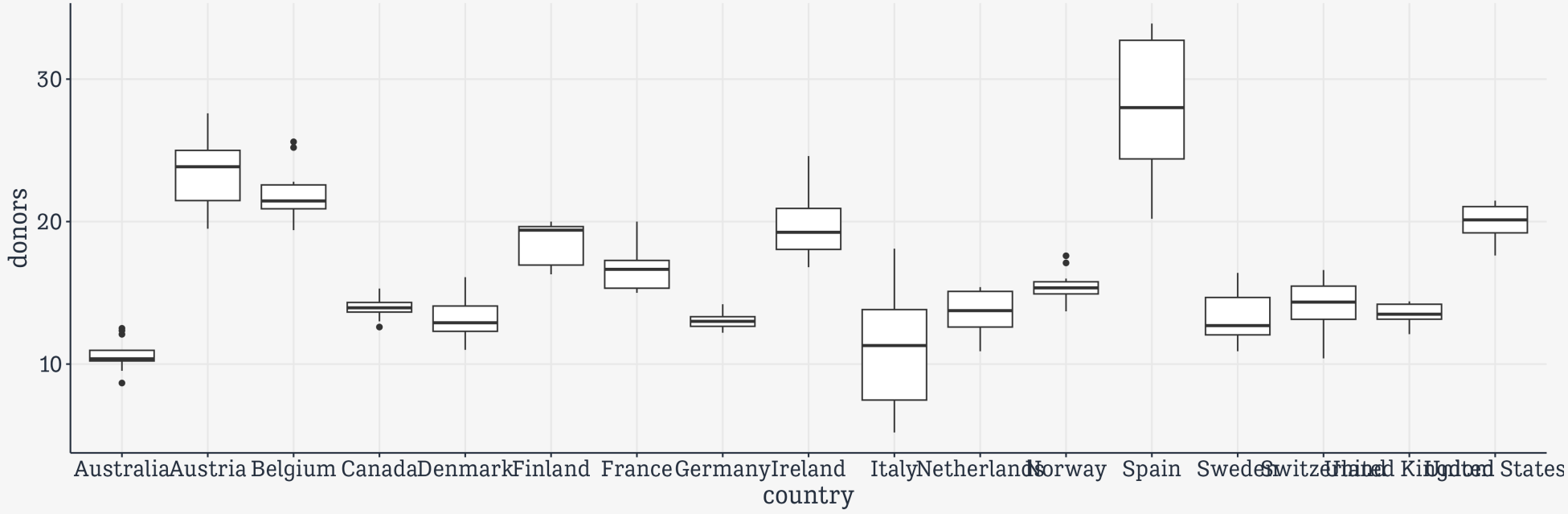
```
p ← ggplot(data = organdata,
           mapping = aes(x = year, y = donors))
p + geom_line() +
  facet_wrap(~ reorder(country, -donors, na.rm = TRUE), nrow = 3)
```



Showing continuous measures by category

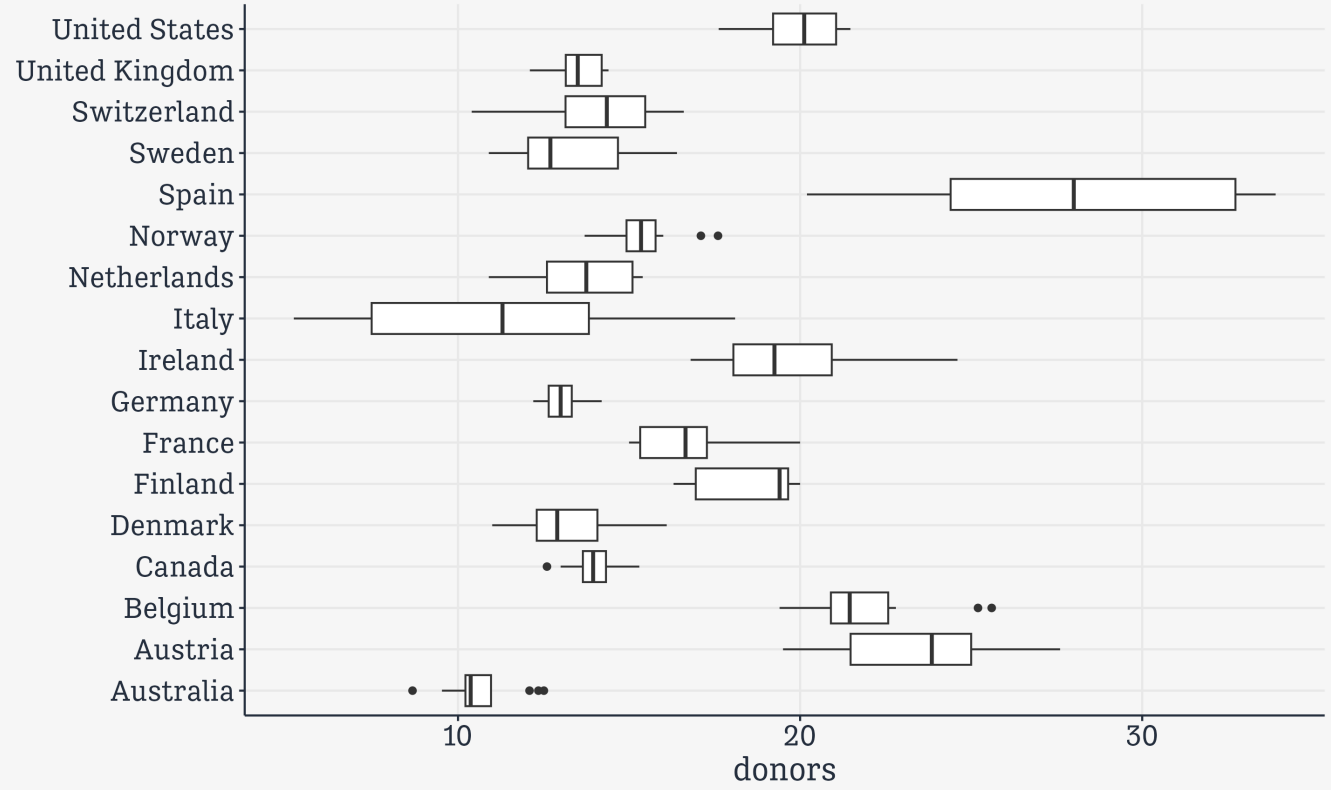
Boxplots: geom_boxplot()

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



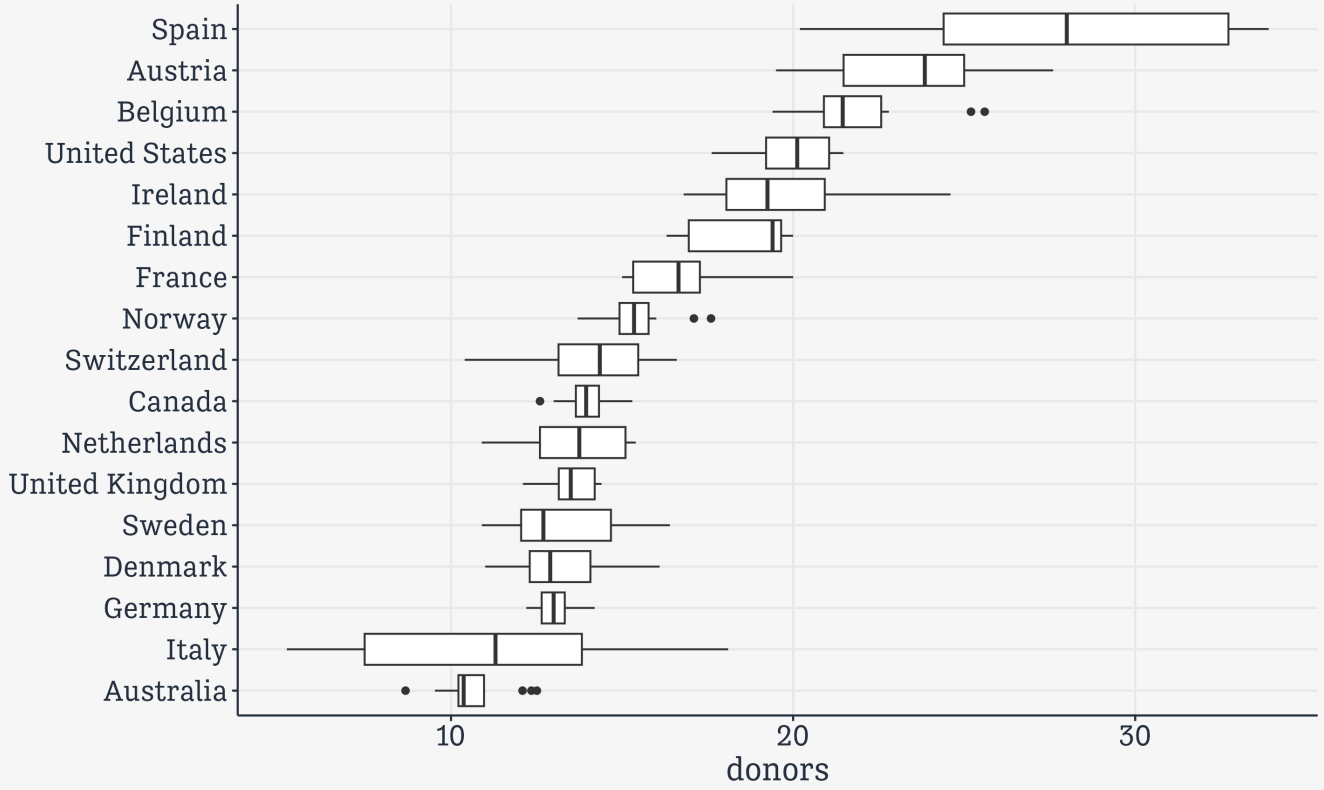
Put categories on the y-axis!

