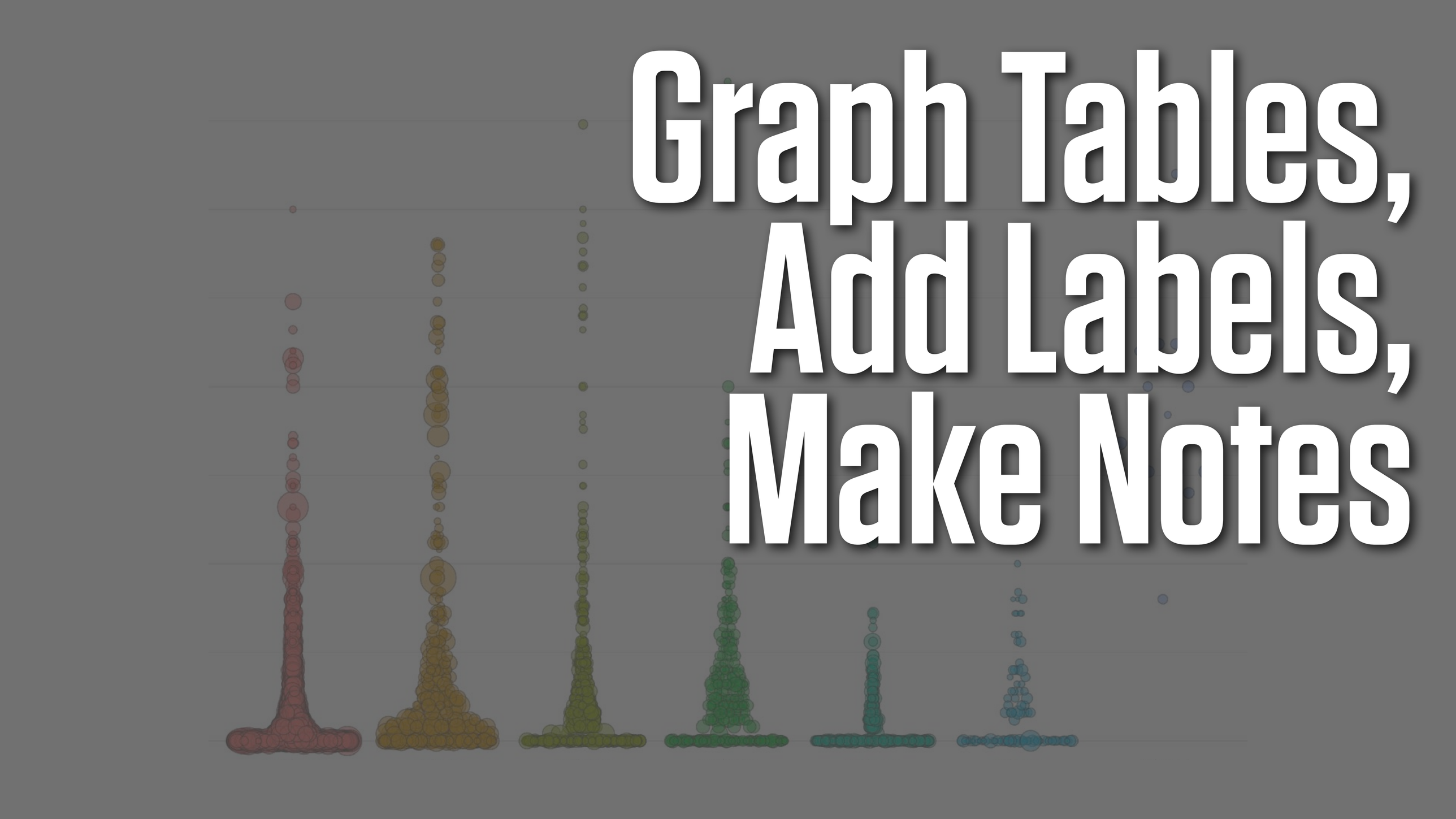
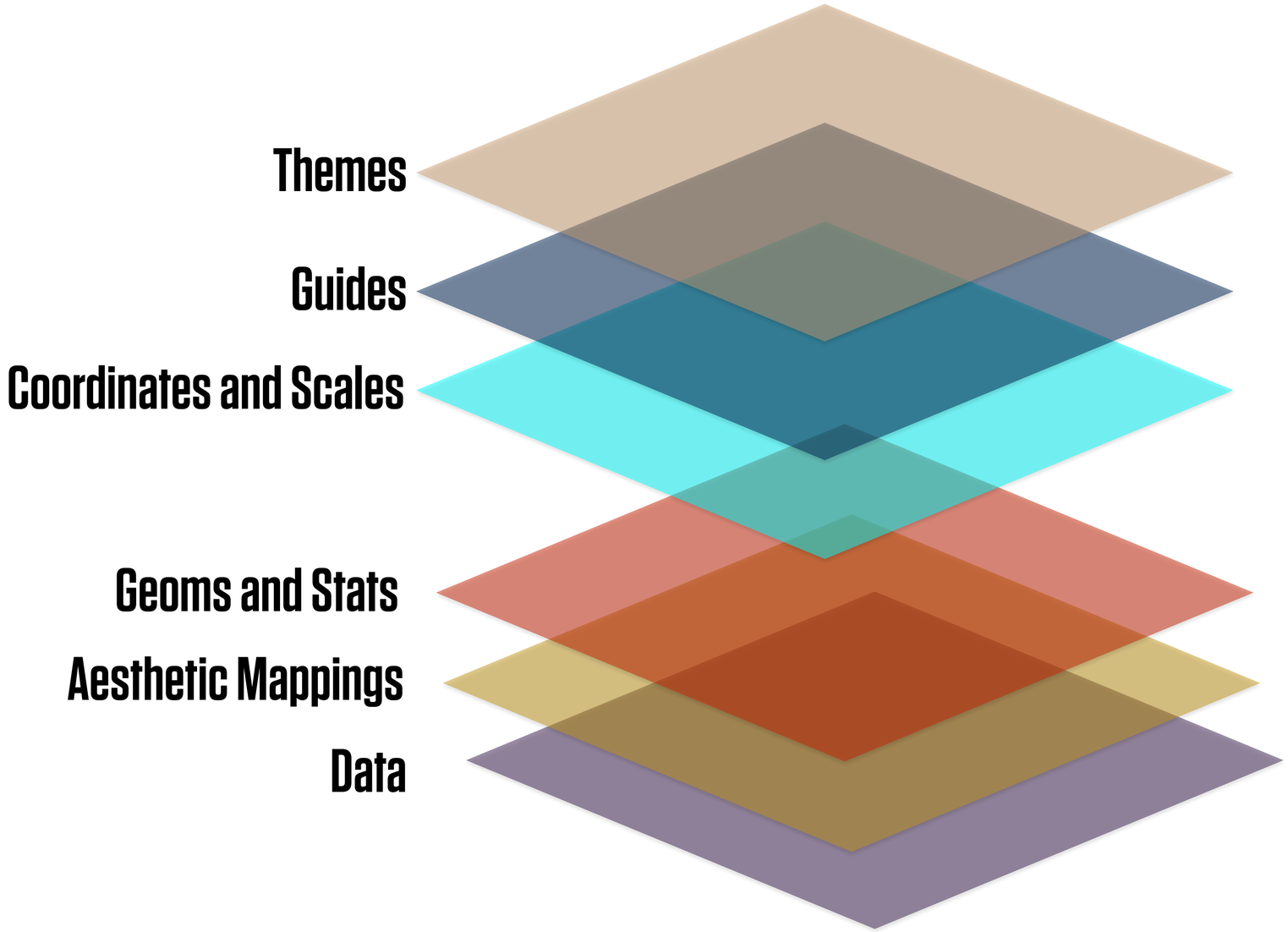
1988F5
20
40
60
80
Time since planting (days)


Graph Tables,
Add Labels,
Make Notes


Themes
Guides
Coordinates and Scales
Geoms and Stats
Aesthetic Mappings
Data

ggplot's FLOW OF ACTION

1. Tidy Data

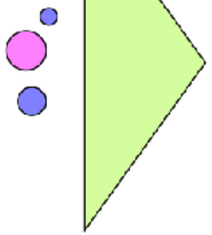
gdp	lifexp	pop	continent
340	65	31	Euro
227	51	200	Amer
909	81	80	Euro
126	40	20	Asia

```
ggplot(data = gapminder,
```

2. Mapping

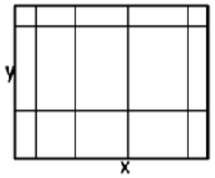

```
mapping =
aes(x = gdp,
y = lifespan,
color = continent,
size = pop))
```

3. Geom



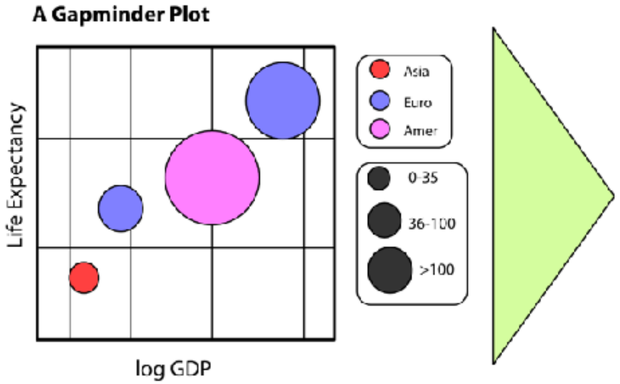
```
geom_point()
```

4. Co-Ordinates, Scales



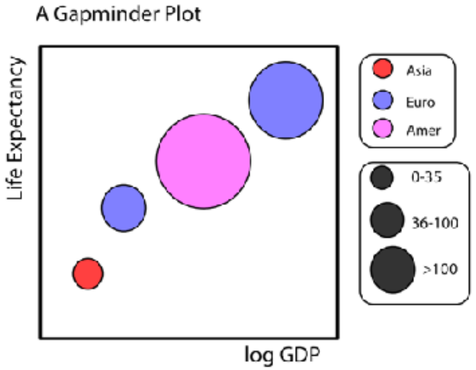

```
coord_cartesian()
scale_x_log10()
```

5. Labels & Guides




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

6. Themes

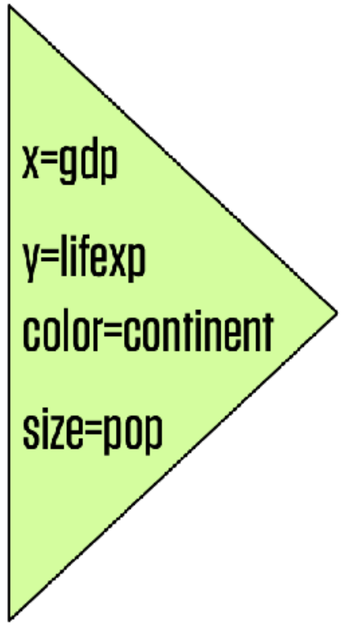



```
theme_minimal()
```

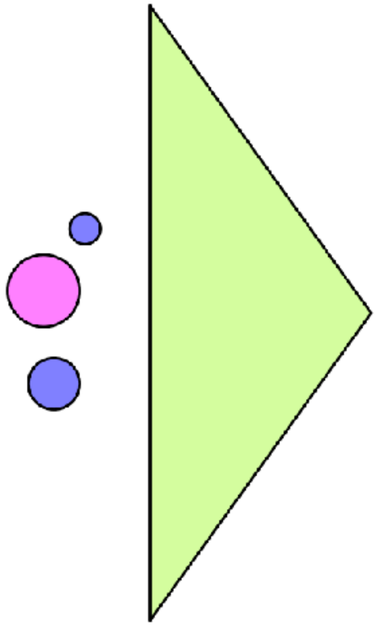
1. Tidy Data

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

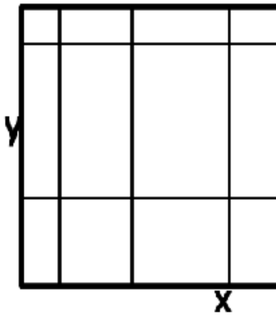
2. Mapping



3. Geom



4. Co-Ordin Scales




```
ggplot(data = gapminder,
```

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

```
geom_point()
```

```
coord_cartes
 scale_x_log
```