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



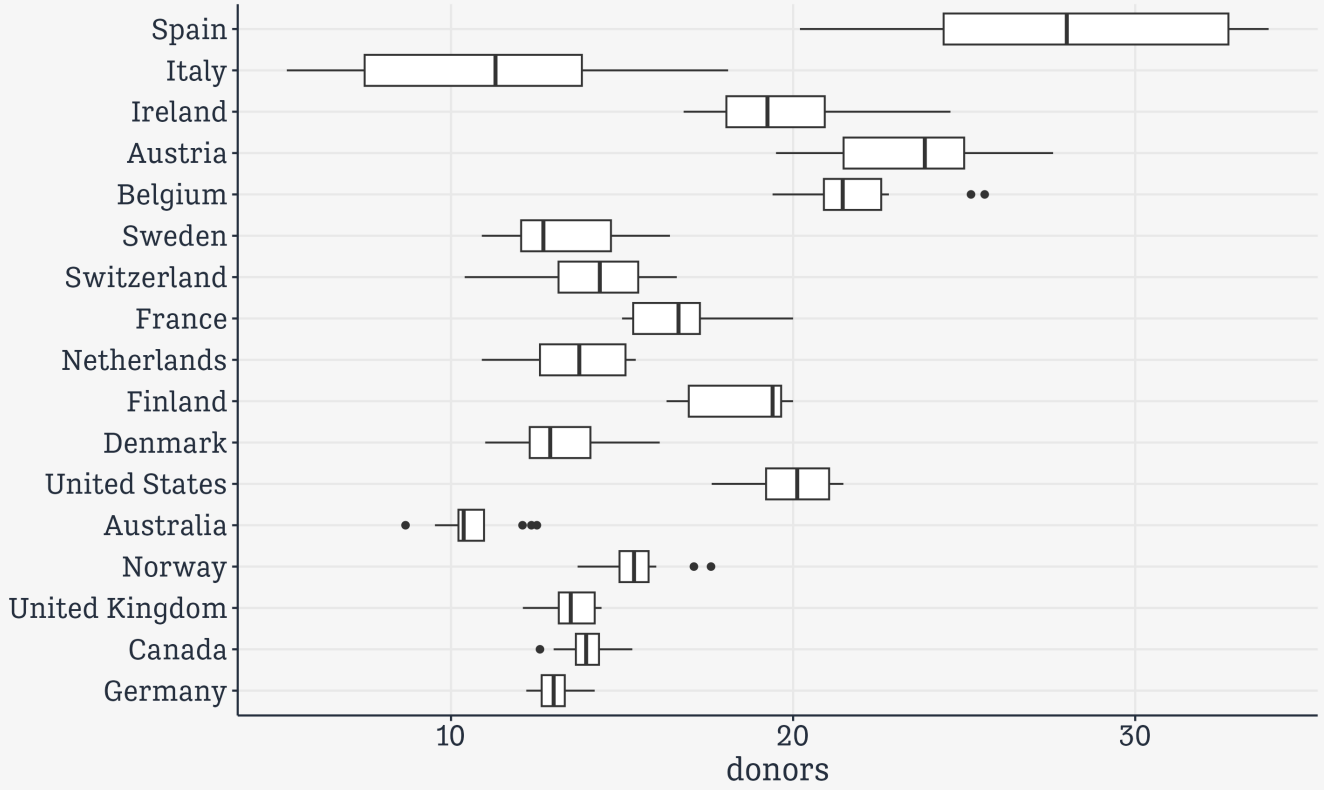
Reorder y by the mean of x

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



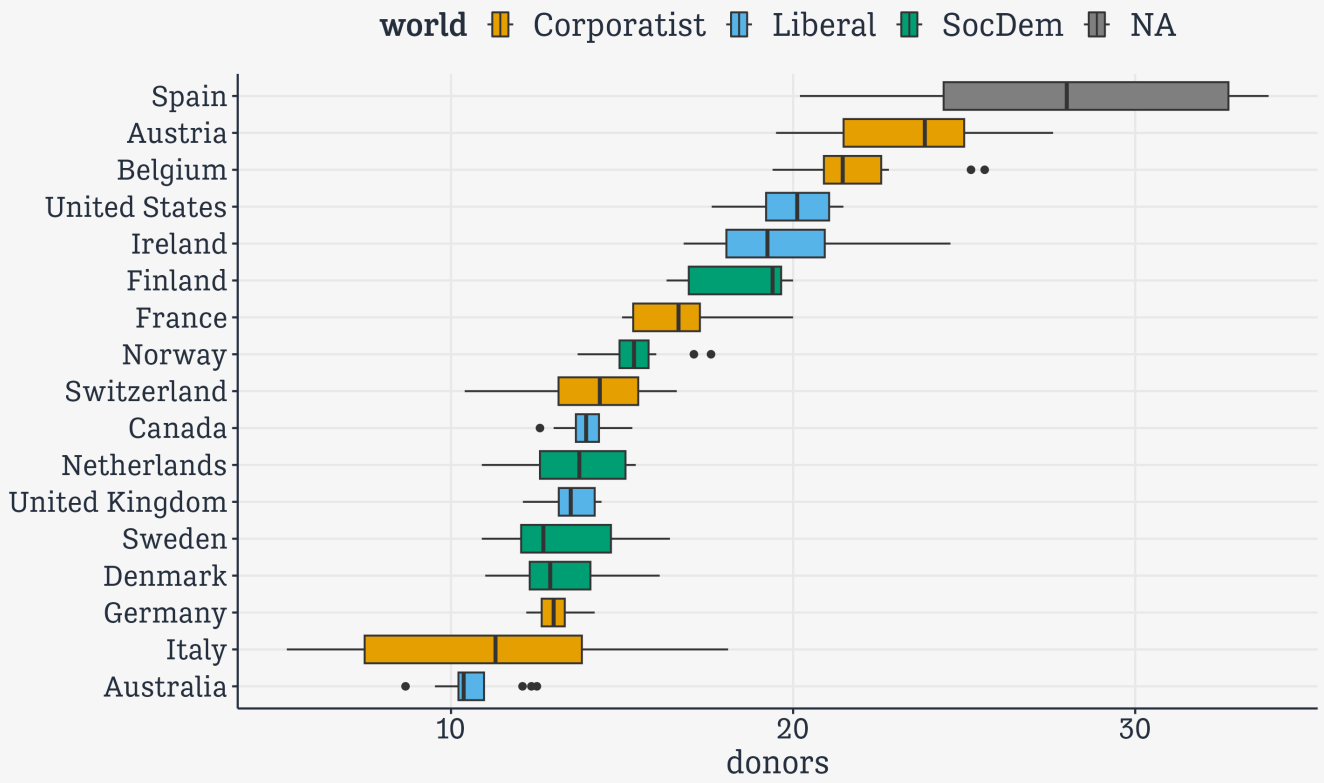
(Reorder y by any statistic you like)

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



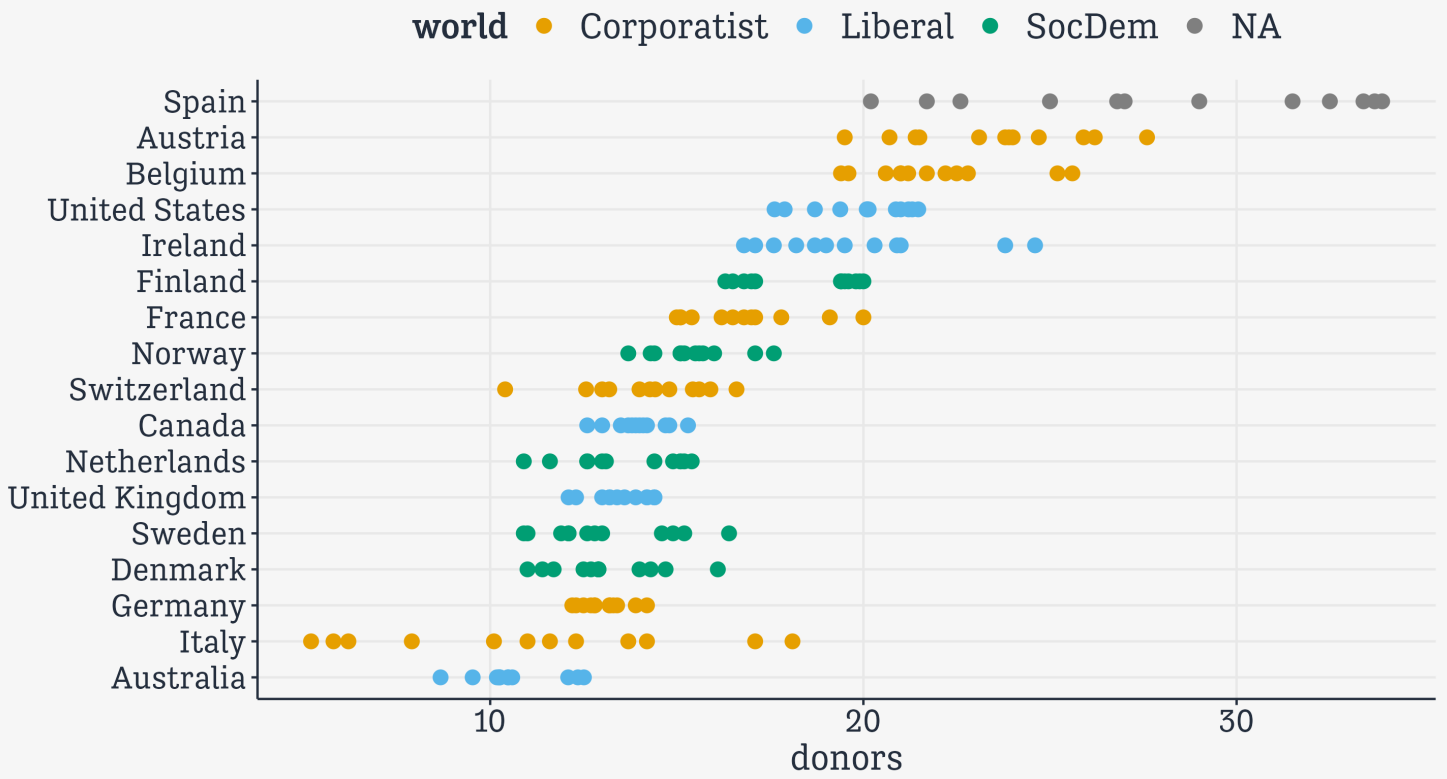
geom_boxplot() can color and fill

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



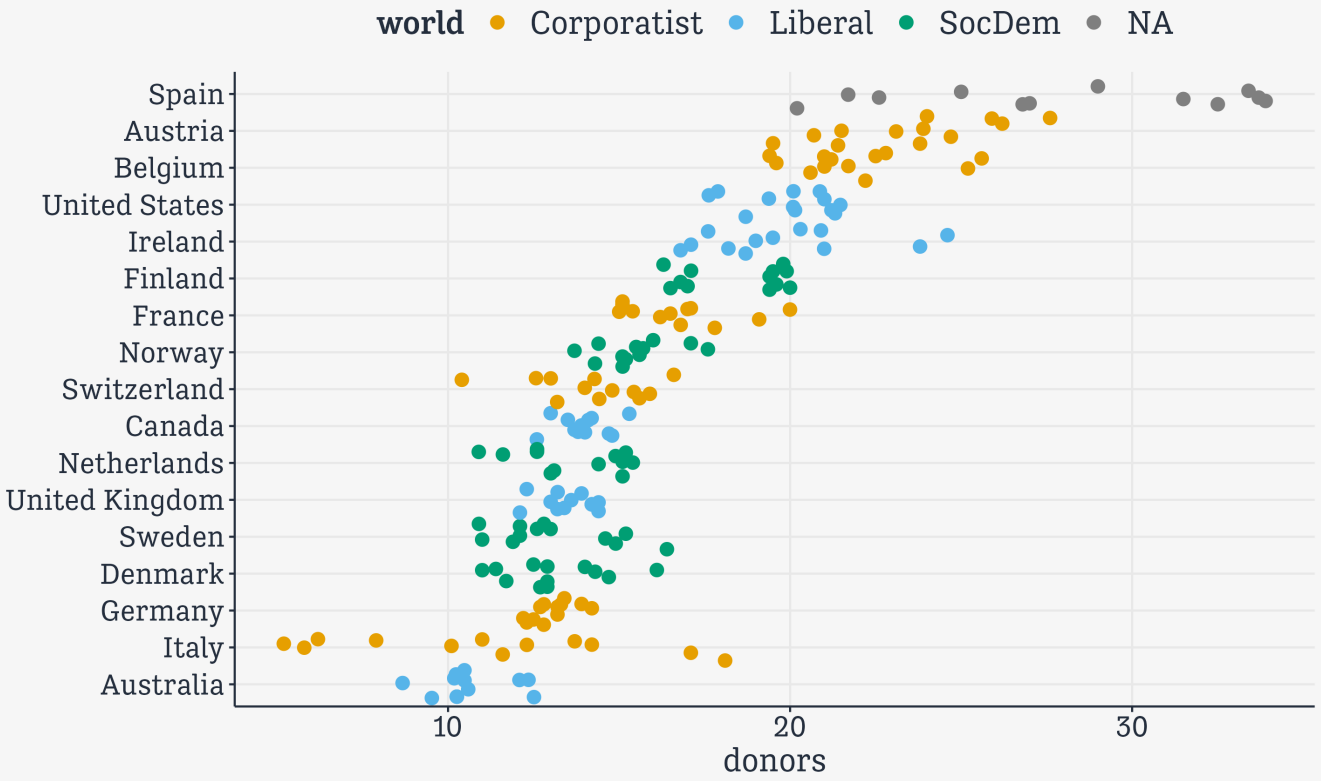
These strategies are quite general

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



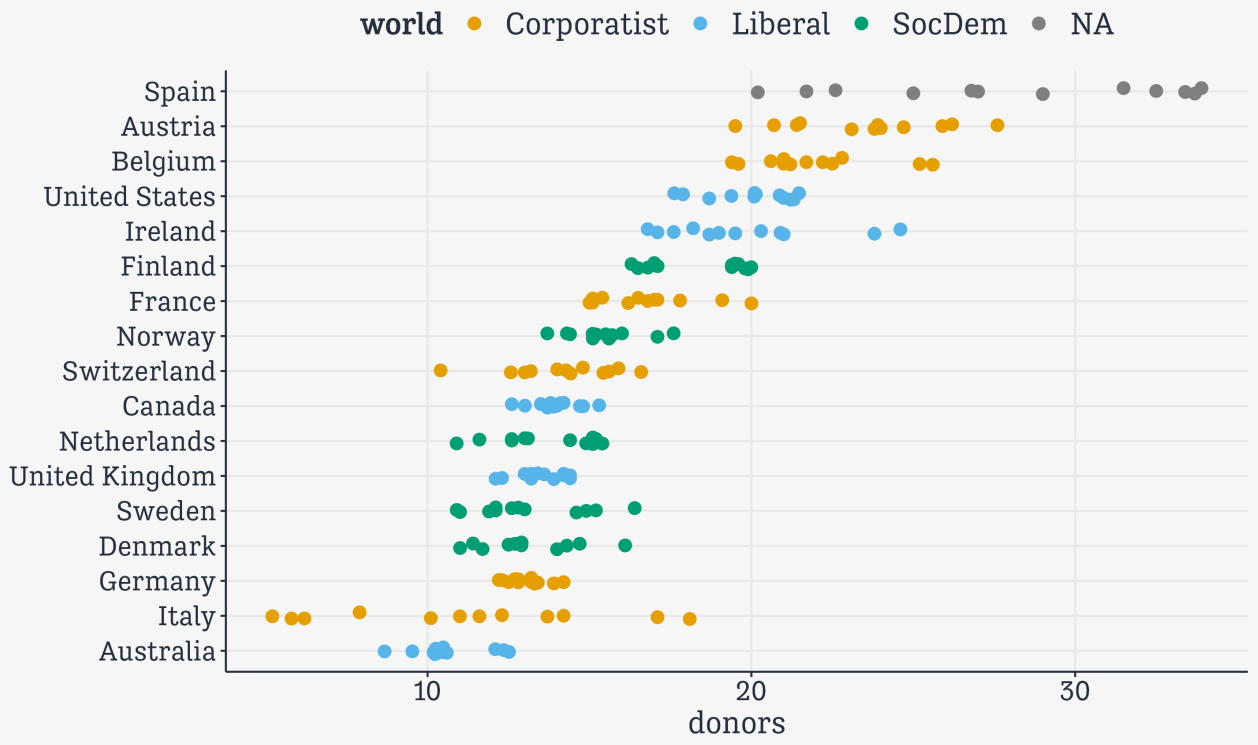
geom-jitter() for overplotting

```
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

```
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)
```



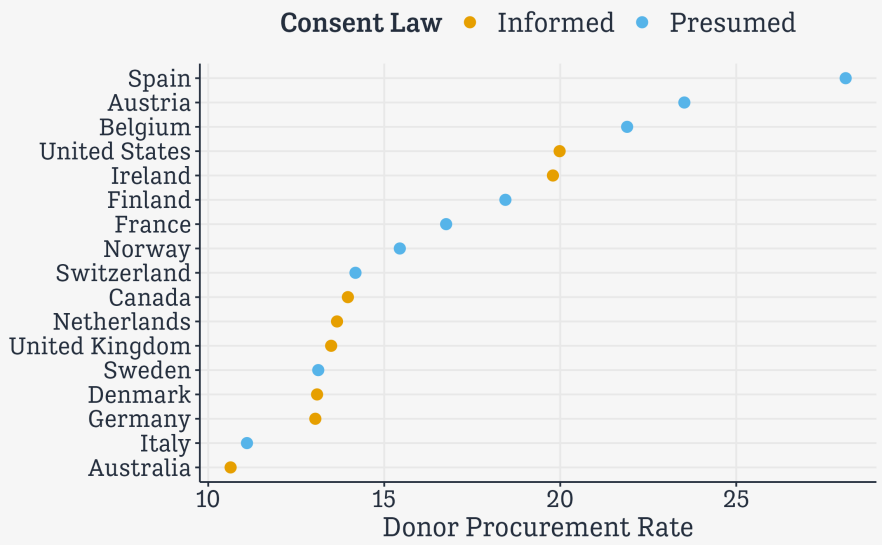
Using `across()` and `where()`

```
by_country ← organdata ▷
  group_by(consent_law, country) ▷
    summarize(across(where(is.numeric),
                     list(mean = \(x) mean(x, na.rm = TRUE),
                          sd = \(x) sd(x, na.rm = TRUE))),
              .groups = "drop")
head(by_country)
```

```
# A tibble: 6 × 28
  consent_law country     donors_mean donors_sd pop_mean pop_sd pop_dens_mean
  <chr>       <chr>             <dbl>     <dbl>    <dbl>  <dbl>         <dbl>
1 Informed    Australia          10.6     1.14    18318.  831.          0.237
2 Informed    Canada             14.0     0.751   29608. 1193.          0.297
3 Informed    Denmark            13.1     1.47     5257.   80.6        12.2
4 Informed    Germany            13.0     0.611   80255. 5158.         22.5
5 Informed    Ireland            19.8     2.48     3674.  132.          5.23
6 Informed    Netherlands        13.7     1.55    15548.  373.         37.4
# ℹ 21 more variables: pop_dens_sd <dbl>, gdp_mean <dbl>, gdp_sd <dbl>,
#   gdp_lag_mean <dbl>, gdp_lag_sd <dbl>, health_mean <dbl>, health_sd <dbl>,
#   health_lag_mean <dbl>, health_lag_sd <dbl>, pubhealth_mean <dbl>,
#   pubhealth_sd <dbl>, roads_mean <dbl>, roads_sd <dbl>, cerebvas_mean <dbl>,
#   cerebvas_sd <dbl>, assault_mean <dbl>, assault_sd <dbl>,
#   external_mean <dbl>, external_sd <dbl>, txp_pop_mean <dbl>,
#   txp_pop_sd <dbl>
```

Plot our summary data

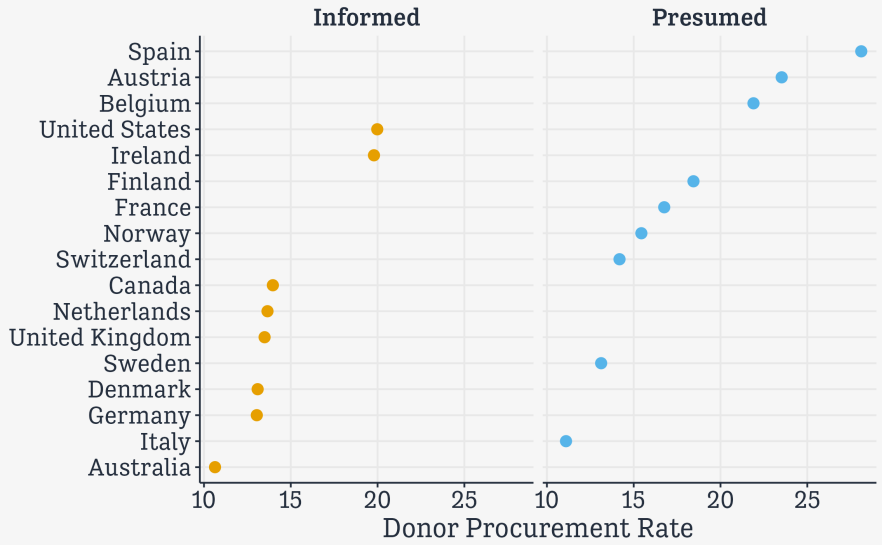
```
by_country ▷
  ggplot(mapping =
           aes(x = donors_mean,
               y = reorder(country, donors_mean
               color = consent_law)) +
  geom_point(size=3) +
  labs(x = "Donor Procurement Rate",
       y = NULL,
       color = "Consent Law")
```



What about faceting it instead?

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

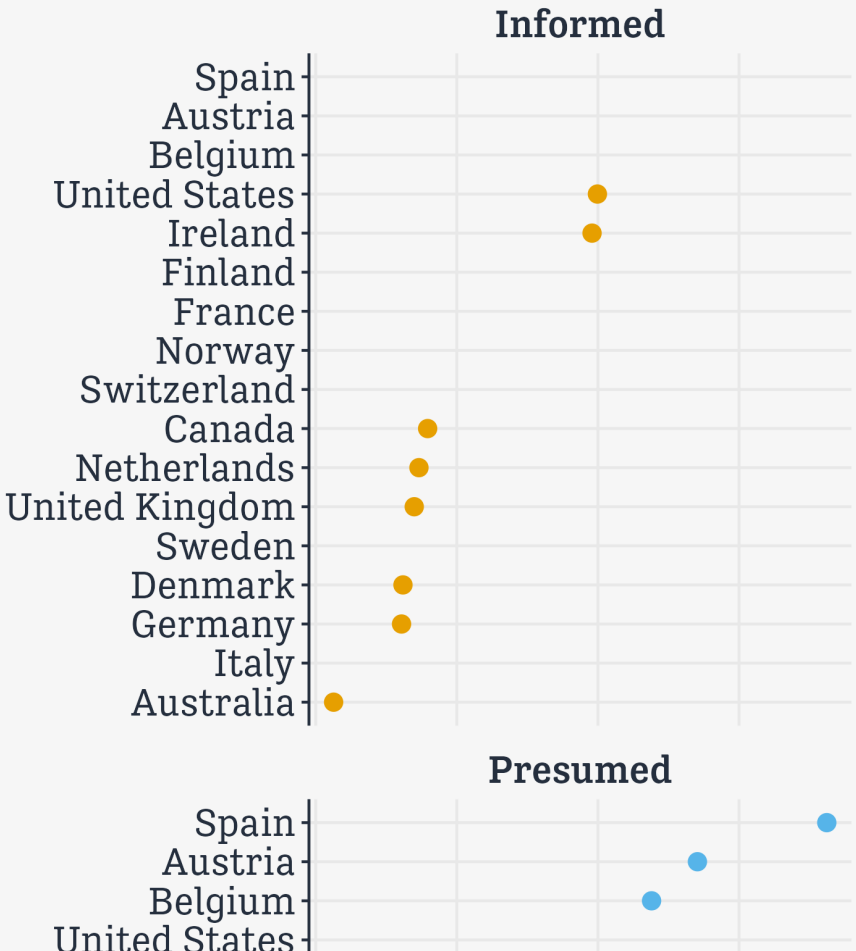
```
by_country ▷
  ggplot(mapping =
           aes(x = donors_mean,
               y = reorder(country, donors_mean
               color = consent_law)) +
  geom_point(size=3) +
  guides(color = "none") +
  facet_wrap(~ consent_law) +
  labs(x = "Donor Procurement Rate",
       y = NULL,
       color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



What about faceting it instead?

Restricting to one column doesn't fix it.

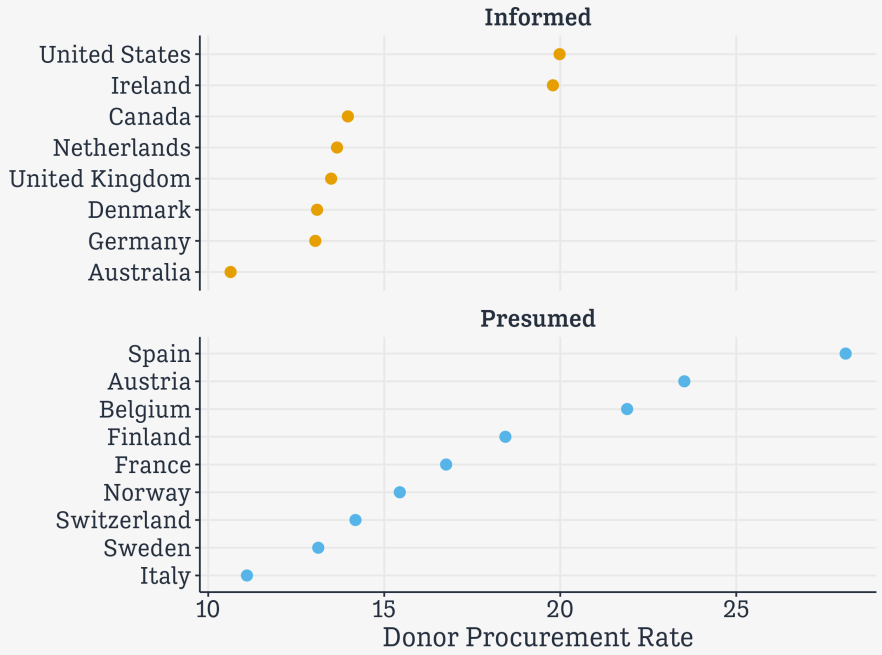
```
by_country ▷
  ggplot(mapping =
           aes(x = donors_mean,
               y = reorder(country, donors_mean
               color = consent_law)) +
  geom_point(size=3) +
  guides(color = "none") +
  facet_wrap(~ consent_law, ncol = 1) +
  labs(x = "Donor Procurement Rate",
       y = NULL,
 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



Allow the y-scale to vary

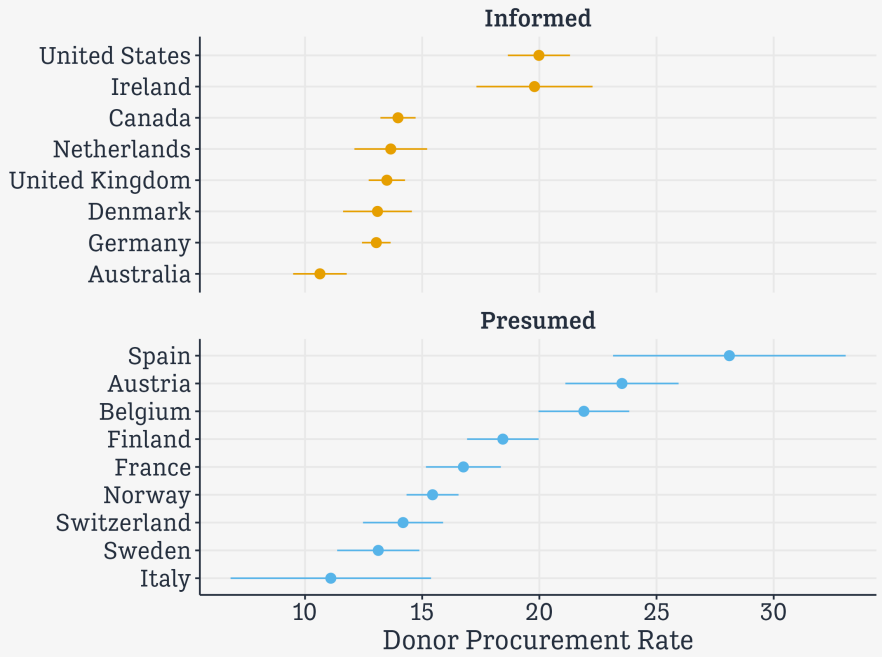
Normally the point of a facet is to preserve comparability between panels by not allowing the scales to vary. But for categorical measures it can be useful to allow this.

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



Again, these methods are general

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



Your turn

Load this data