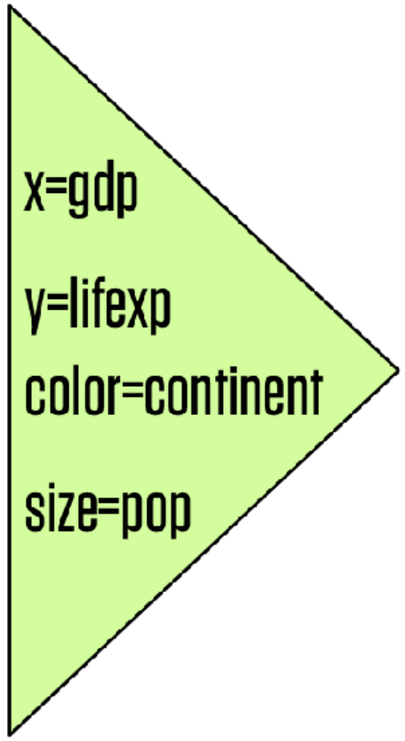
2. Mapping

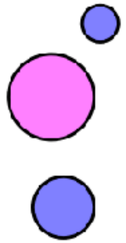
3. Geom

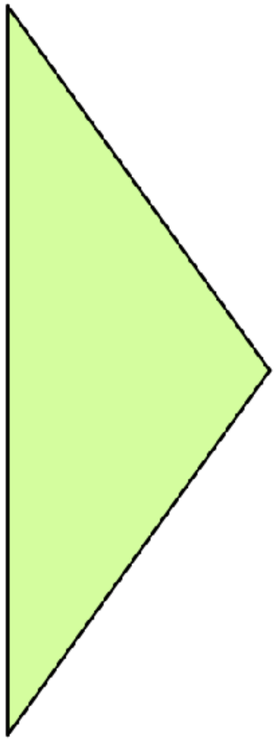
4. Co-Ordinates, Scales

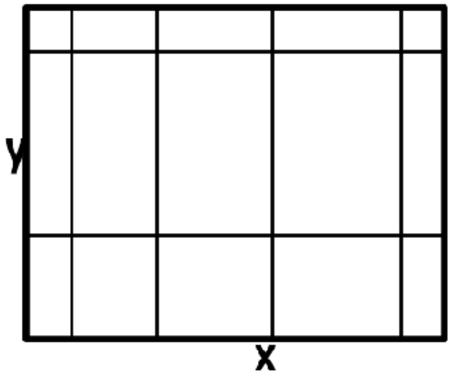
5. Labels & Guides

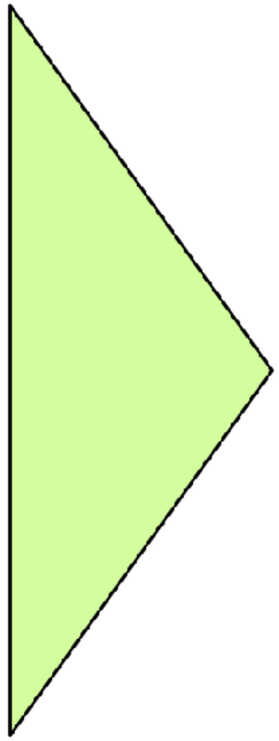
continent
Euro
Amer
Euro
Asia

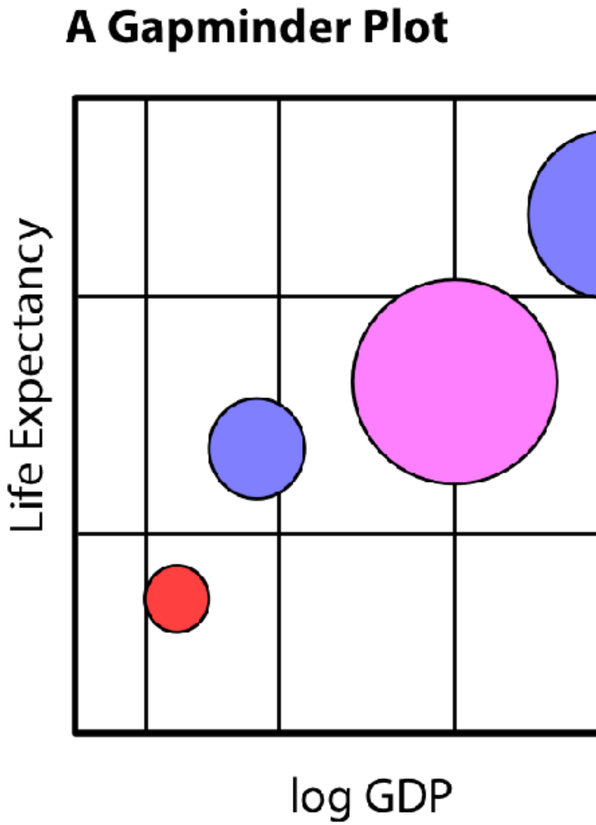












= gapminder,

mapping =
aes(x = gdp,
y = lifespan,

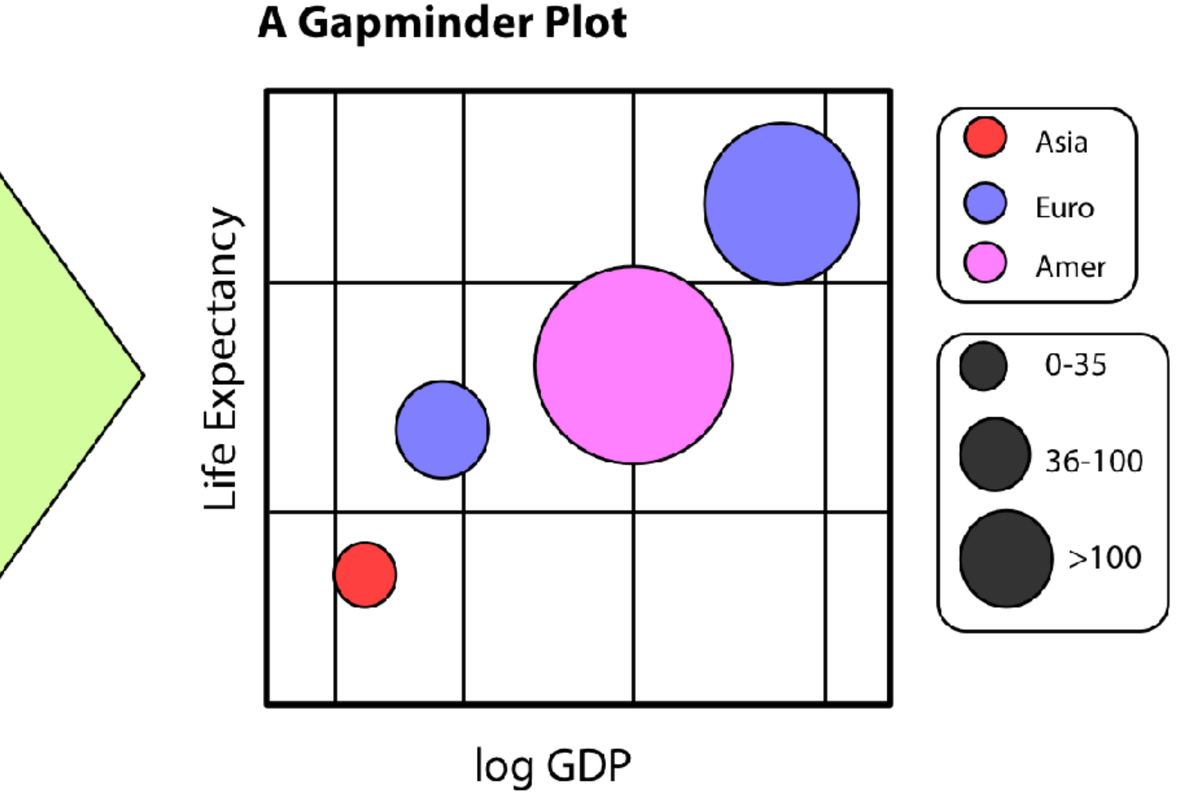
geom_point()

coord_cartesian()
scale_x_log10()

labs()

guides()

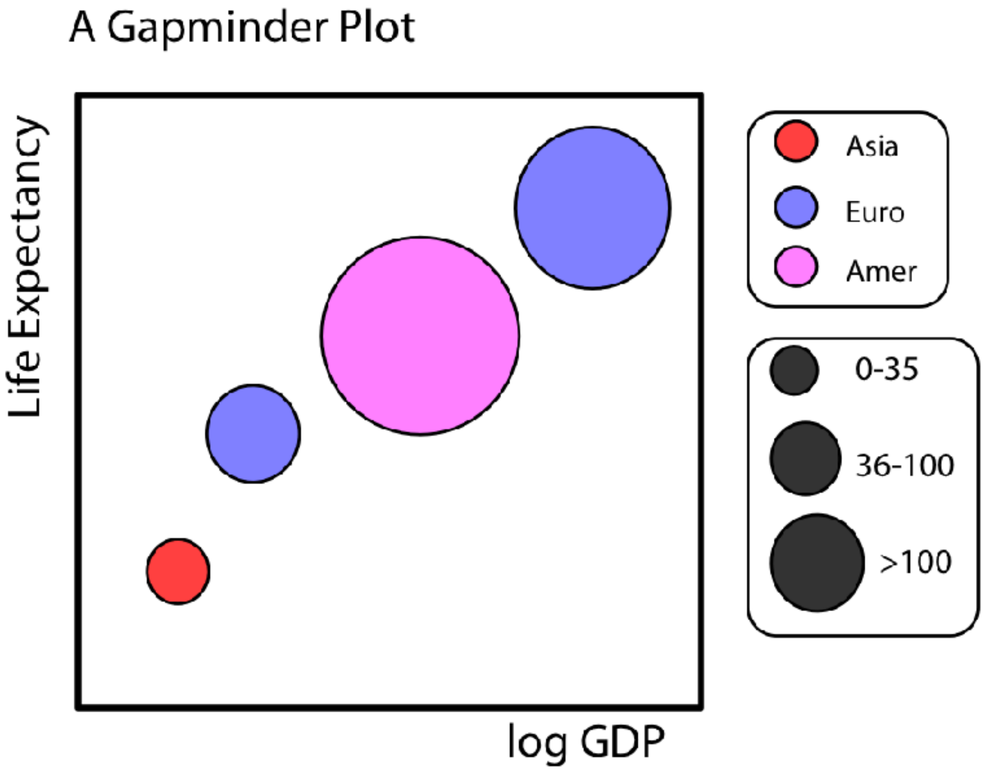
5. Labels & Guides



labs()

guides()

6. Themes



theme_minimal()

TRANSFORM AND SUMMARIZE FIRST

THEN SEND CLEAN TABLES TO ggplot

CROSSTABULATION

	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
	100	100	100	100	100	100

	Protestant	Catholic	Jewish	None	Other	NA	
Northeast	32.4	33.2	5.5	23.0	5.7	0.2	100
Midwest	46.8	24.7	0.4	22.6	4.7	0.7	100
South	61.8	15.2	1.0	16.2	4.8	1.0	100
West	37.7	24.5	1.6	28.5	7.6	0.2	100

dplyr lets you manipulate tables in a series of steps, or pipeline

dplyr draws on the logic of database queries, where the focus is managing and summarizing tables

Group the data at the level we want, such as "Religion by Region" or "Authors by Publications by Year".

`group_by()`

Filter or Select pieces of the data. This gets us the subset of the table we want to work on.

`filter()` rows
`select()` columns

Mutate the data by creating new variables at the current level of grouping. Mutating adds new columns to the table.

`mutate()`

Summarize the grouped data. This creates new variables at a higher level of grouping. For example we might calculate means with mean() or counts with n(). This results in a smaller, summary table, which we might do more things with if we want.