```
movies ← read_csv("https://kjhealy.co/movies.csv")

movies
```

```
# A tibble: 4,343 × 9
   title     year runtime maturity_rating genre box_office rating_imdb metascore
   <chr>    <dbl>   <dbl> <chr>           <chr>      <dbl>       <dbl>     <dbl>
 1 102 Dal…  2000     100 G               Fami…       67           4.8        35
 2 28 Days   2000     103 PG-13           Come…       37.2         6.1        46
 3 3 Strik…  2000      82 R               Come…        9.8         4.6        11
 4 A Shot …  2000     114 R               Sport        0.1         6.2        66
 5 About A…  2000      97 R               Come…        0.2         5.8        64
 6 All the…  2000     116 PG-13           West…       15.5         5.8        55
 7 Almost …  2000     122 R               Come…       32.5         7.9        90
 8 America…  2000     102 R               Horr…       15.1         7.6        64
 9 An Ever…  2000     103 R               Come…        0.1         6.2        56
10 Autumn …  2000     103 PG-13           Roma…       37.8         5.6        24
# ℹ 4,333 more rows
# ℹ 1 more variable: awards <dbl>
```

Data courtesty of Aaron Gullickson

Overview

English-language movies produced in the US; at least 80 minutes long and no longer than 3.5 hours; received at least 500 votes on the Internet Movie Database; MPAA rating between G and R; made at least $100,000 domestically

Overview

year: The calendar year of the film's release.

runtime: The length of the movie in minutes.

maturity_rating: The movie's MPA maturity rating (G, PG, PG-13, or R).

genre: The genre of the film (one only).

box_office: Gross domestic (US only) box office returns for the movie in millions of US dollars. Not adjusted for inflation.

rating_imdb: This is average score (between 1 and 10) for a movie provided by IMDB users.

metascore: The movie's metascore rating from metacritic. The metascore is a curated weighted average of reviewer scores from a variety of sources.

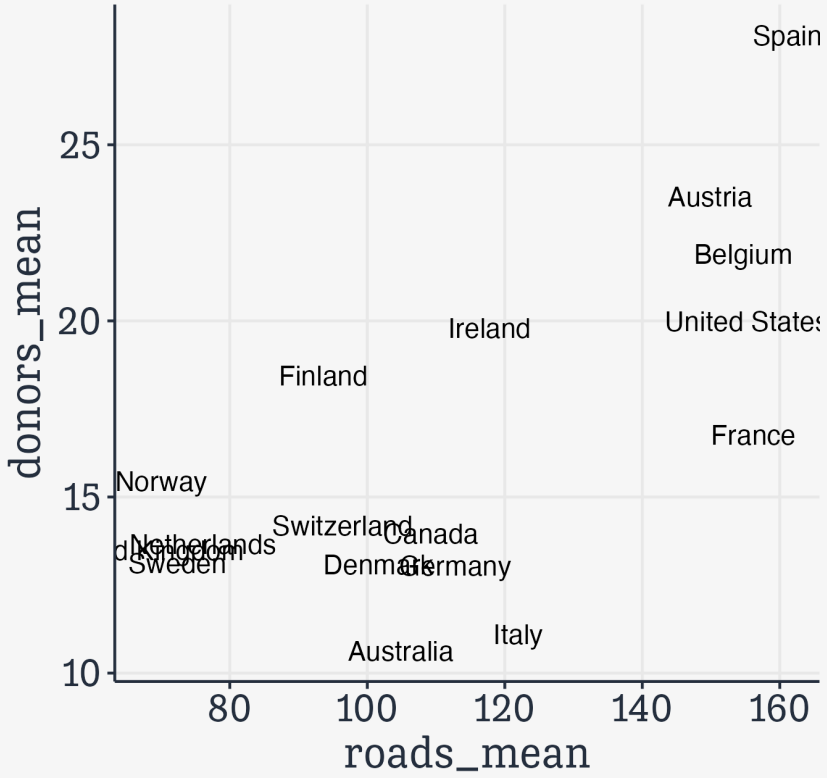
awards: The number of Oscar awards that this movie received.

What can we learn from visualizing this data?

Plot text directly

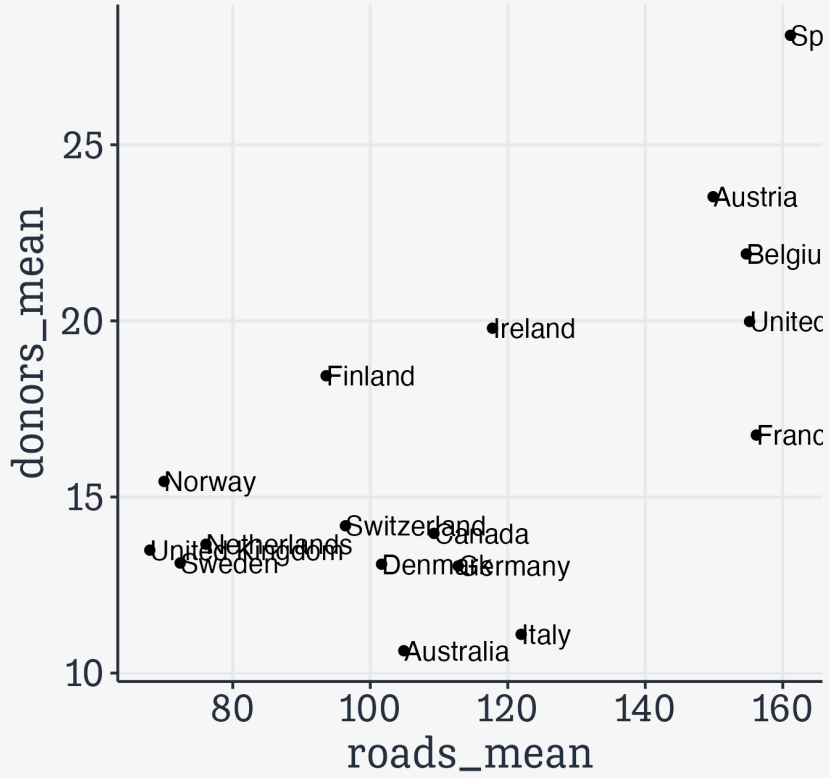
geom_text() for basic labels

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



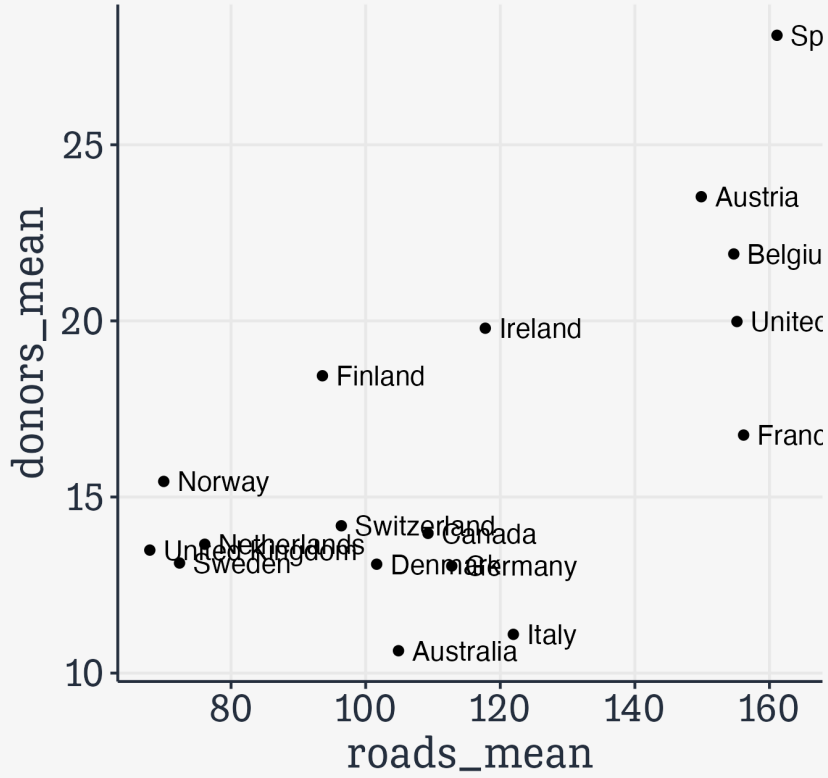
It's not very flexible

```
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()`

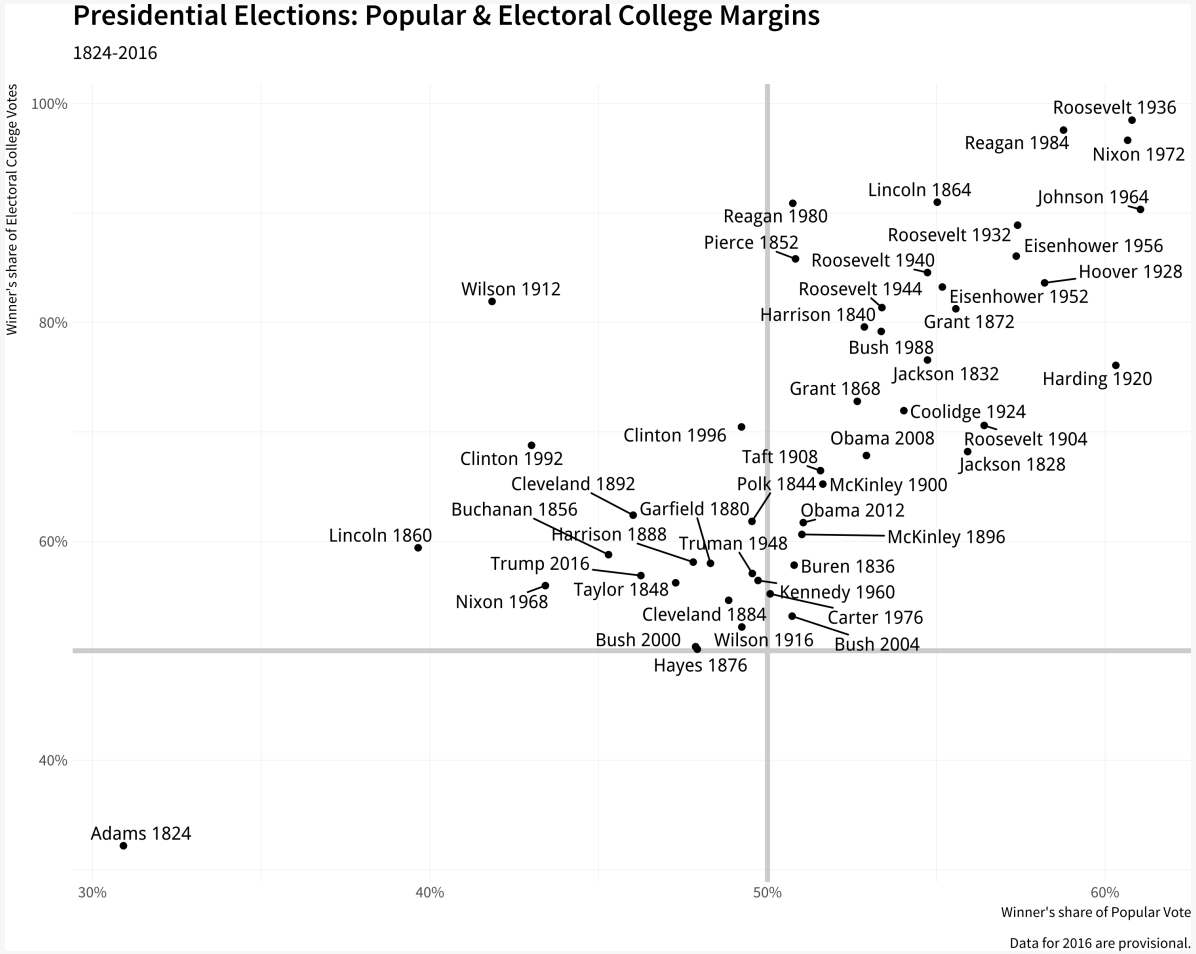
Example: U.S. Historic Presidential Elections

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 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



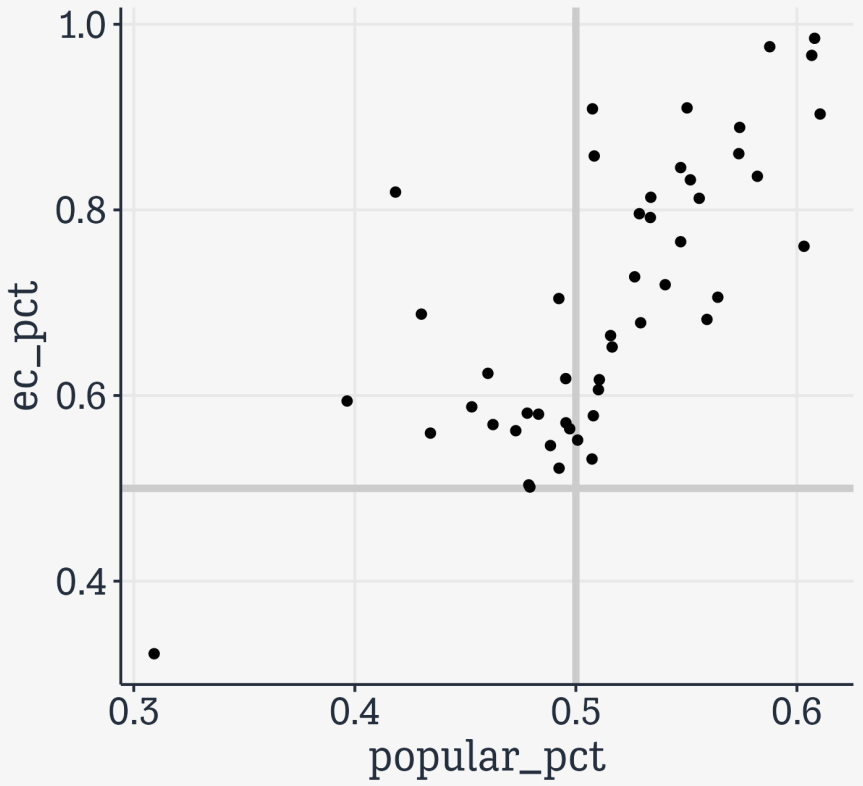
Presidential elections

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

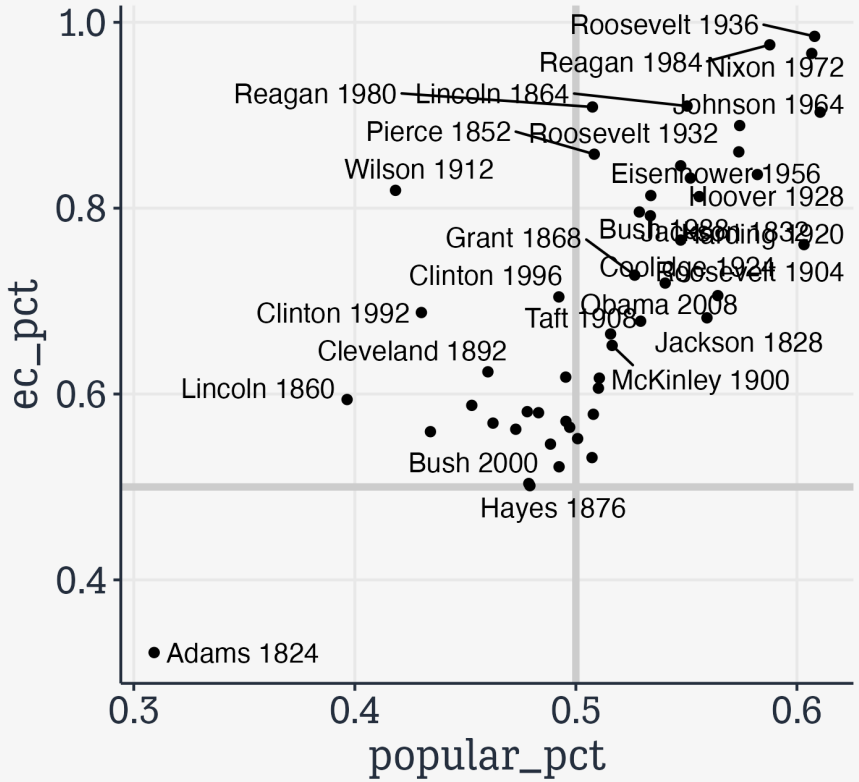
```
p ← ggplot(data = elections_historic,
           mapping = aes(x = popular_pct,
                         y = ec_pct,
                         label = winner_label)

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

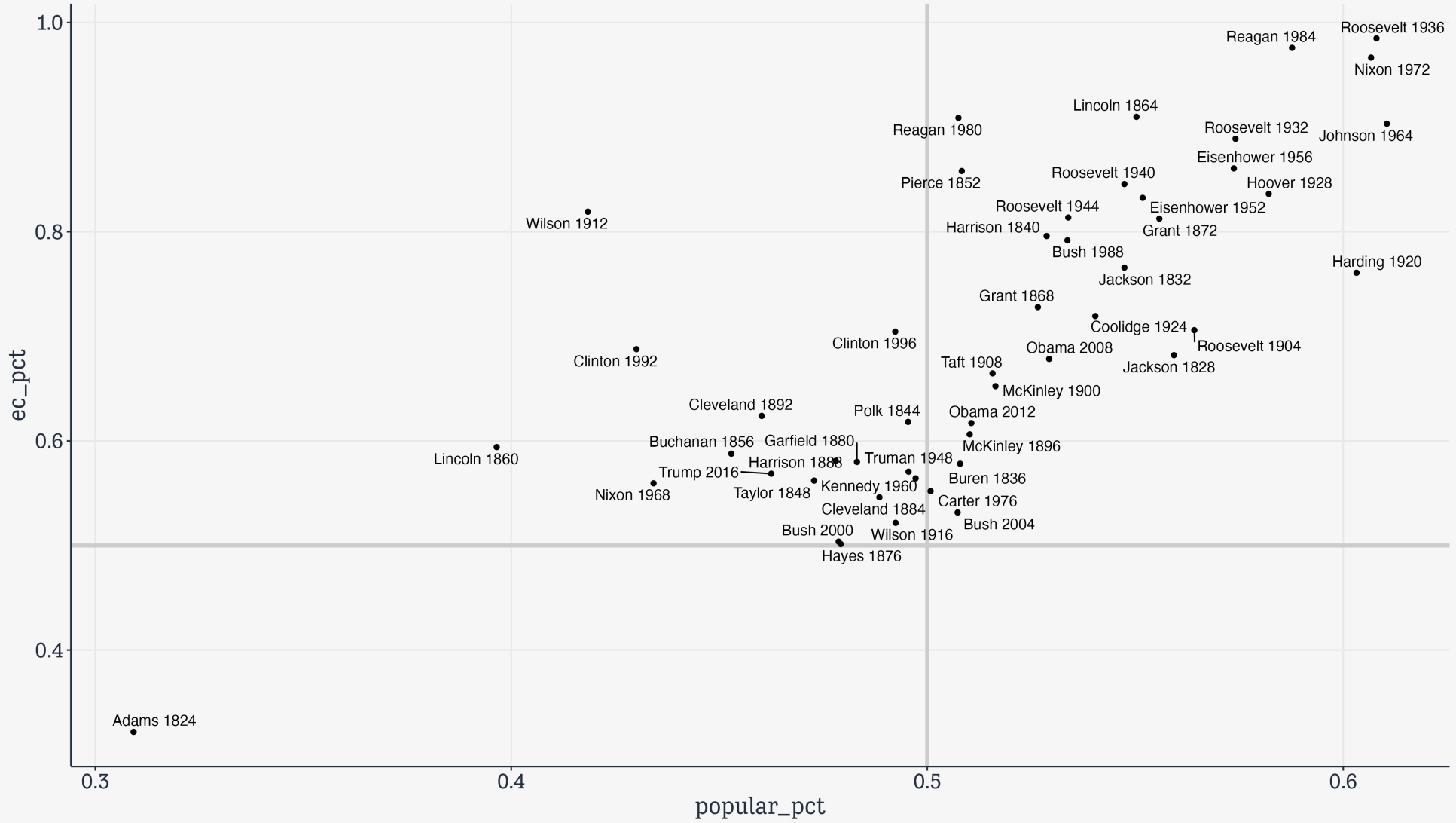
This looks terrible here because `geom_text_repel()` uses the dimensions of the available graphics device to iteratively figure out the labels. Let's allow it to draw on the whole slide.

```
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()
```



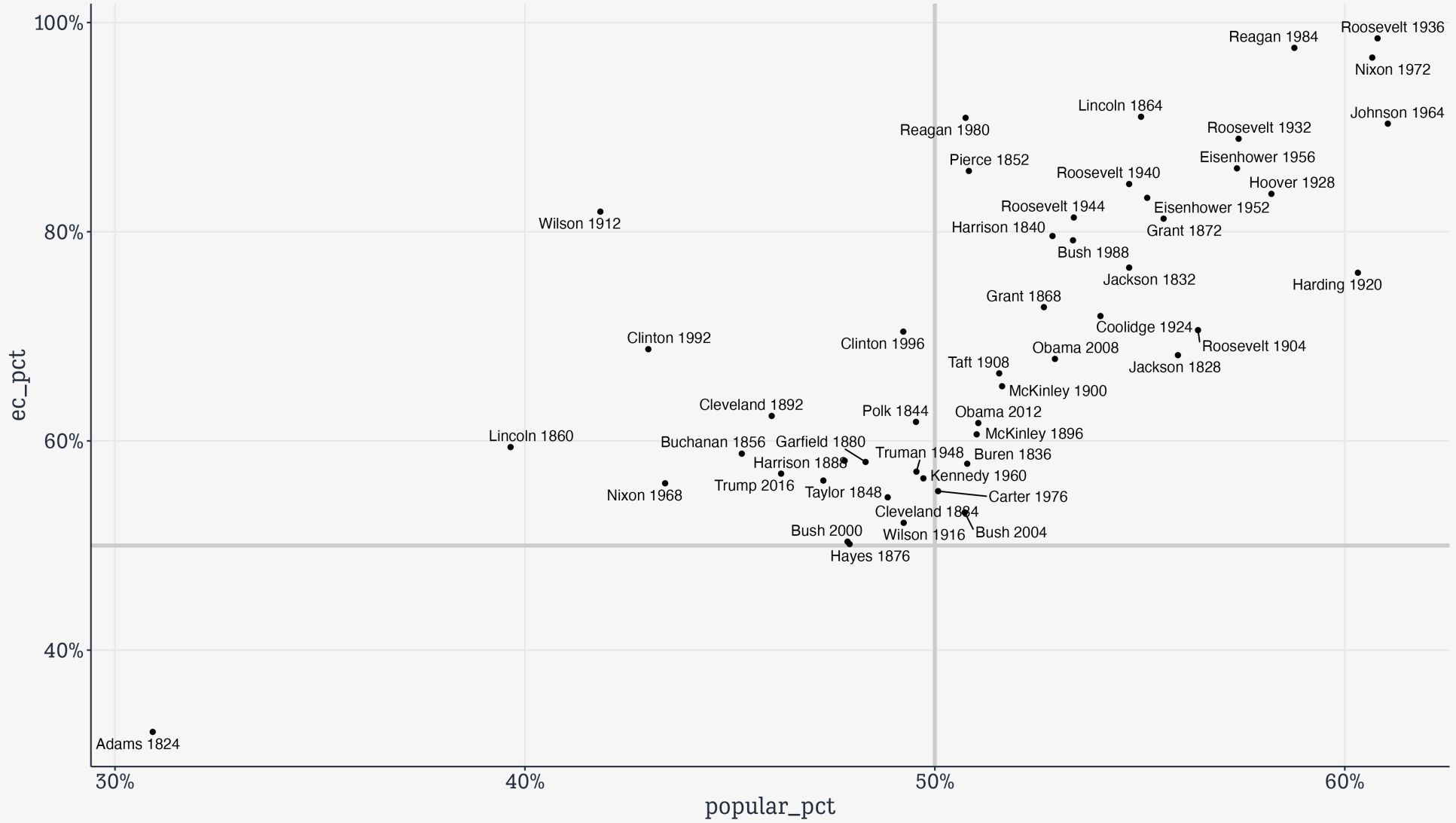
Labeling is with respect to the plot size

```
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()
```


1.0
0.8
0.6
0.4
ec_pct
0.3
0.4
0.5
0.6
popular_pct
Roosevelt 1936
Reagan 1984
Nixon 1972
Lincoln 1864
Reagan 1980
Roosevelt 1932
Johnson 1964
Eisenhower 1956
Pierce 1852
Roosevelt 1940
Hoover 1928
Roosevelt 1944
Eisenhower 1952
Wilson 1912
Harrison 1840
Grant 1872
Bush 1988
Harding 1920
Jackson 1832
Grant 1868
Coolidge 1924
Clinton 1996
Roosevelt 1904
Obama 2008
Clinton 1992
Taft 1908
Jackson 1828
McKinley 1900
Cleveland 1892
Polk 1844
Obama 2012
Buchanan 1856
Garfield 1880
McKinley 1896
Lincoln 1860
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

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())
```