`summarize()`

Create a pipeline of tabular transformations with the pipe operator

%>%

Individual Level GSS Data Table

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

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

Percent Religious Preferences by Census Region

bigregion	religion	pct
Northeast	Protestant	28.3
Northeast	Catholic	34.3
Northeast	Jewish	3.4
Northeast	None	22.3
Northeast	Christian	3.2
Northeast	Other	7.1

REORGANIZING TABLES WITH dplyr

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

```
rel_by_region <- gss_sm
```

```
> rel_by_region
# A tibble: 2,867 x 32
    year    id ballot   age childs  sibs degree race  sex   region income16 relig marital padeg madeg partyid polviews
   <dbl> <dbl>  <dbl> <dbl>  <dbl> <dbl> <fct>  <fct> <fct> <fct>  <fct>    <fct> <fct>   <fct> <fct> <fct>   <fct>
 1  2016     1      1    47      3     2 Bache… White Male  New E… $170000… None  Married Grad… High… Indepe… Moderate
 2  2016     2      2    61      0     3 High … White Male  New E… $50000 … None  Never … Lt H… High… Ind,ne… Liberal
 3  2016     3      3    72      2     3 Bache… White Male  New E… $75000 … Cath… Married High… Lt H… Not St… Conserv…
 4  2016     4      1    43      4     3 High … White Fema… New E… $170000… Cath… Married NA    High… Not St… Moderate
 5  2016     5      3    55      2     2 Gradu… White Fema… New E… $170000… None  Married Bach… High… Not St… Slightl…
 6  2016     6      2    53      2     2 Junio… White Fema… New E… $60000 … None  Married NA    High… Not St… Slightl…
 7  2016     7      1    50      2     2 High … White Male  New E… $170000… None  Married High… High… Not St… Slightl…
 8  2016     8      3    23      3     6 High … Other Fema… Middl… $30000 … Cath… Married Lt H… Lt H… Ind,ne… Slightl…
 9  2016     9      1    45      3     5 High … Black Male  Middl… $60000 … Prot… Married Lt H… Lt H… Strong… NA
10  2016    10      3    71      4     1 Junio… White Male  Middl… $60000 … None  Divorc… High… High… Strong… Conserv…
# … with 2,857 more rows, and 15 more variables: happy <fct>, partners <fct>, grass <fct>, zodiac <fct>, pres12 <dbl>,
#   wtssall <dbl>, income_rc <fct>, agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
#   bigregion <fct>, partners_rc <fct>, obama <dbl>
```

```
rel_by_region <- gss_sm %>%
    group_by(bigregion, religion)
```

```
> rel_by_region
# A tibble: 2,867 x 32
# Groups:   bigregion, religion [24]
    year    id ballot   age childs  sibs degree race  sex   region income16 relig marital padeg madeg partyid polviews
   <dbl> <dbl>  <dbl> <dbl>  <dbl> <dbl> <fct>  <fct> <fct> <fct>  <fct>    <fct> <fct>   <fct> <fct> <fct>   <fct>
 1  2016     1      1    47      3     2 Bache… White Male  New E… $170000… None  Married Grad… High… Indepe… Moderate
 2  2016     2      2    61      0     3 High … White Male  New E… $50000 … None  Never … Lt H… High… Ind,ne… Liberal
 3  2016     3      3    72      2     3 Bache… White Male  New E… $75000 … Cath… Married High… Lt H… Not St… Conserv…
 4  2016     4      1    43      4     3 High … White Fema… New E… $170000… Cath… Married NA    High… Not St… Moderate
 5  2016     5      3    55      2     2 Gradu… White Fema… New E… $170000… None  Married Bach… High… Not St… Slightl…
 6  2016     6      2    53      2     2 Junio… White Fema… New E… $60000 … None  Married NA    High… Not St… Slightl…
 7  2016     7      1    50      2     2 High … White Male  New E… $170000… None  Married High… High… Not St… Slightl…
 8  2016     8      3    23      3     6 High … Other Fema… Middl… $30000 … Cath… Married Lt H… Lt H… Ind,ne… Slightl…
 9  2016     9      1    45      3     5 High … Black Male  Middl… $60000 … Prot… Married Lt H… Lt H… Strong… NA
10  2016    10      3    71      4     1 Junio… White Male  Middl… $60000 … None  Divorc… High… High… Strong… Conserv…
# … with 2,857 more rows, and 15 more variables: happy <fct>, partners <fct>, grass <fct>, zodiac <fct>, pres12 <dbl>,
#   wtssall <dbl>, income_rc <fct>, agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
#   bigregion <fct>, partners_rc <fct>, obama <dbl>
```

```
rel_by_region <- gss_sm %>%
    group_by(bigregion, religion) %>%
    summarize(n = n())
```

A function to count how many items there are in the current group

The result of the calculation

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

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

mutate() operations add columns to existing tables

```
> rel_by_region
# A tibble: 24 x 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
# … with 14 more rows
```

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

Objects in a pipeline carry forward some assumptions about context

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

Grouping with group_by() carries forward; summary calculations are applied to the innermost group

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

mutate() adds or modifies columns, it doesn't change the grouping level or the number of rows in the table

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

Notice how we can create variables on the fly and use them immediately

```
rel_by_region
```

```
## Source: local data frame [24 x 5]
## Groups: bigregion [4]
##
## # A tibble: 24 x 5
##    bigregion   religion     n       freq   pct
##       <fctr>     <fctr> <int>      <dbl> <dbl>
##  1 Northeast Protestant   158 0.32377049  32.4
##  2 Northeast   Catholic   162 0.33196721  33.2
##  3 Northeast     Jewish    27 0.05532787   5.5
##  4 Northeast       None   112 0.22950820  23.0
##  5 Northeast      Other    28 0.05737705   5.7
##  6 Northeast         NA     1 0.00204918   0.2
##  7   Midwest Protestant   325 0.46762590  46.8
##  8   Midwest   Catholic   172 0.24748201  24.7
##  9   Midwest     Jewish     3 0.00431655   0.4
## 10   Midwest       None   157 0.22589928  22.6
## # ... with 14 more rows
```

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

We're going to be doing this a lot, so some shorthand for it would be useful

```
gss_sm %>%
  group_by(bigregion, religion) %>%
  summarize(n = n())
```

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

n()

Do it all yourself;
Result is a grouped tibble

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

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

tally()

Do the grouping yourself;
Result is grouped

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

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

count()

Group and add up;
Result is not grouped

Use dplyr to create summary tables, and then graph them

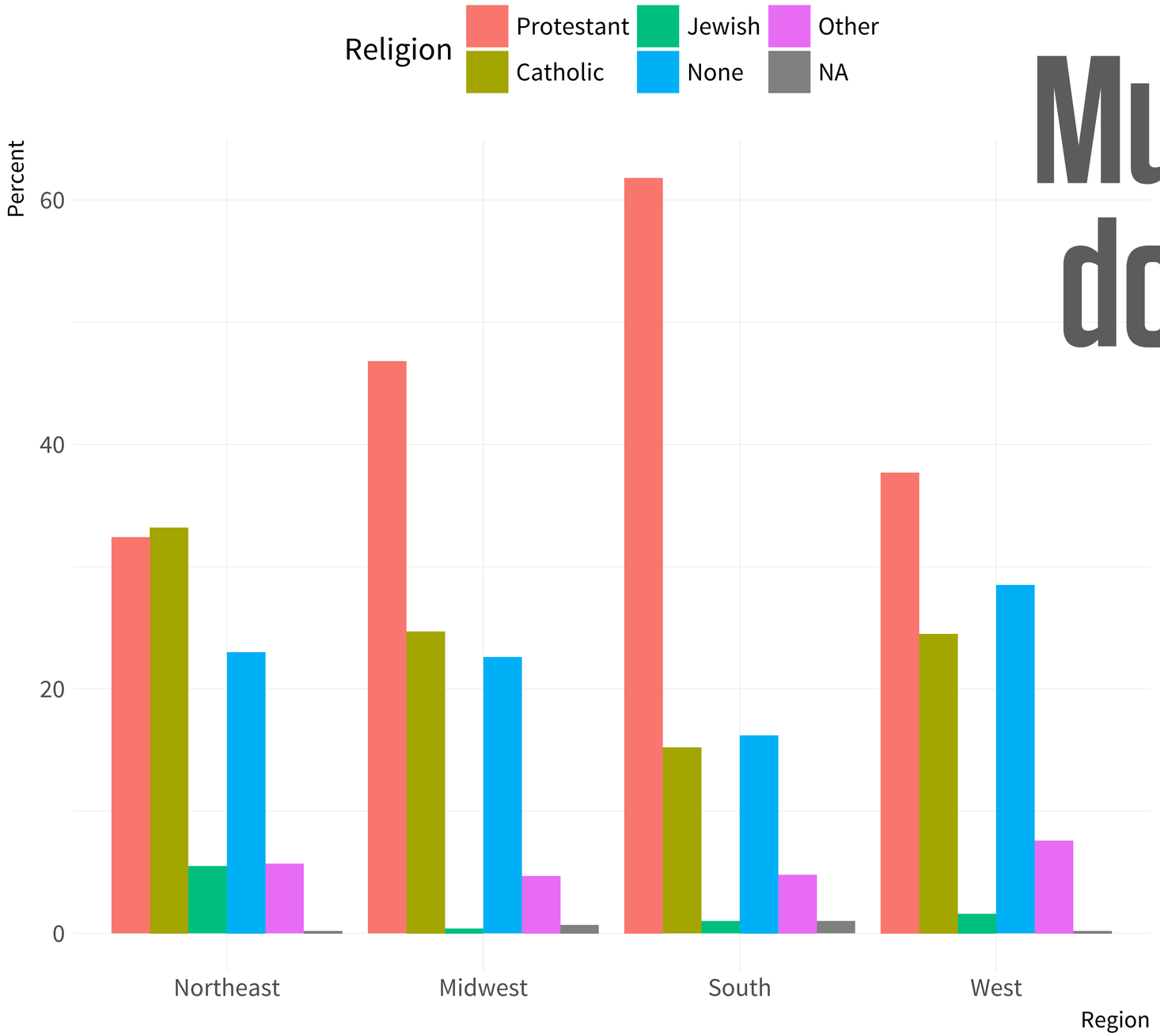
```
rel_by_region %>%
    group_by(bigregion) %>%
    summarize(total = sum(pct))
```

```
## # A tibble: 4 x 2
##   bigregion total
##      <fctr> <dbl>
## 1 Northeast 100.0
## 2   Midwest  99.9
## 3     South 100.0
## 4      West 100.1
```

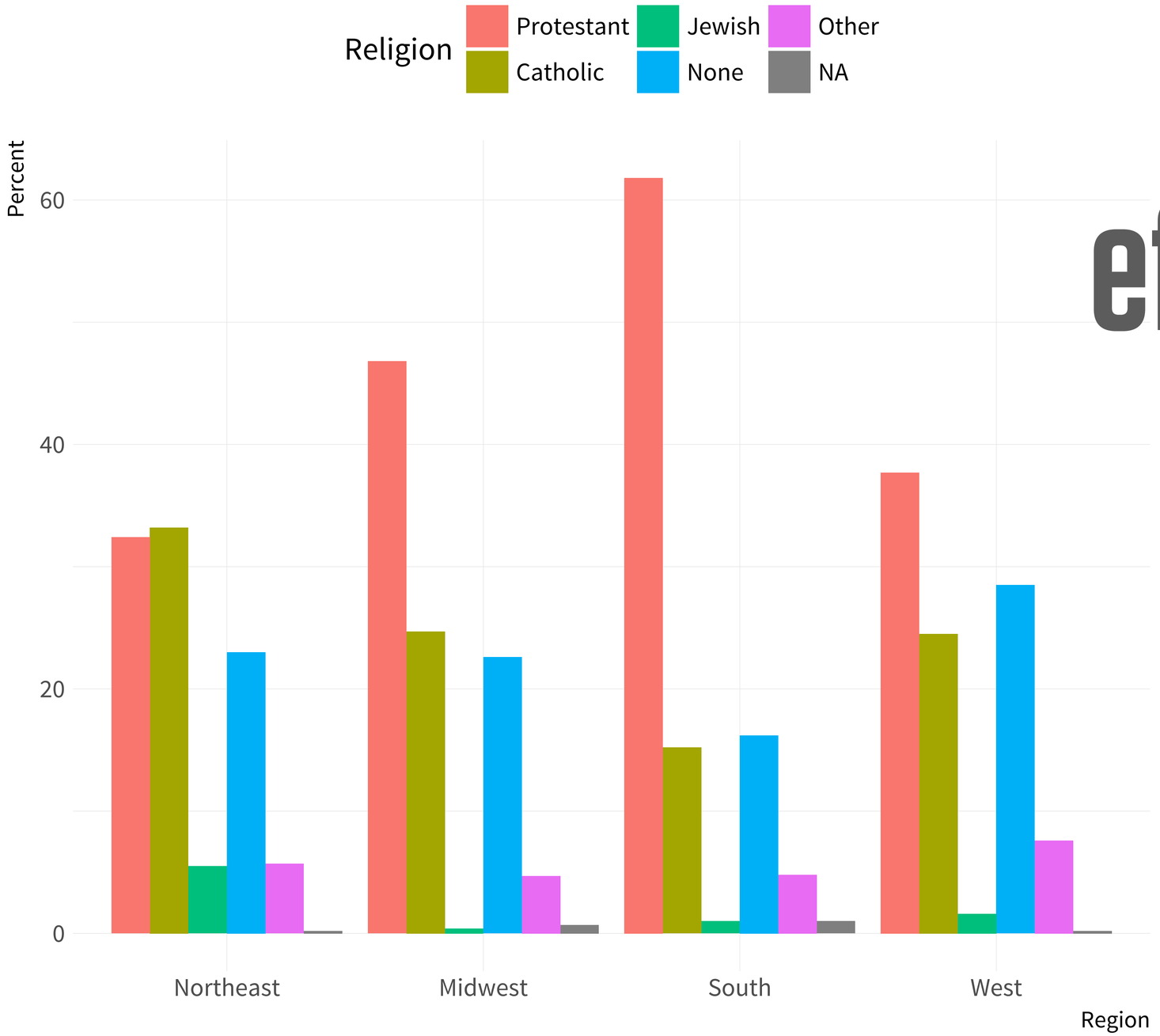
Pipelined tables are easier to check for errors

```r
p <- ggplot(data = rel_by_region,
            mapping = aes(x = bigregion,
                          y = pct,
                          fill = religion))
p + geom_col(position = "dodge") +
    labs(x = "Region",
         y = "Percent",
         fill = "Religion") +
    theme(legend.position = "top")
```

OK, back to making graphs ...



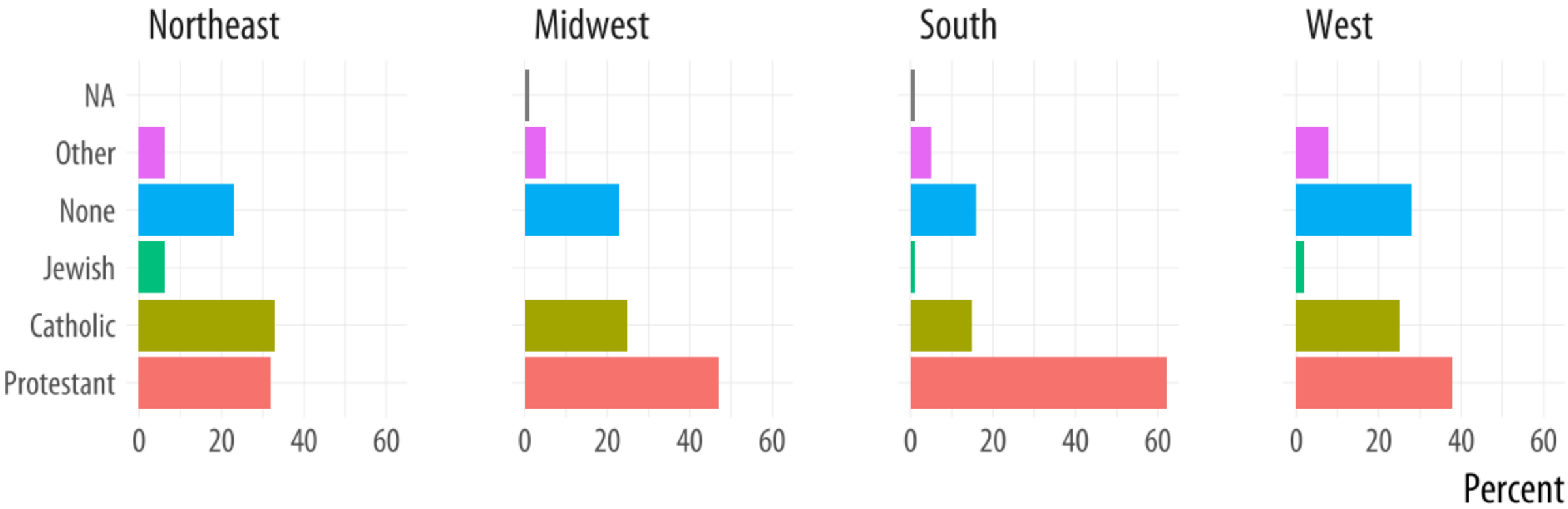
Much easier than doing everything inside ggplot



But is this an effective graph?

Not Really!

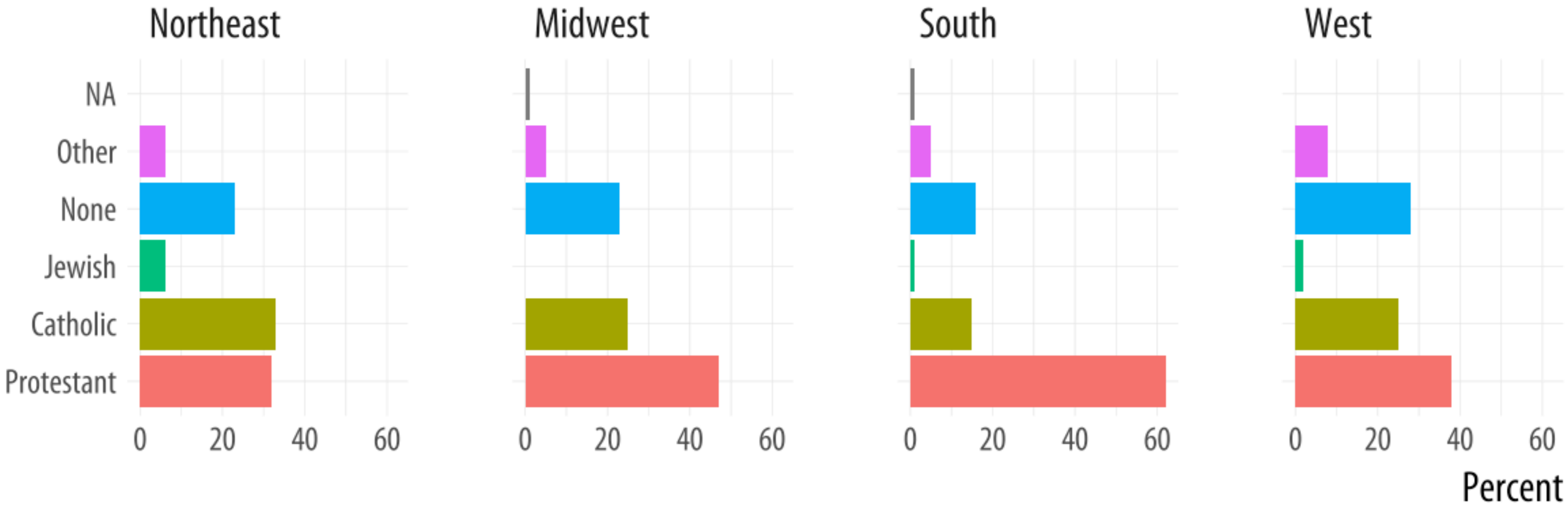
```
p <- ggplot(data = rel_by_region,
            mapping = aes(x = pct, y = religion, fill = religion))
p + geom_col() +
    labs(x = "Percent", y = NULL) +
    guides(fill = FALSE) +
    facet_wrap(~ bigregion, nrow = 1)
```



Try putting categories on the y-axis

Try faceting variables instead of mapping them

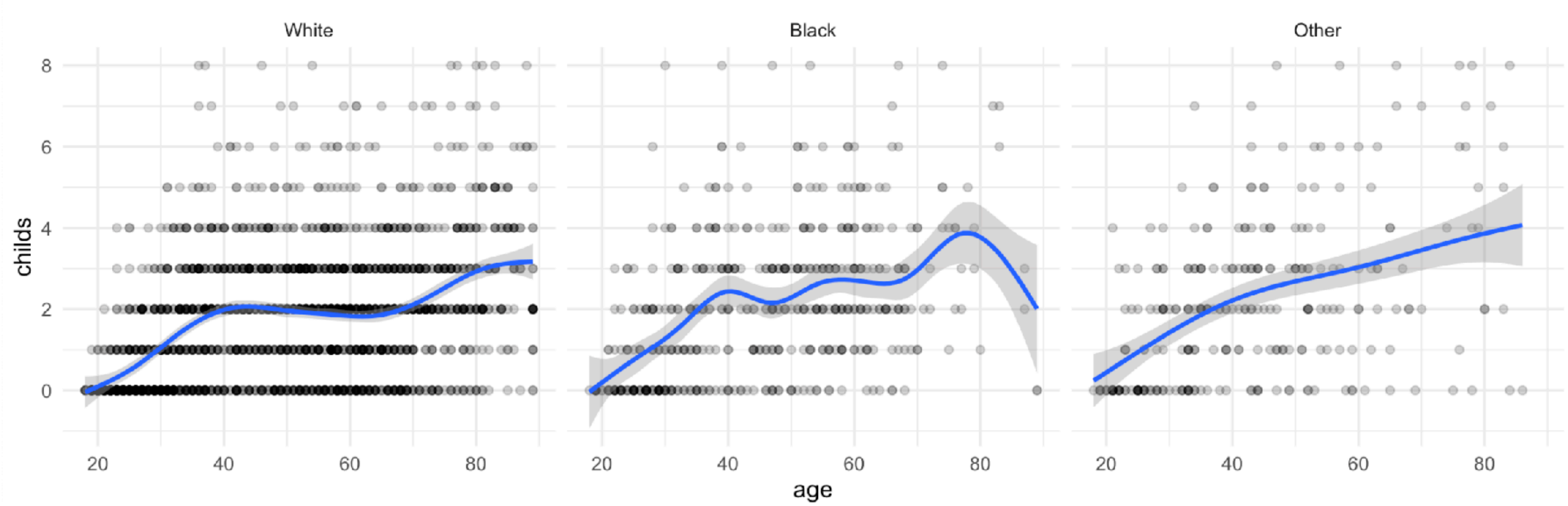
Try to minimize the need for guides and legends