100%
80%
60%
40%
ec_pct
30%
40%
50%
60%
popular_pct
Roosevelt 1936
Reagan 1984
Nixon 1972
Lincoln 1864
Johnson 1964
Reagan 1980
Roosevelt 1932
Pierce 1852
Eisenhower 1956
Roosevelt 1940
Hoover 1928
Roosevelt 1944
Eisenhower 1952
Wilson 1912
Harrison 1840
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Jackson 1832
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Garfield 1880
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Harrison 1888
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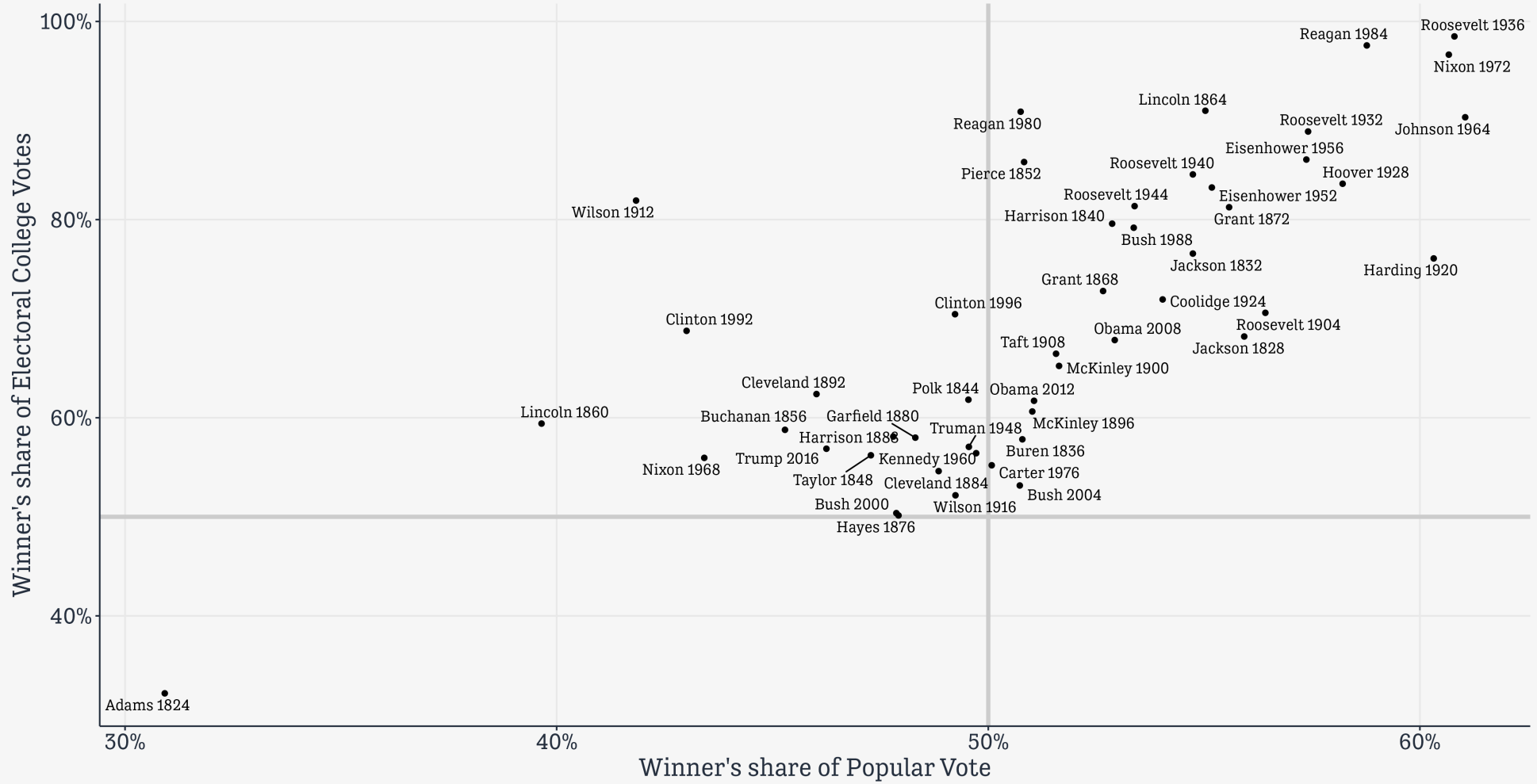
Trump 2016
Taylor 1848
Carter 1976
Nixon 1968
Cleveland 1884
Bush 2000
Wilson 1916
Bush 2004
Hayes 1876
Adams 1824

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

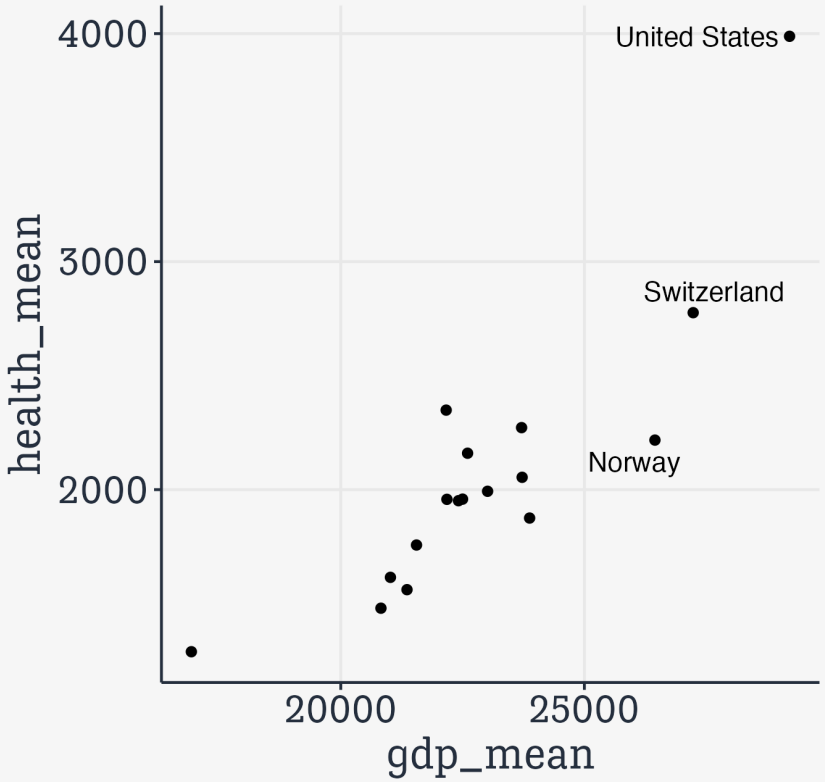


Data for 2016 are provisional.

Labeling points of interest

Option 1: On the fly in ggplot

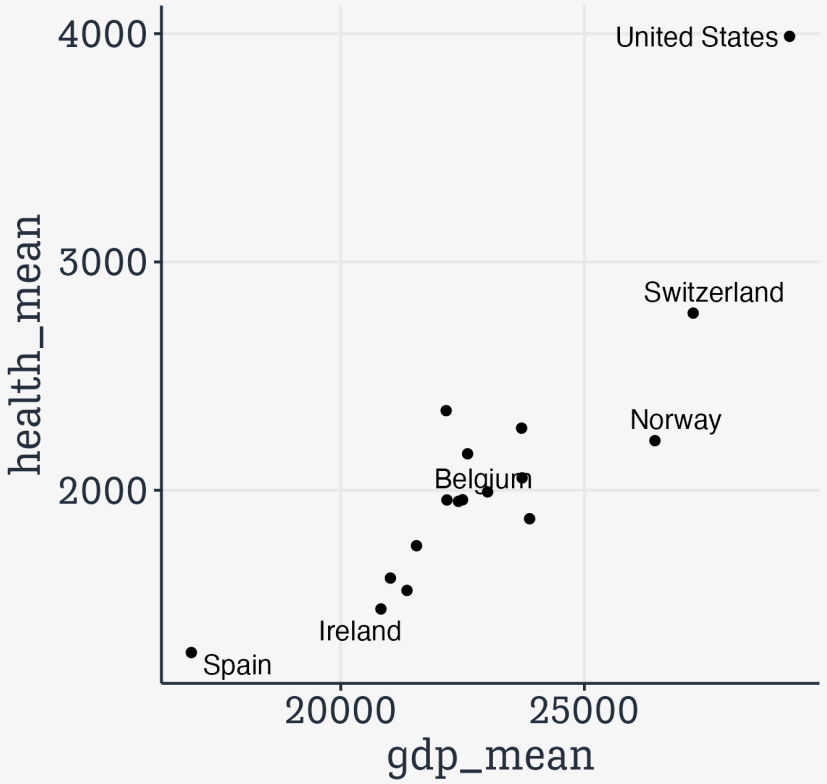
```
by_country ▷
  ggplot(mapping = aes(x = gdp_mean,
                       y = health_mean)) +
  geom_point() +
  geom_text_repel(data = subset(by_country, gdp
                  mapping = aes(label = country
```



Option 1: On the fly inside `ggplot`

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

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



Option 2: Use dplyr first

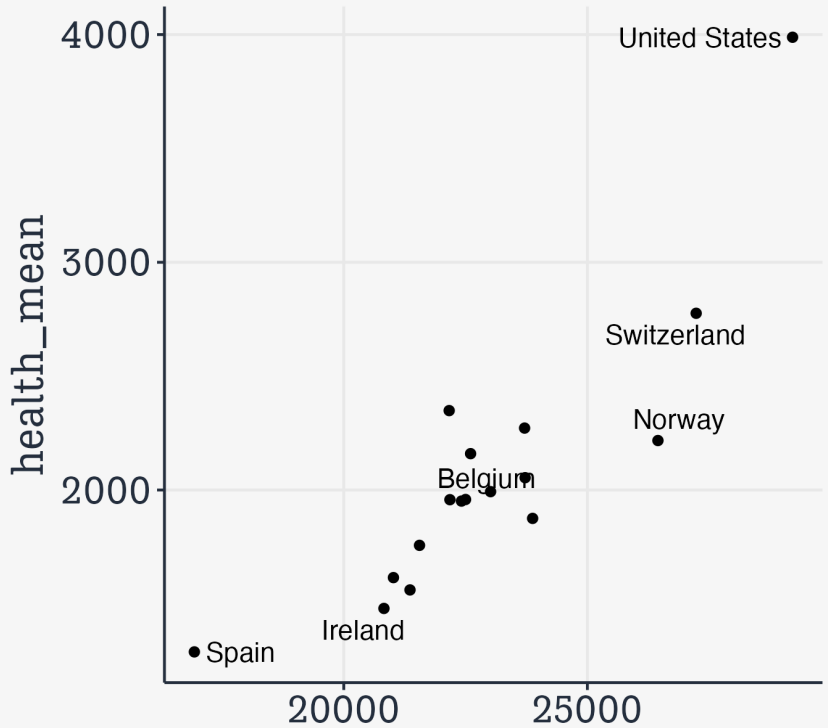
```
df_hl ← by_country ▷
  filter(gdp_mean > 25000 |
           health_mean < 1500 |
           country %in% "Belgium")

df_hl
```

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

Option 2: Use `dplyr` first

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

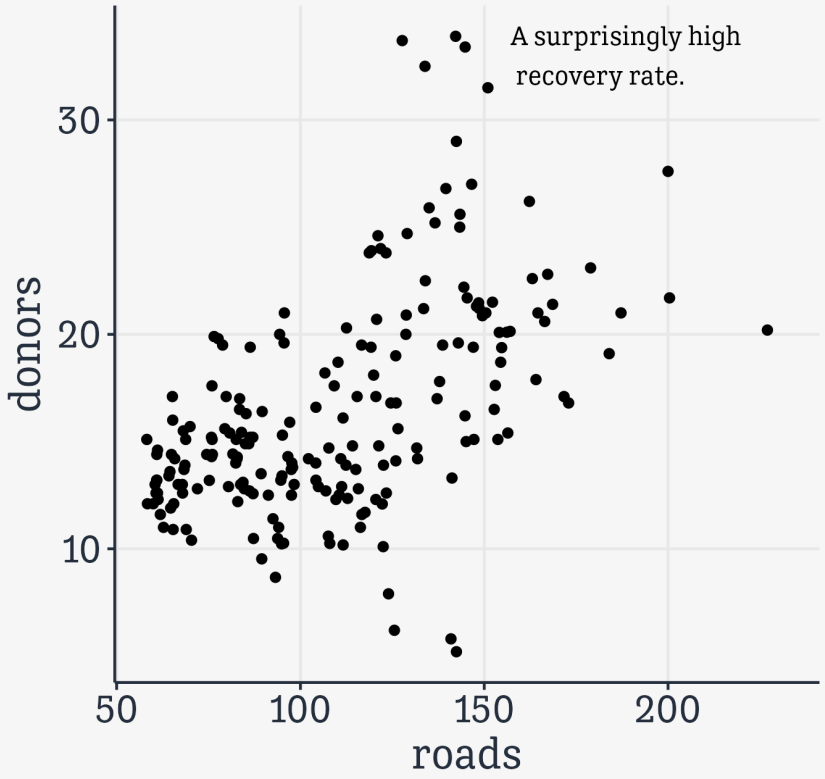
```
by_country ▷
  ggplot(mapping = aes(x = gdp_mean,
                       y = health_mean)) +
  geom_point() +
  geom_text_repel(data = df_hl,
                  mapping = aes(label = country
```