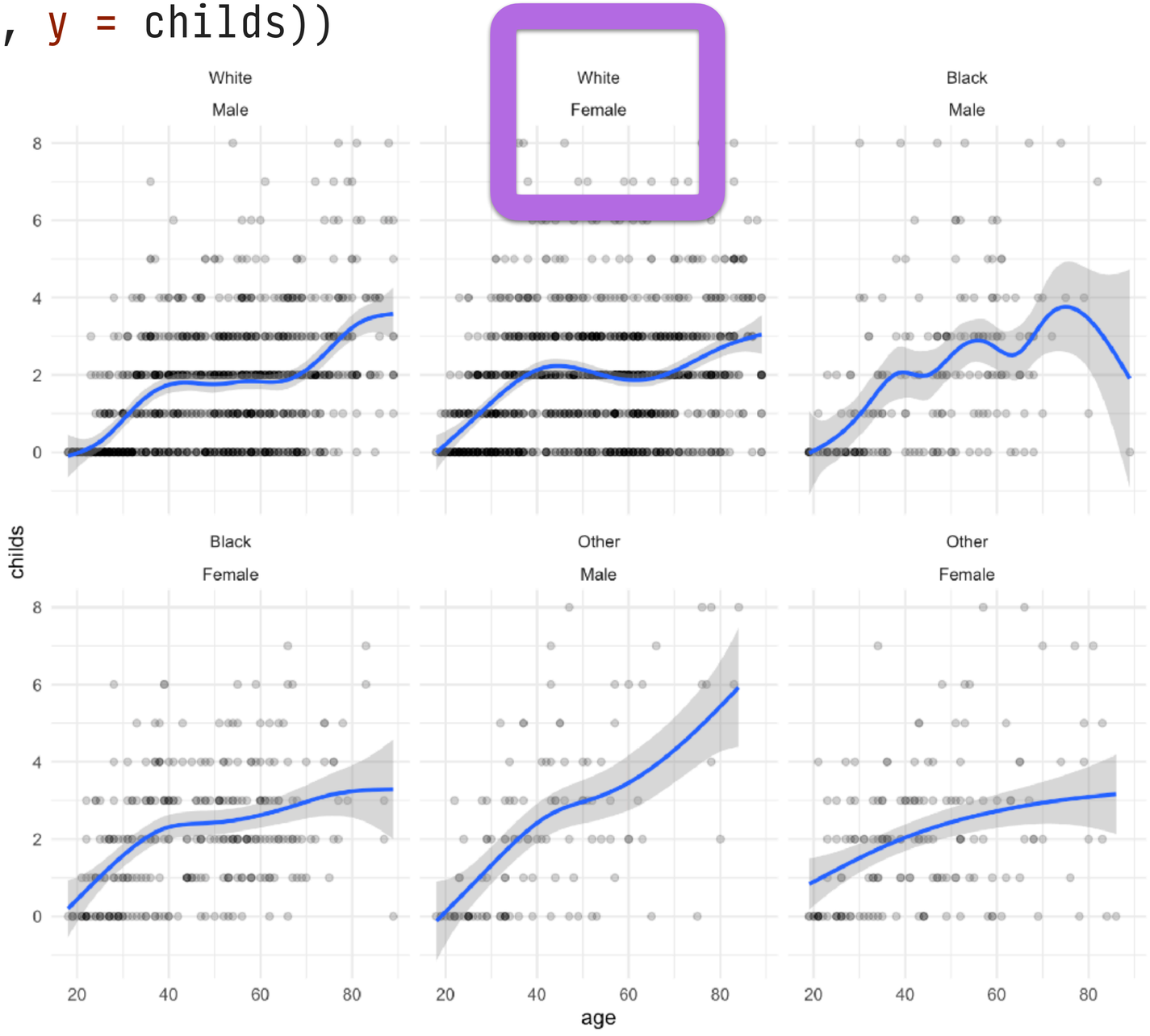
Two kinds of facet

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

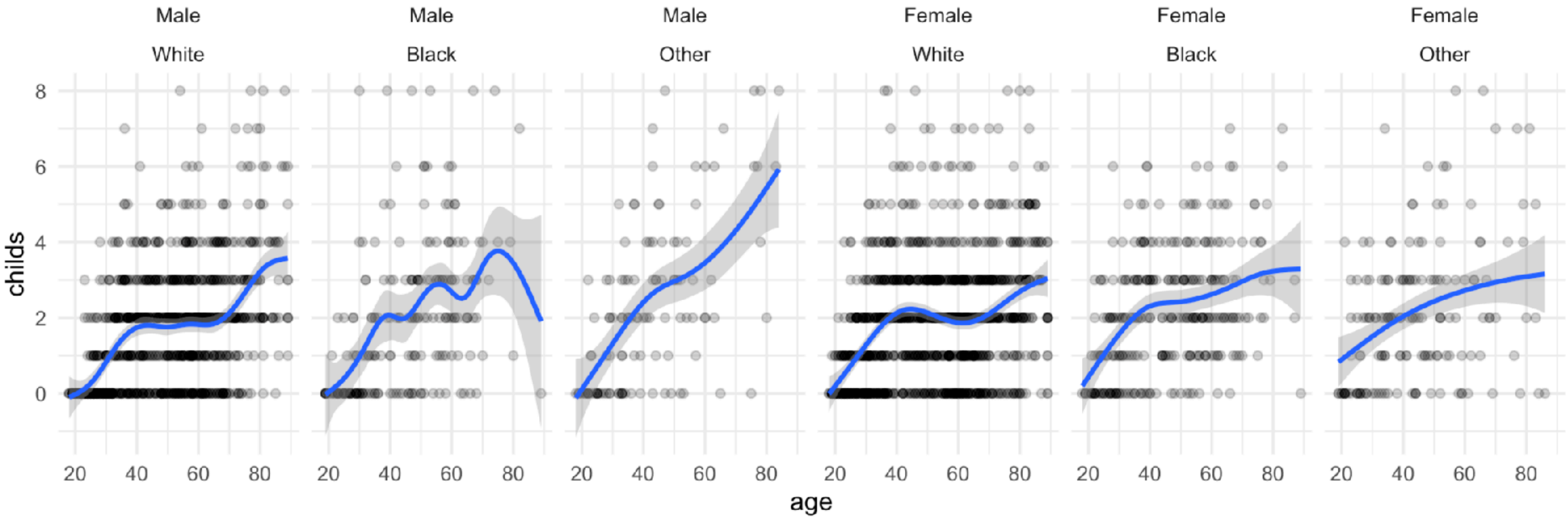
The formula syntax isn't limited to one variable



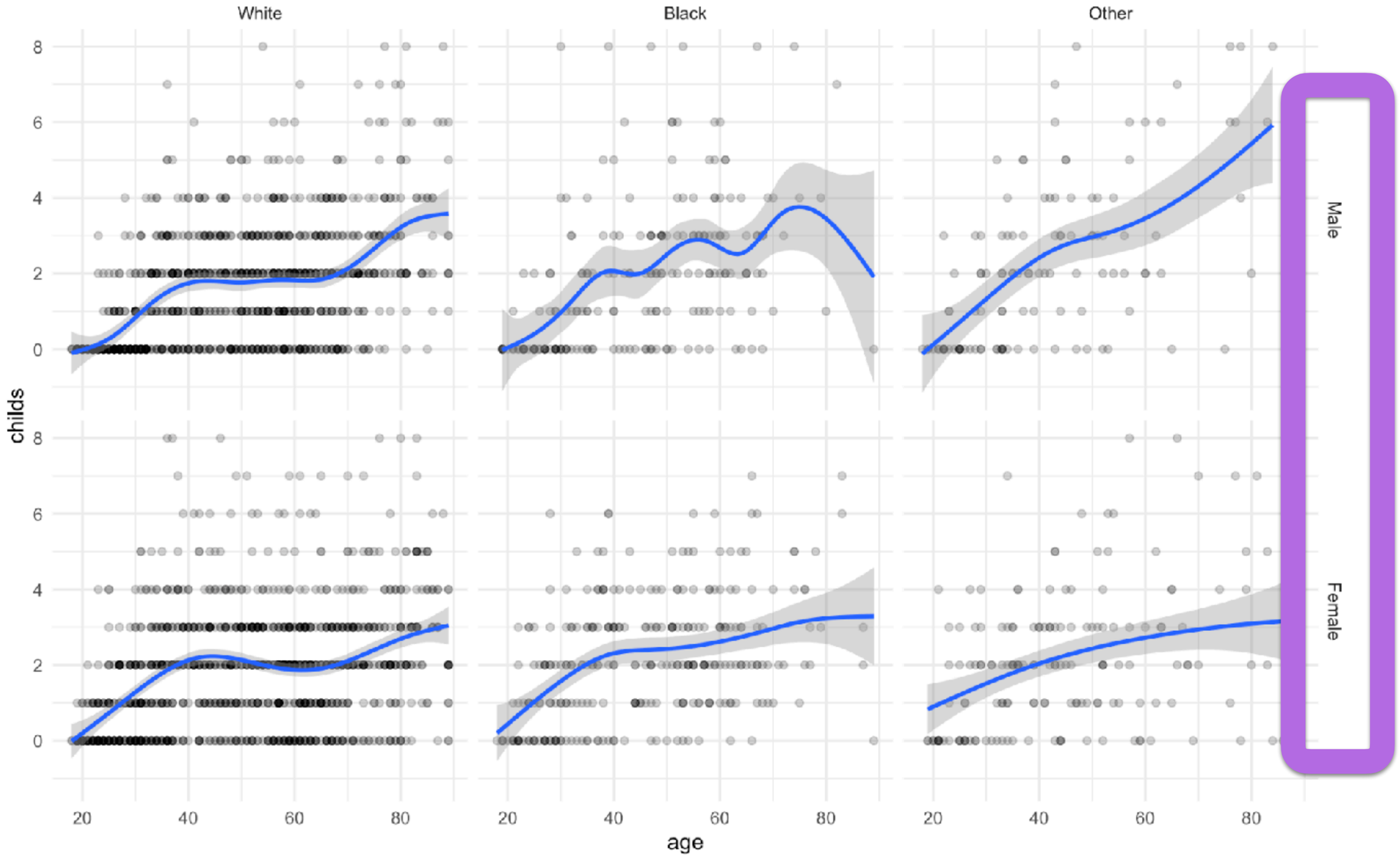
```r
p <- ggplot(data = gss_sm,
            mapping = aes(x = age, y = childs))
p + geom_point(alpha = 0.2) +
    geom_smooth() +
    facet_wrap(~ sex + race)
```



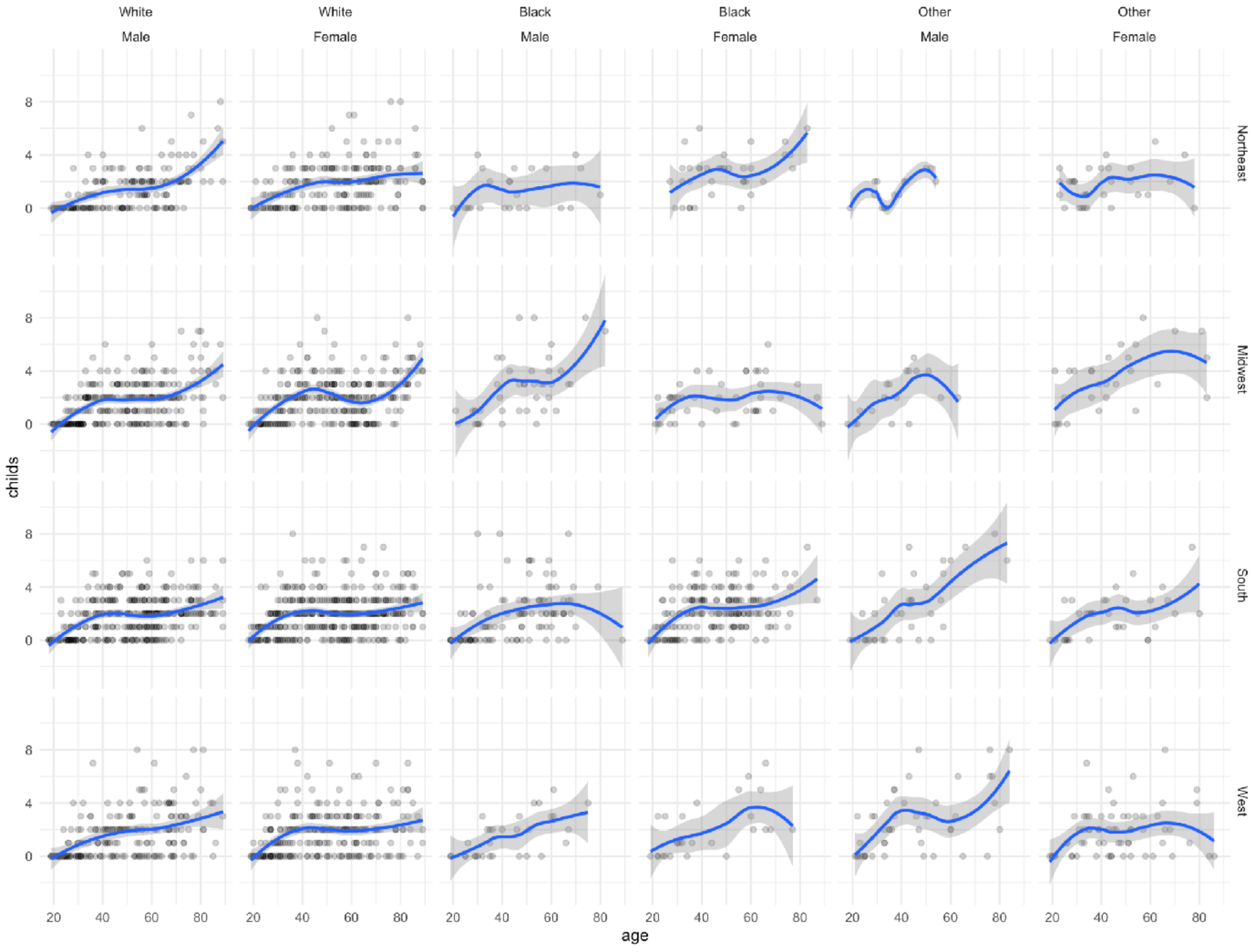
```r
p <- ggplot(data = gss_sm, mapping = aes(x = age, y = childs))
p + geom_point(alpha = 0.2) +
    geom_smooth() + facet_wrap(~ sex + race, nrow = 1)
```



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



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

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

```
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()
```

```
geom_point()
```

```
geom_line()
```

```
geom_smooth()
```

```
geom_bar()
```

```
geom_histogram()
```

```
geom_density()
```

```
geom_boxplot()
```