Write and draw inside the plot area

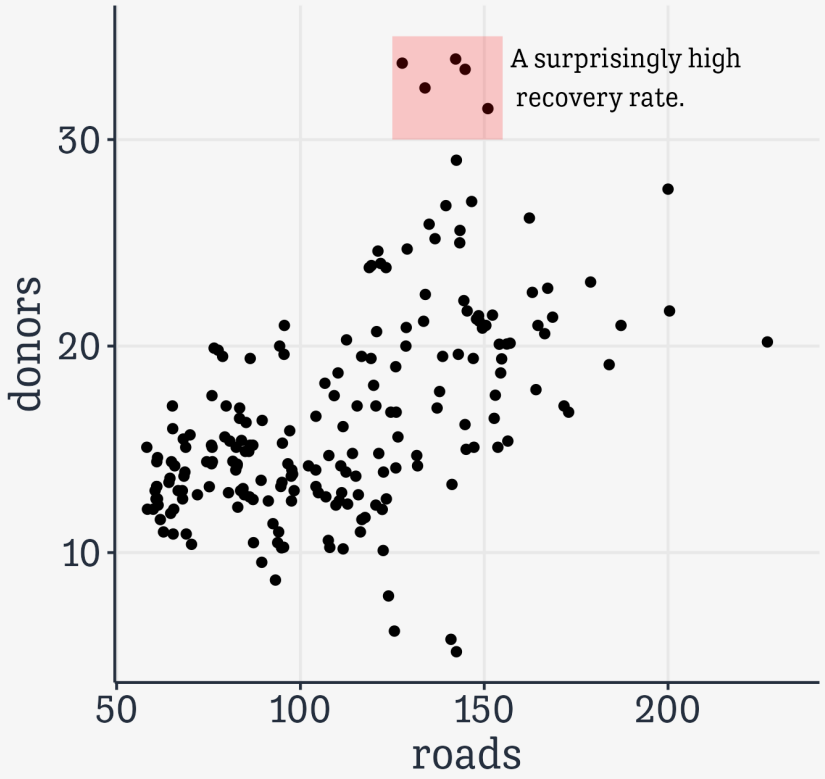
`annotate()` can imitate geoms

```
organdata ▷
  ggplot(mapping = aes(x = roads,
                       y = donors)) +
  geom_point() +
  annotate(geom = "text",
           family = "Tenso Slide",
           x = 157,
           y = 33,
           label = "A surprisingly high \n reco
           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 reco
           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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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_continous()

scale_x_discrete()

scale_y_discrete()

scale_x_log10()

scale_x_sqrt()

Naming conventions

scale_<MAPPING>_<KIND>()

scale_x_continuous()

scale_y_continous()

scale_x_discrete()

scale_y_discrete()

scale_x_log10()

scale_x_sqrt()

scale_color_discrete()

scale_color_gradient()

scale_color_gradient2()

scale_color_brewer()

scale_fill_discrete()

scale_fill_gradient()

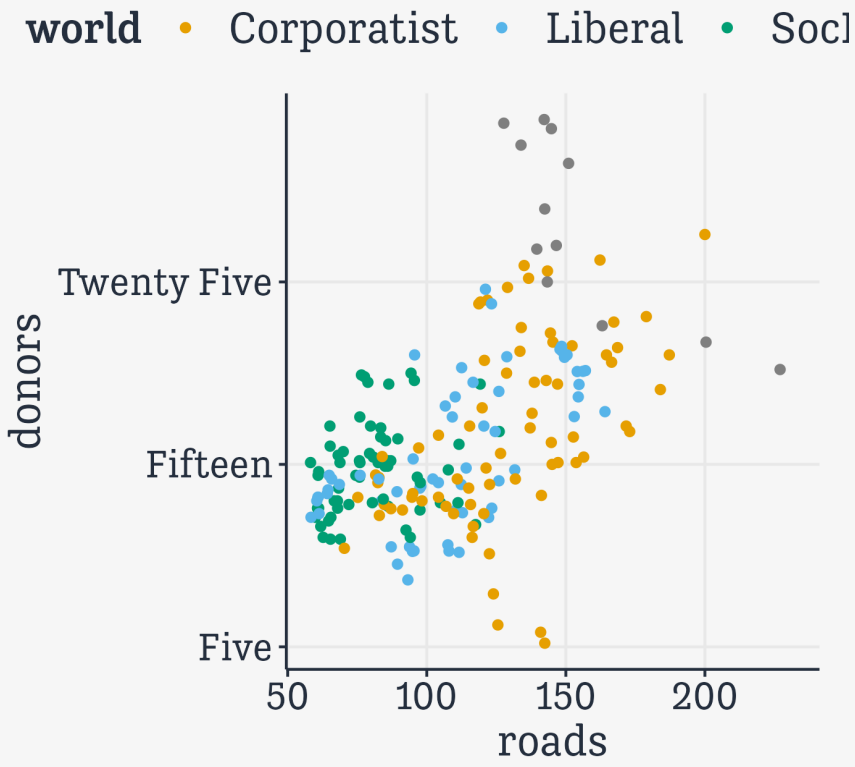
scale_fill_gradient2()

scale_fill_brewer()

Scale functions in practice

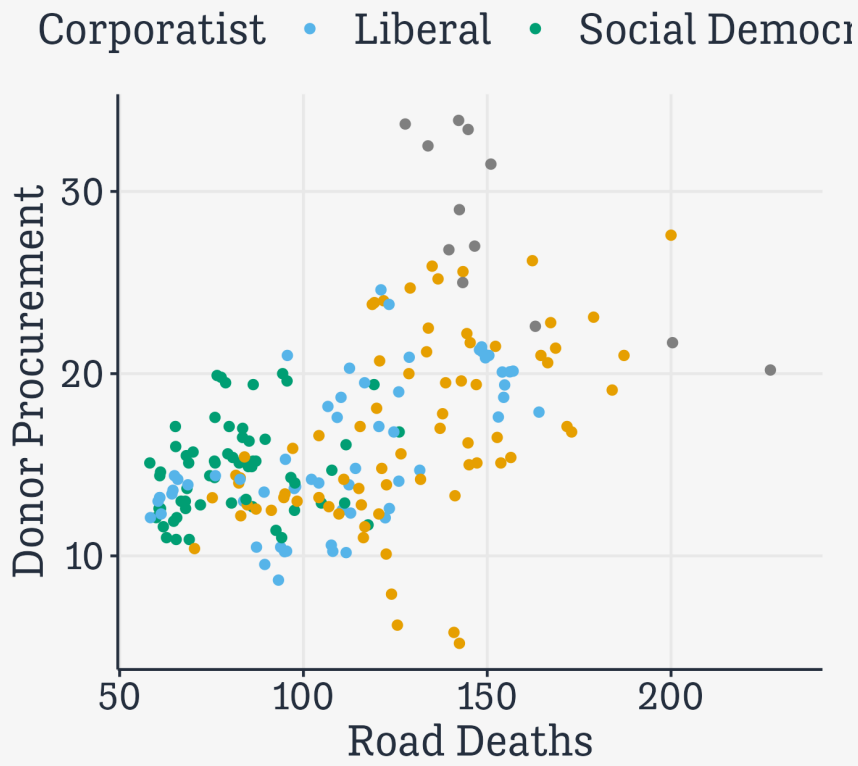
Scale functions take arguments appropriate to their mapping and kind