EXTENDING YOUR VOCABULARY

THE ORGAN DONATION DATA

```
organdata %>% select(1:6) %>% sample_n(size = 10)
```

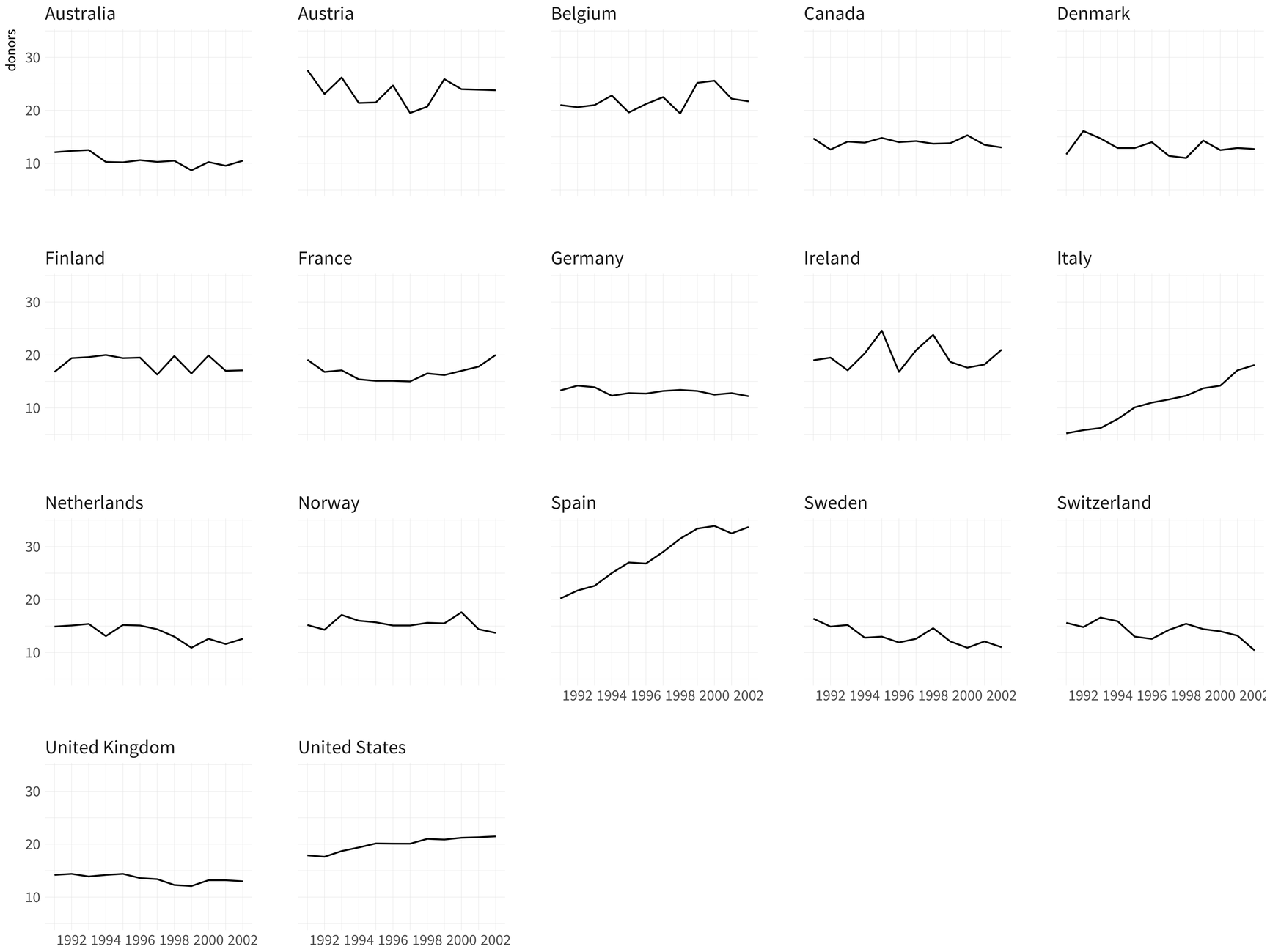
```
## # A tibble: 10 x 6
##    country        year       donors   pop pop_dens   gdp
##    <chr>          <date>      <dbl> <int>    <dbl> <int>
##  1 Switzerland    NA             NA    NA       NA    NA
##  2 Switzerland    1997-01-01   14.3  7089     17.2  27675
##  3 United Kingdom 1997-01-01   13.4 58283     24.0  22442
##  4 Sweden         NA             NA  8559      1.90 18660
##  5 Ireland        2002-01-01   21.0  3932      5.60 32571
##  6 Germany        1998-01-01   13.4 82047     23.0  23283
##  7 Italy          NA             NA 56719     18.8  17430
##  8 Italy          2001-01-01   17.1 57894     19.2  25359
##  9 France         1998-01-01   16.5 58398     10.6  24044
## 10 Spain          1995-01-01   27.0 39223      7.75 15720
```

Everyday use of dplyr and pipes

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

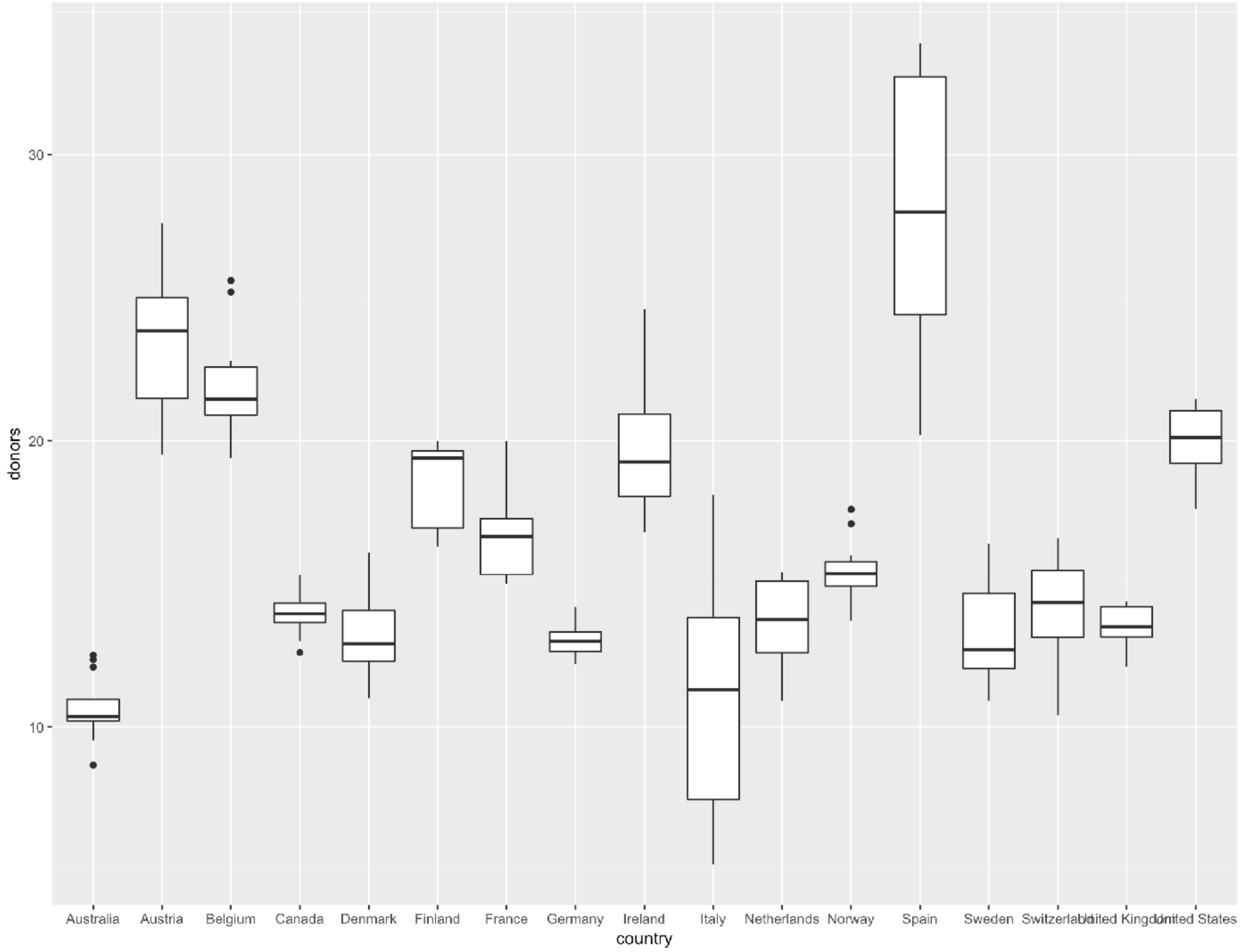
```
## Warning: Removed 34 rows containing missing values
## (geom_point).
```

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


Australia
Austria
Belgium
Canada
Denmark
Finland
France
Germany
Ireland
Italy
Netherlands
Norway
Spain
Sweden
Switzerland
United Kingdom
United States
donors
30
20
10
1992 1994 1996 1998 2000 2002
year

Continuous Variables by Categories

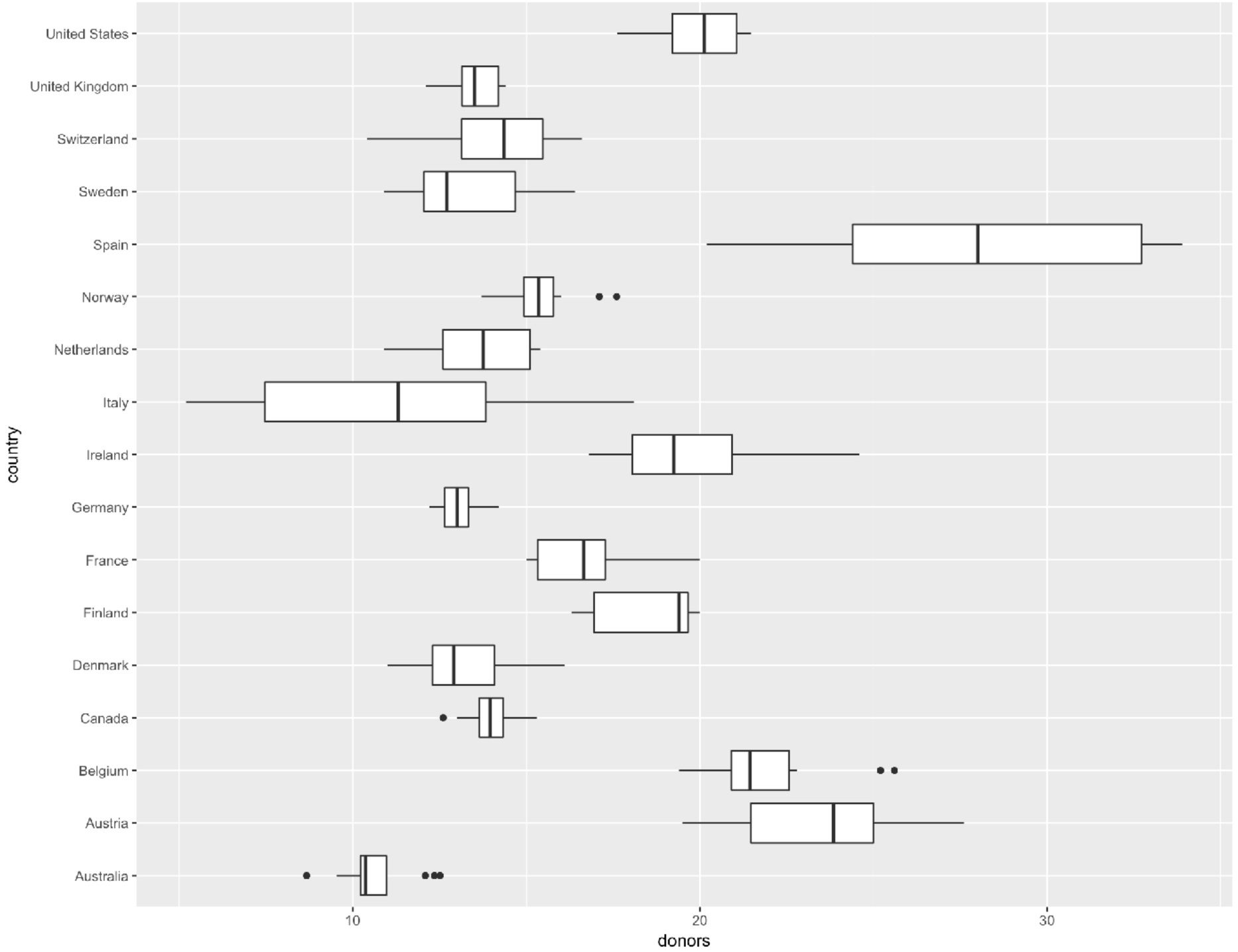
```r
p <- ggplot(data = organdata,
            mapping = aes(x = country, y = donors))

p + geom_boxplot()
```


donors
30
20
10
Australia
Austria
Belgium
Canada
Denmark
Finland
France
Germany
Ireland
Italy
Netherlands
Norway
Spain
Sweden
Switzerland
United Kingdom
United States
country

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

p + geom_boxplot() + coord_flip()
```

Explicit use of a coordinate system transformation.

This used to be required to get geom_boxplot() to work with categorical variables on the y-axis, but this is no longer true. I'm using it here just to emphasize that coordinate systems are part of the grammar, even if we don't usually see them explicitly. In everyday use, just say x = donors, y = country


United States
United Kingdom
Switzerland
Sweden
Spain
Norway
Netherlands
Italy
Ireland
Germany
France
Finland
Denmark
Canada
Belgium
Austria
Australia
country
10
20
30
donors

variable

default is mean()

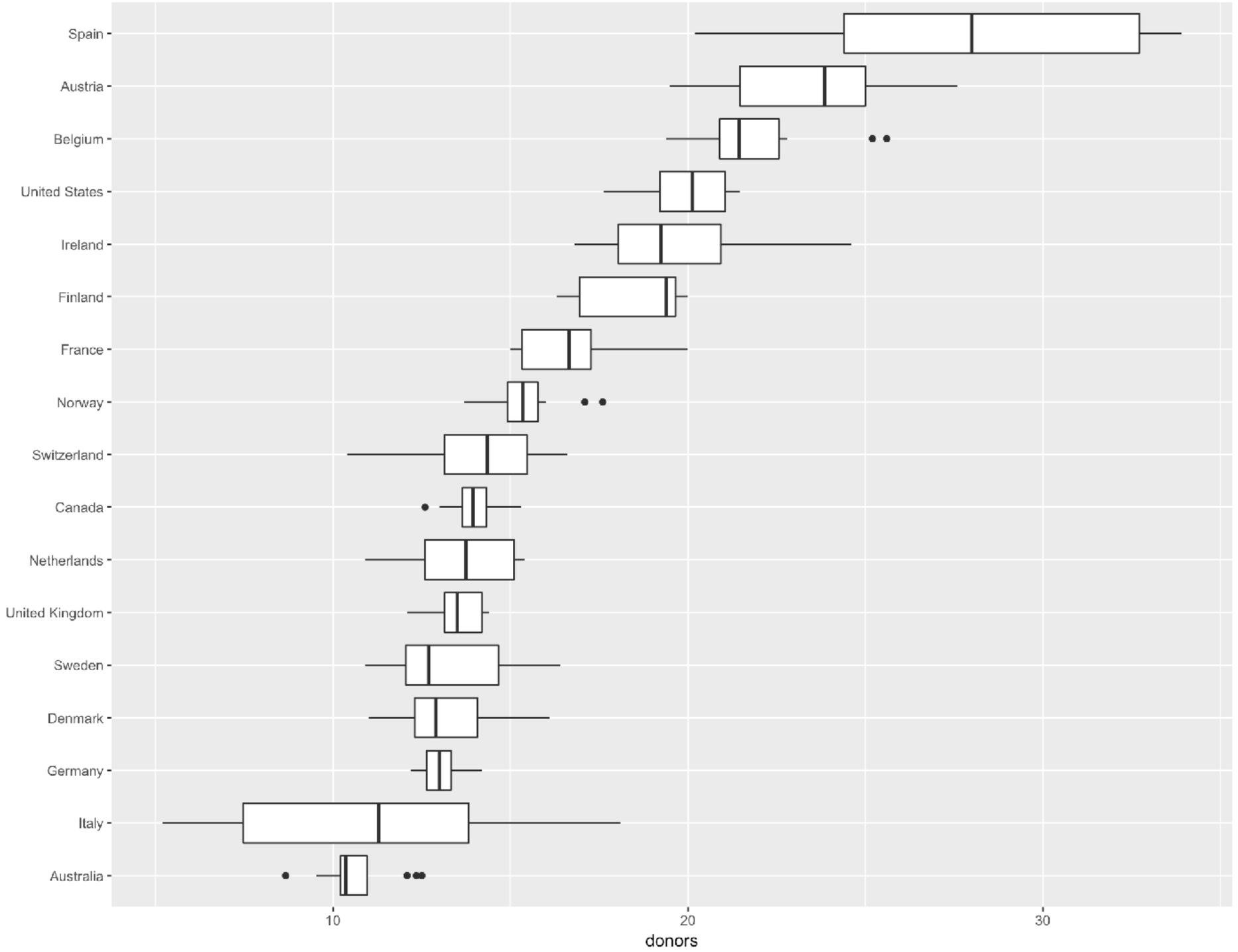
```
p <- ggplot(data = organdata,
            mapping = aes(x = reorder(country, donors, na.rm=TRUE),
                          y = donors))
```

by

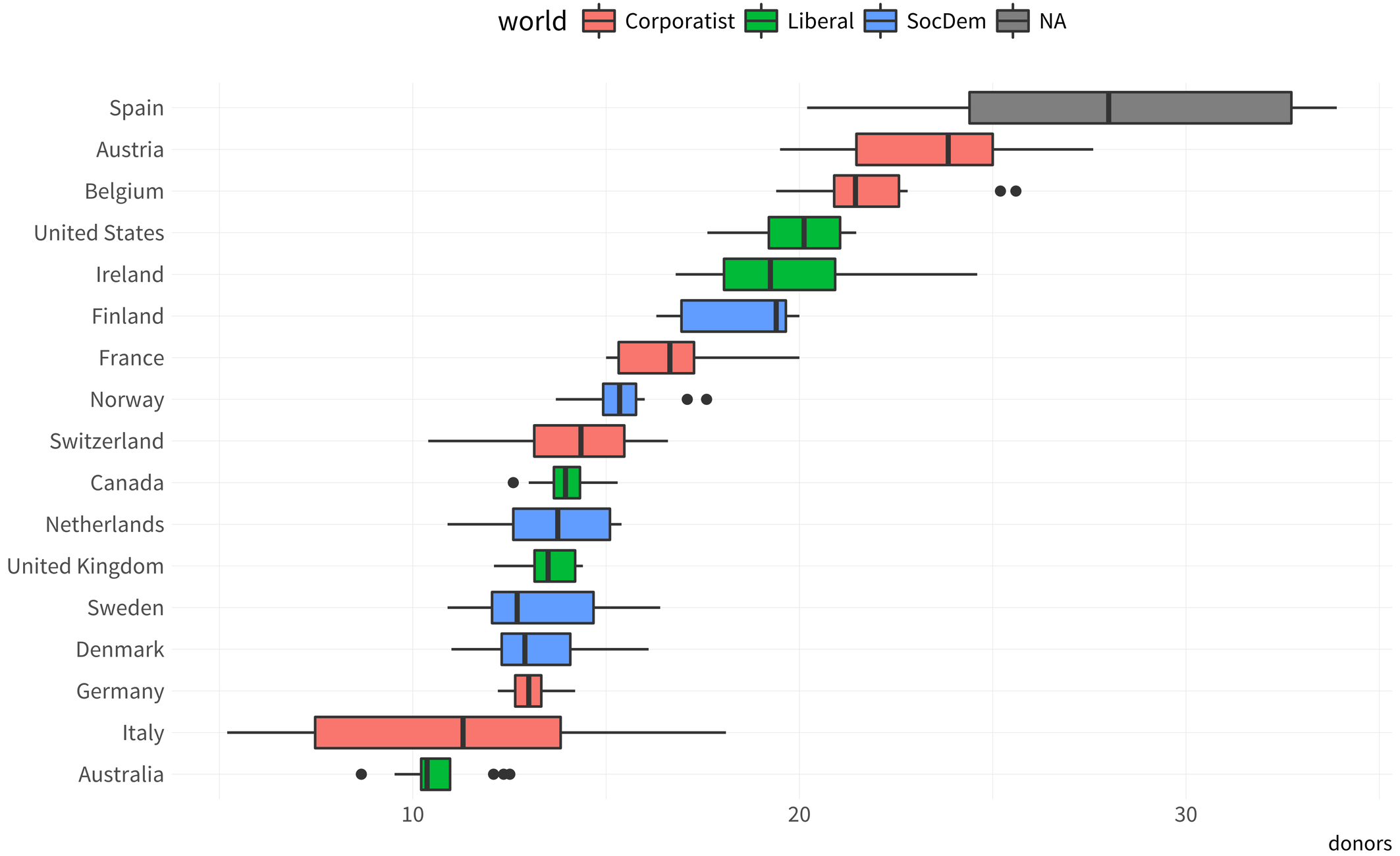
passed to mean()

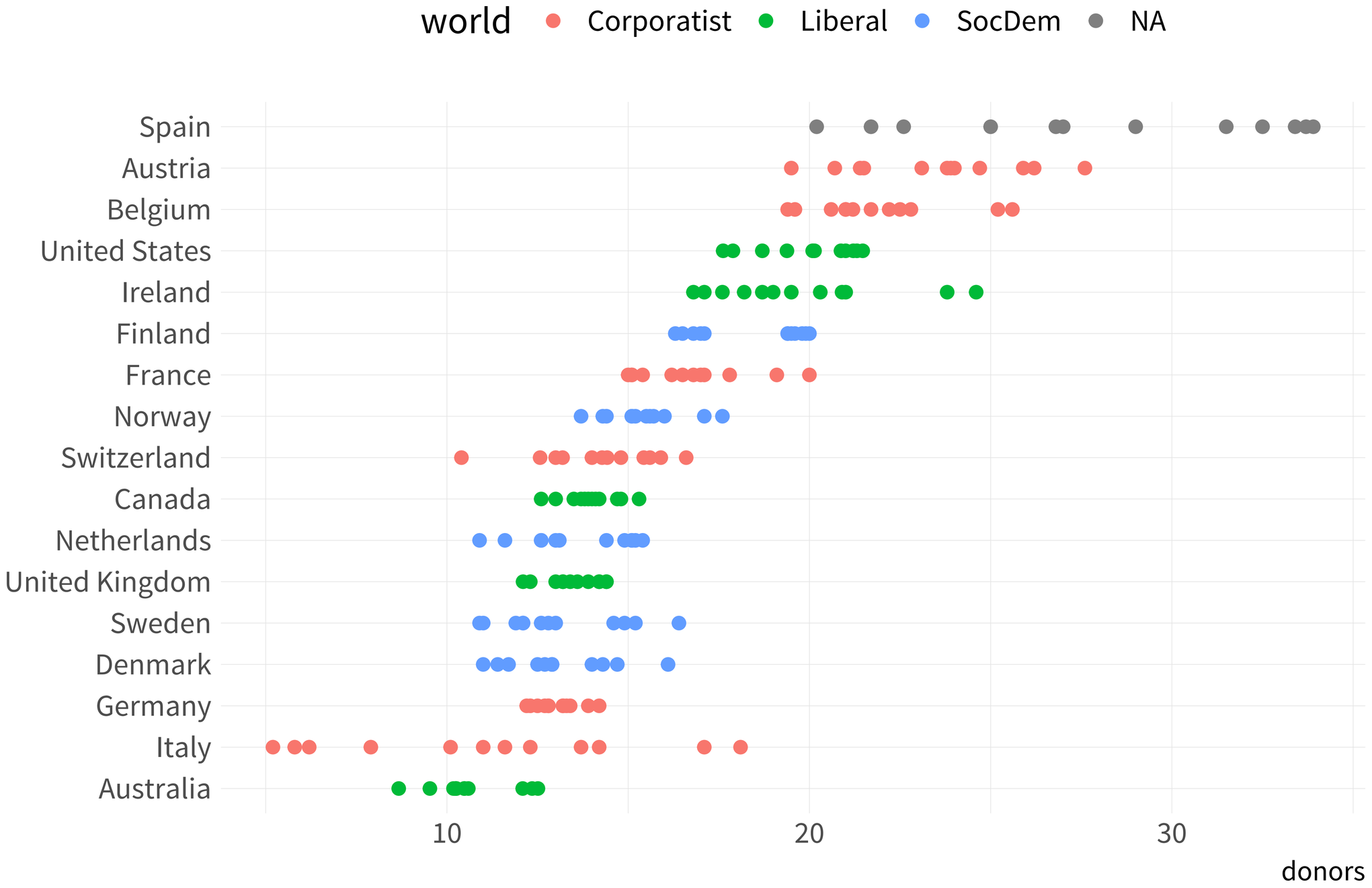
```
p + geom_boxplot() + labs(x = NULL) + coord_flip()
```

reorder() your data in a sensible way


Spain
Austria
Belgium
United States
Ireland
Finland
France
Norway
Switzerland
Canada
Netherlands
United Kingdom
Sweden
Denmark
Germany
Italy
Australia
10
20
30
donors

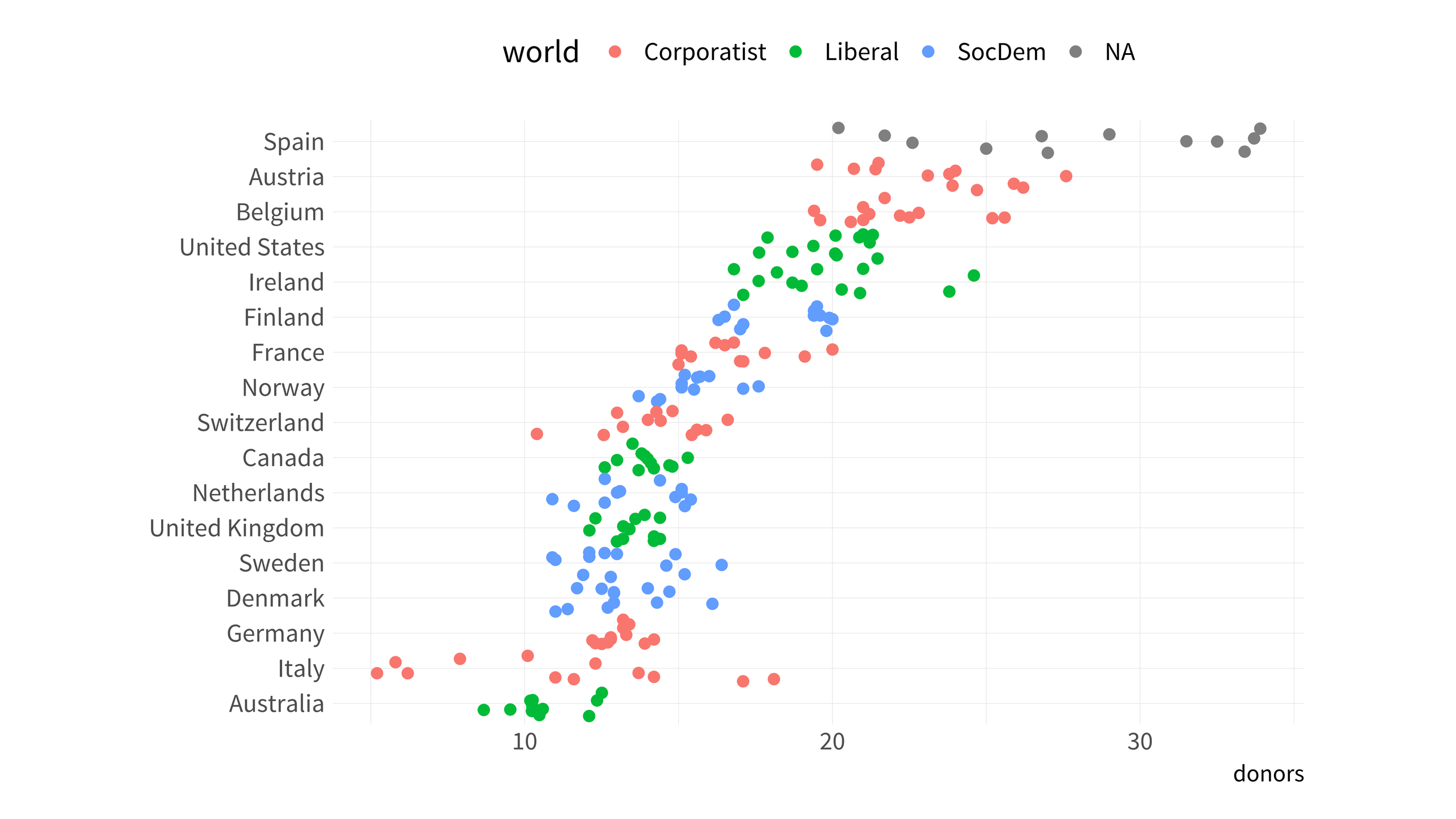
```r
p <- ggplot(data = organdata,
            mapping = aes(x = reorder(country, donors, na.rm=TRUE),
                          y = donors,
                          fill = world))