```
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"))
```



More usefully ...

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



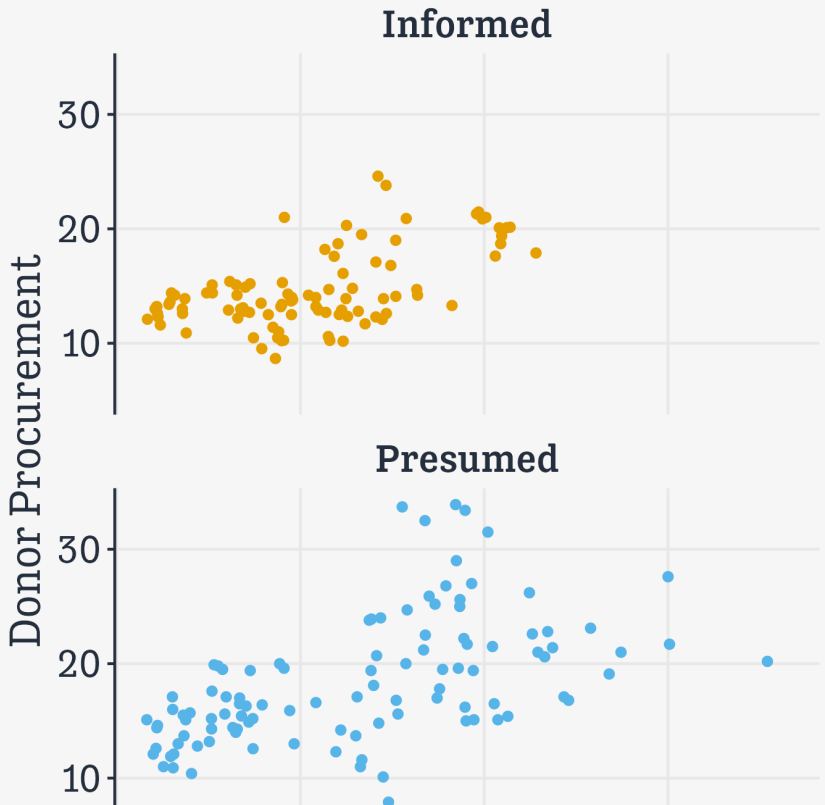
The guides() function

Control overall properties of the guide labels.

Common use: turning it off.

We'll see more advanced uses later.

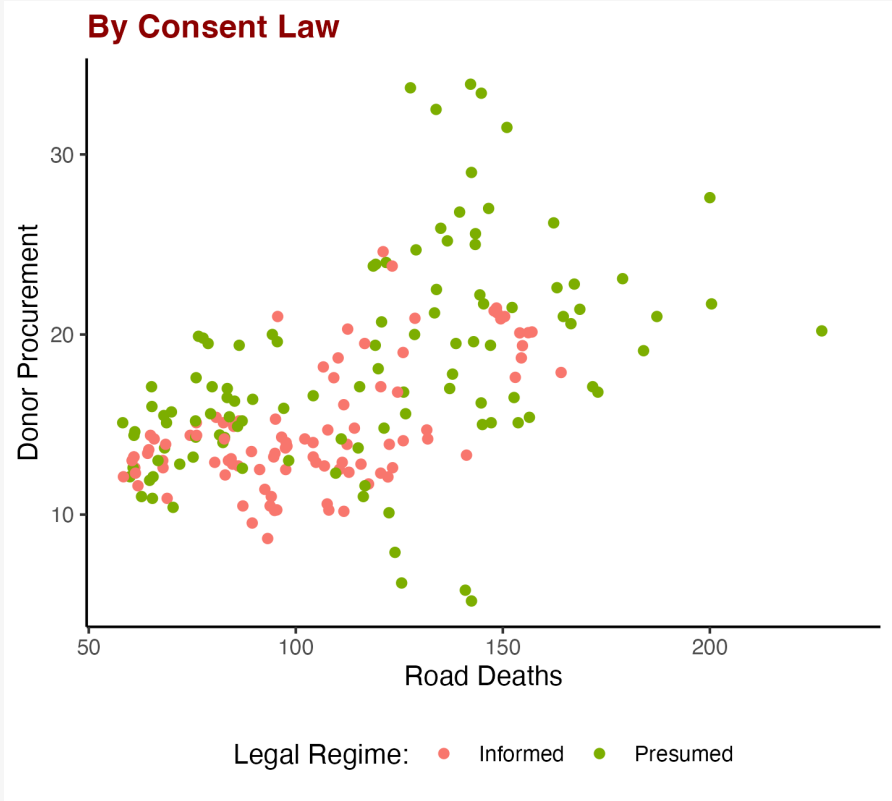
```
organdata ▷
  ggplot(mapping = aes(x = roads,
                       y = donors,
                       color = consent_law)) +
  geom_point() +
  facet_wrap(~ consent_law, ncol = 1) +
  guides(color = "none") +
  labs(x = "Road Deaths",
       y = "Donor Procurement")
```



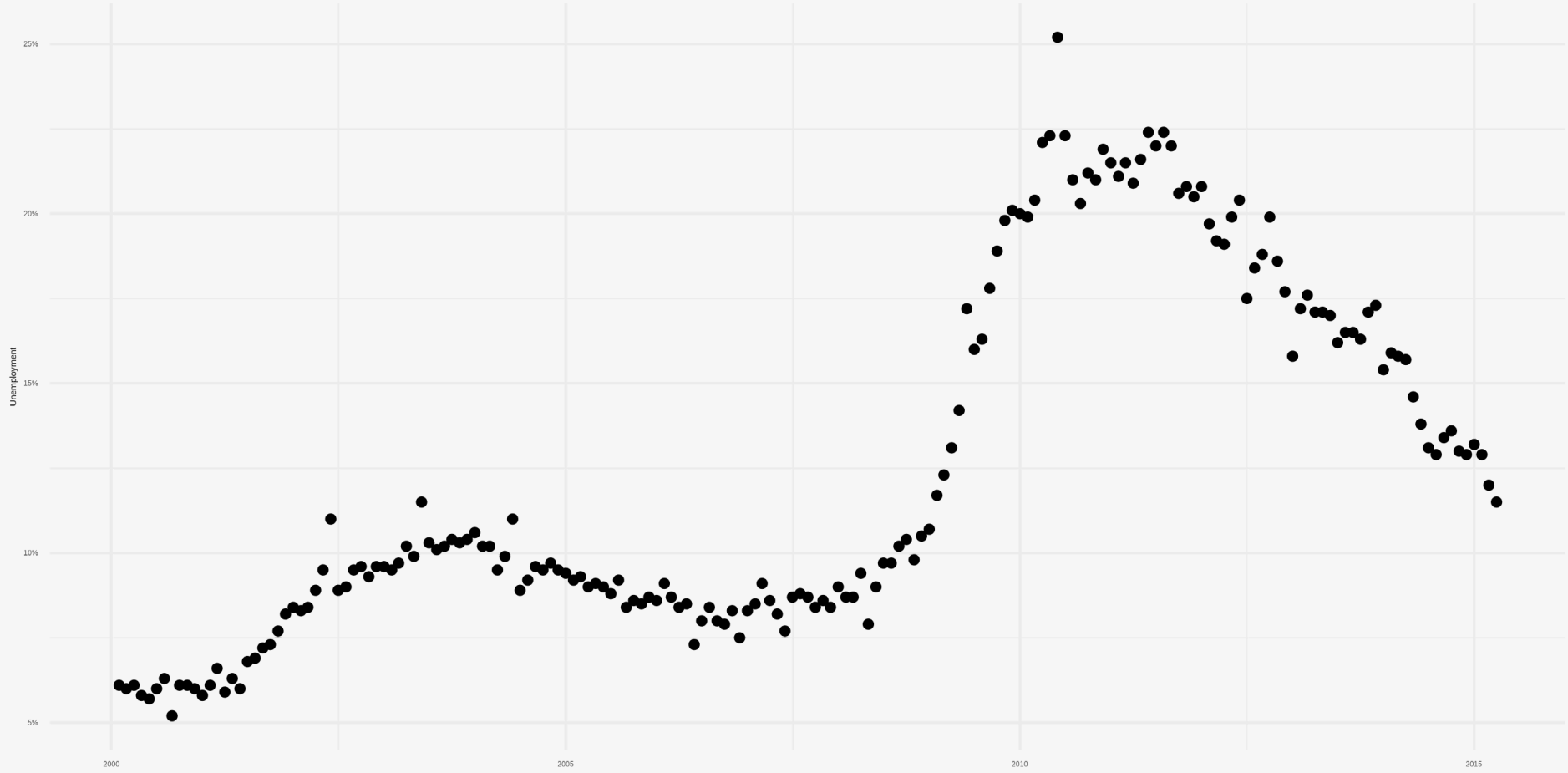
The `theme()` function

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

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

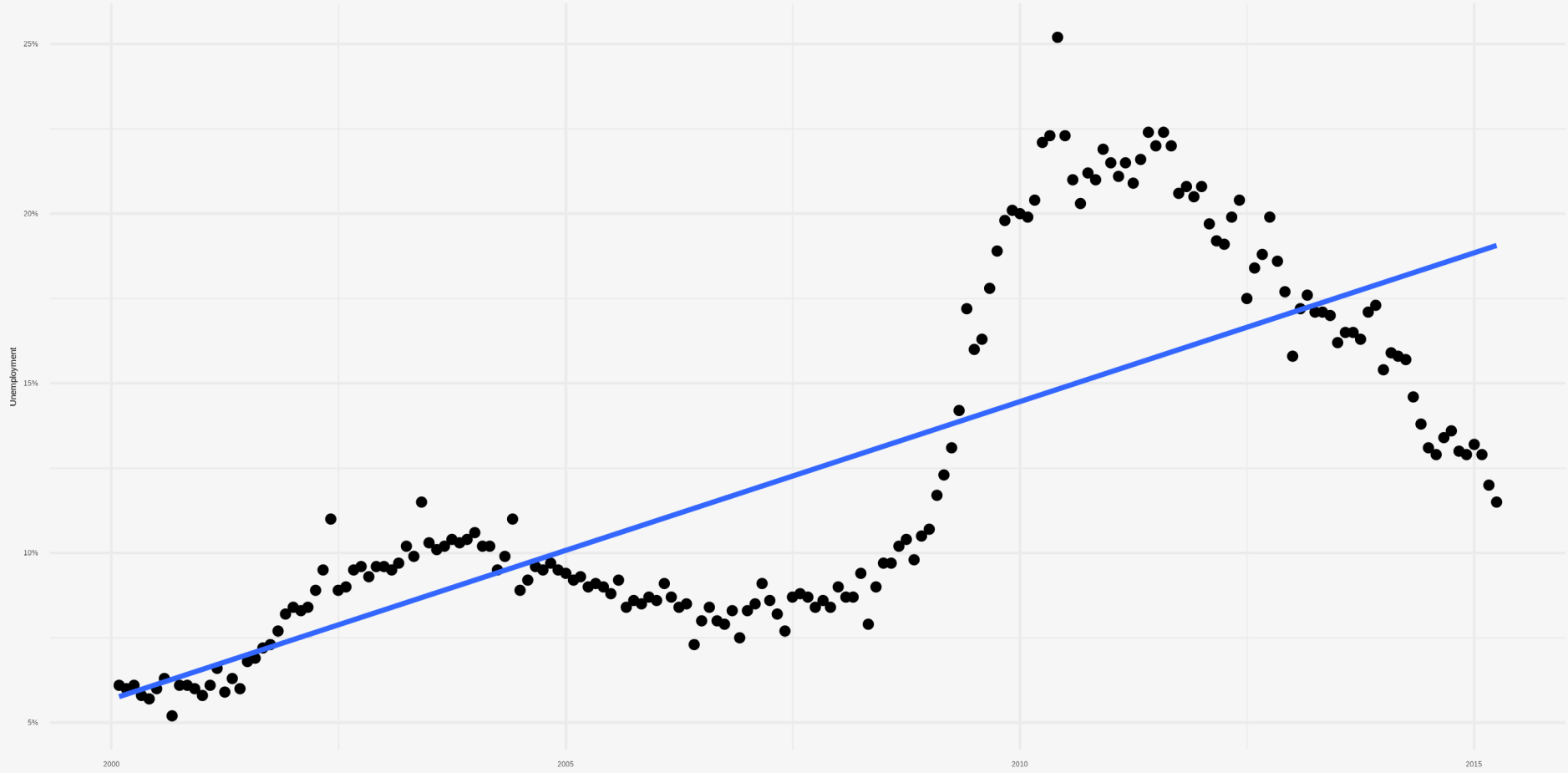


Sidenote: Smoothers



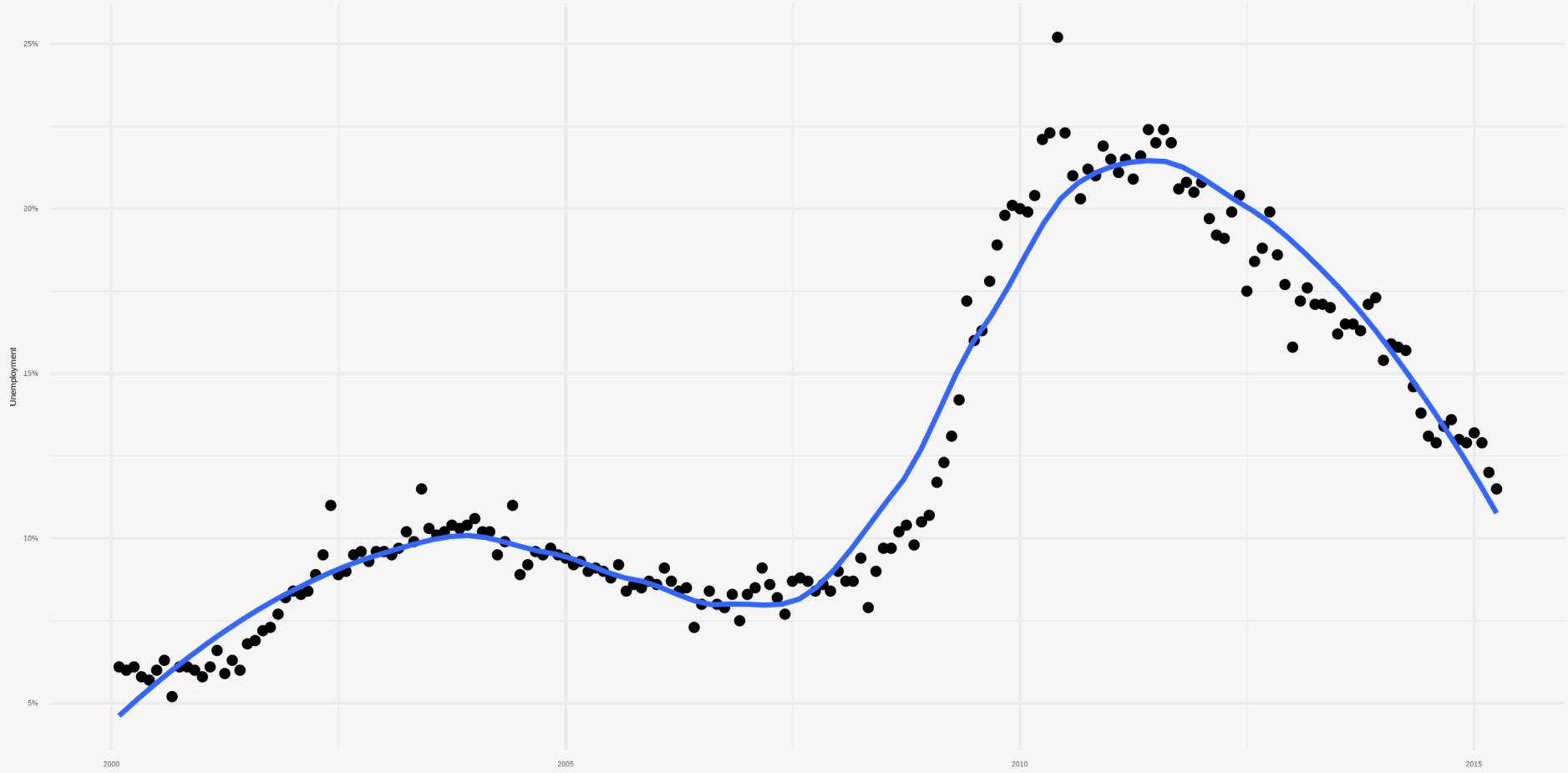
A trend

Sidenote: Smoothers



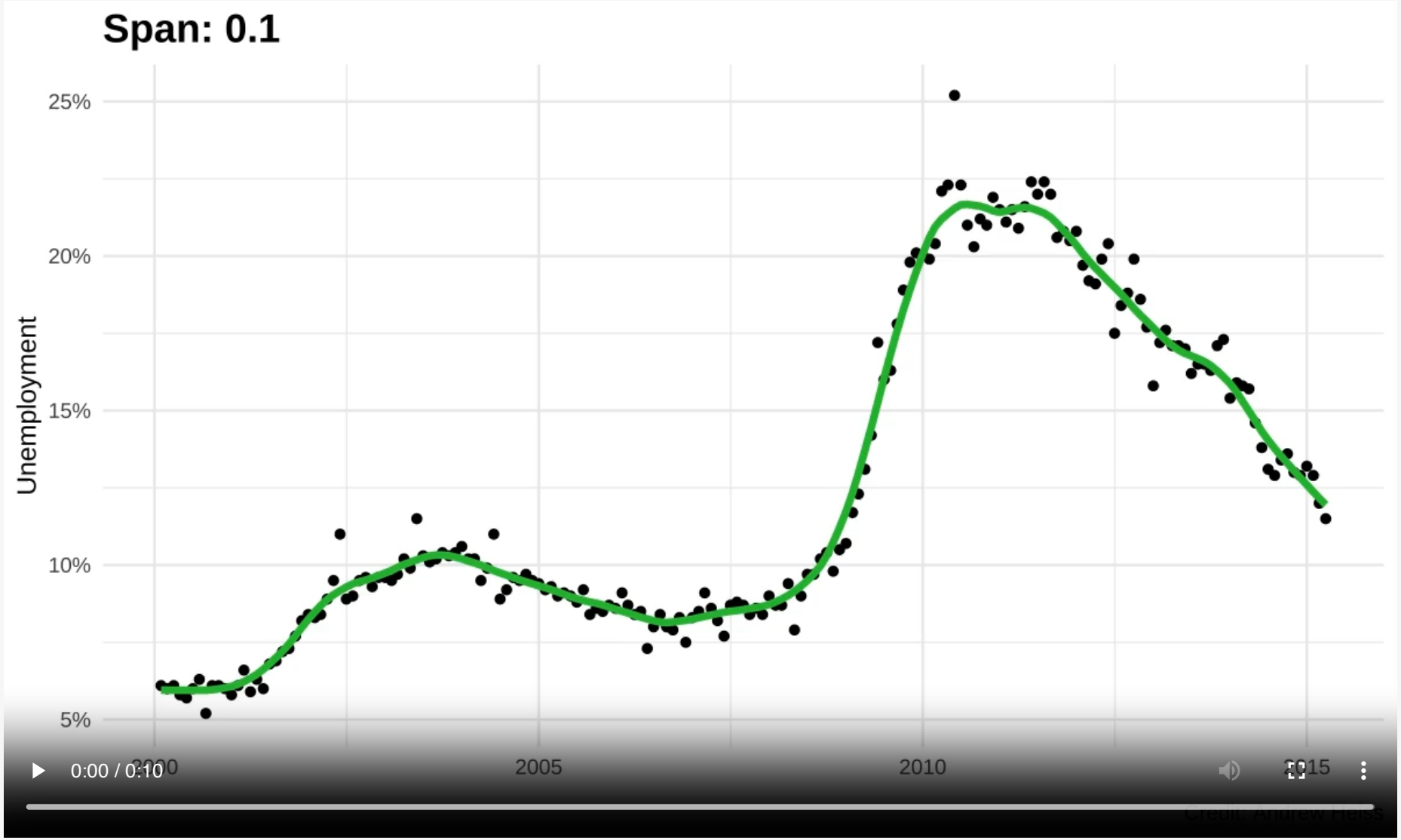
Smoother with bad linear fit

Sidenote: Smoothers



Smoother with loess fit

Sidenote: Smoothers



Sidenote: Smoothers