p + geom_boxplot() + labs(x=NULL) +
    coord_flip() + theme(legend.position = "top")
```


world
Corporatist
Liberal
SocDem
NA
Spain
Austria
Belgium
United States
Ireland
Finland
France
Norway
Switzerland
Canada
Netherlands
United Kingdom
Sweden
Denmark
Germany
Italy
Australia
10
20
30
donors


world
Corporatist
Liberal
SocDem
NA
Spain
Austria
Belgium
United States
Ireland
Finland
France
Norway
Switzerland
Canada
Netherlands
United Kingdom
Sweden
Denmark
Germany
Italy
Australia
10
20
30
donors

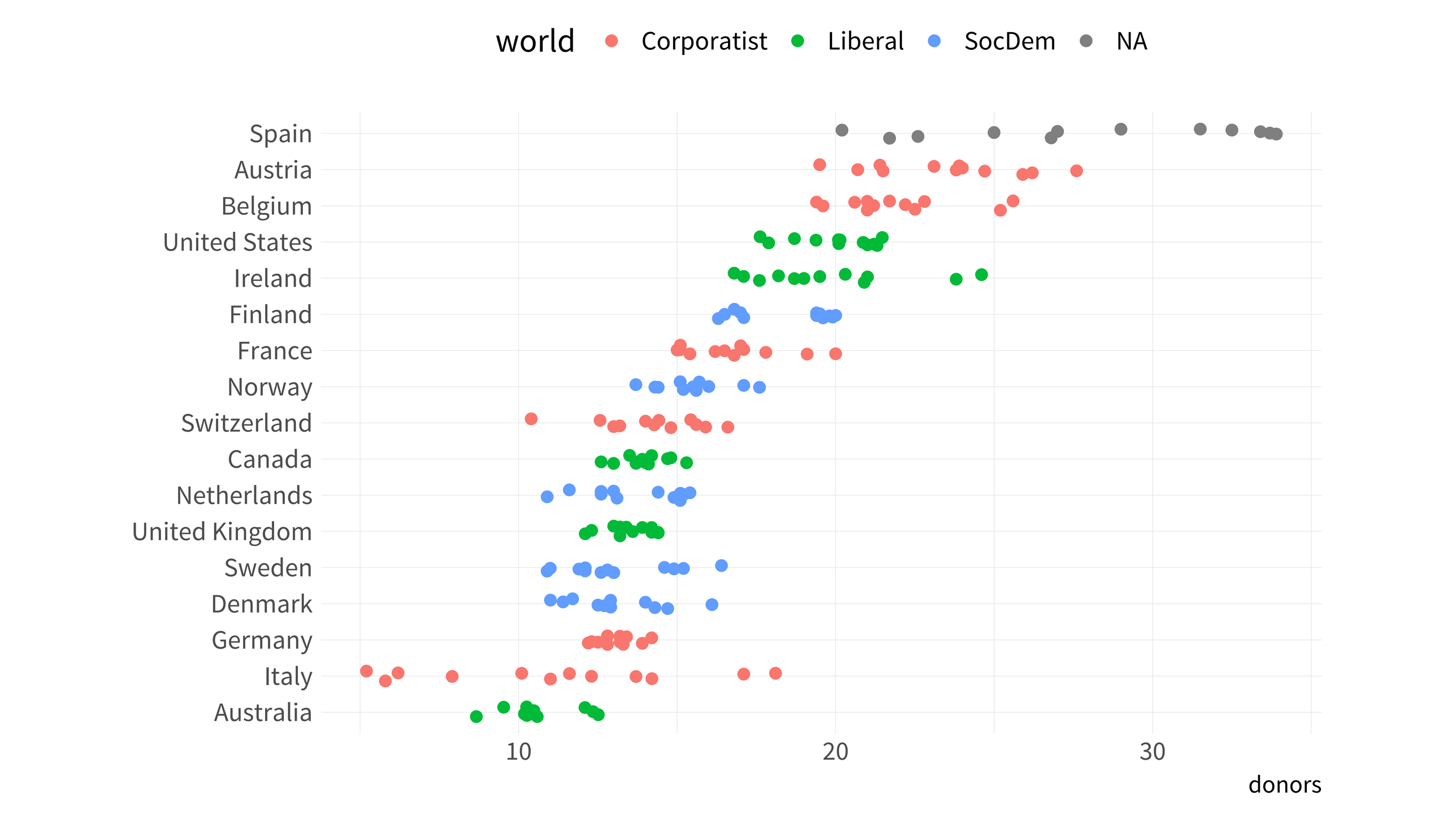
```
p <- ggplot(data = organdata,
            mapping = aes(x = reorder(country, donors, na.rm=TRUE),
                          y = donors, color = world))

p + geom_jitter() + labs(x=NULL) +
    coord_flip() + theme(legend.position = "top")
```

geom_jitter() can help with overplotting


world
Corporatist
Liberal
SocDem
NA
Spain
Austria
Belgium
United States
Ireland
Finland
France
Norway
Switzerland
Canada
Netherlands
United Kingdom
Sweden
Denmark
Germany
Italy
Australia
10
20
30
donors

```
p <- ggplot(data = organdata,
            mapping = aes(x = reorder(country, donors, na.rm=TRUE),
                          y = donors, color = world))

p + geom_jitter(position = position_jitter(width=0.15)) +
    labs(x=NULL) +
    coord_flip() +
    theme(legend.position = "top")
```

geom_jitter() can help with overplotting


world
Corporatist
Liberal
SocDem
NA
Spain
Austria
Belgium
United States
Ireland
Finland
France
Norway
Switzerland
Canada
Netherlands
United Kingdom
Sweden
Denmark
Germany
Italy
Australia
10
20
30
donors

SUMMARIZE BETTER WITH dplyr

```r
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(gdp, na.rm = TRUE),
              health = mean(health, na.rm = TRUE),
              roads_mean = mean(roads_mean, na.rm = TRUE),
              cerebvas = mean(cerebvas, na.rm = TRUE))
```

This direct method works fine, But there's lots of code repetition

```
by_country
```

```
## Source: local data frame [17 x 8]
## Groups: consent_law [?]
##
## # A tibble: 17 x 8
##    consent_law        country donors_mean donors_sd   gdp health roads_mean cerebvas
##          <chr>          <chr>       <dbl>     <dbl> <dbl>  <dbl> <dbl>      <dbl>
##  1    Informed      Australia          11       1.1 22179   1958   105        558
##  2    Informed         Canada          14       0.8 23711   2272   109        422
##  3    Informed        Denmark          13       1.5 23722   2054   102        641
##  4    Informed        Germany          13       0.6 22163   2349   113        707
##  5    Informed        Ireland          20       2.5 20824   1480   118        705
##  6    Informed    Netherlands          14       1.6 23013   1993    76        585
##  7    Informed United Kingdom          13       0.8 21359   1561    68        708
##  8    Informed  United States          20       1.3 29212   3988   155        444
##  9    Presumed        Austria          24       2.4 23876   1875   150        769
## 10    Presumed        Belgium          22       1.9 22500   1958   155        594
## 11    Presumed        Finland          18       1.5 21019   1615    94        771
## 12    Presumed         France          17       1.6 22603   2160   156        433
## 13    Presumed          Italy          11       4.3 21554   1757   122        712
## 14    Presumed         Norway          15       1.1 26448   2217    70        662
## 15    Presumed          Spain          28       5.0 16933   1289   161        655
## 16    Presumed         Sweden          13       1.8 22415   1951    72        595
## 17    Presumed    Switzerland          14       1.7 27233   2776    96        424
```

Use across() and where() instead

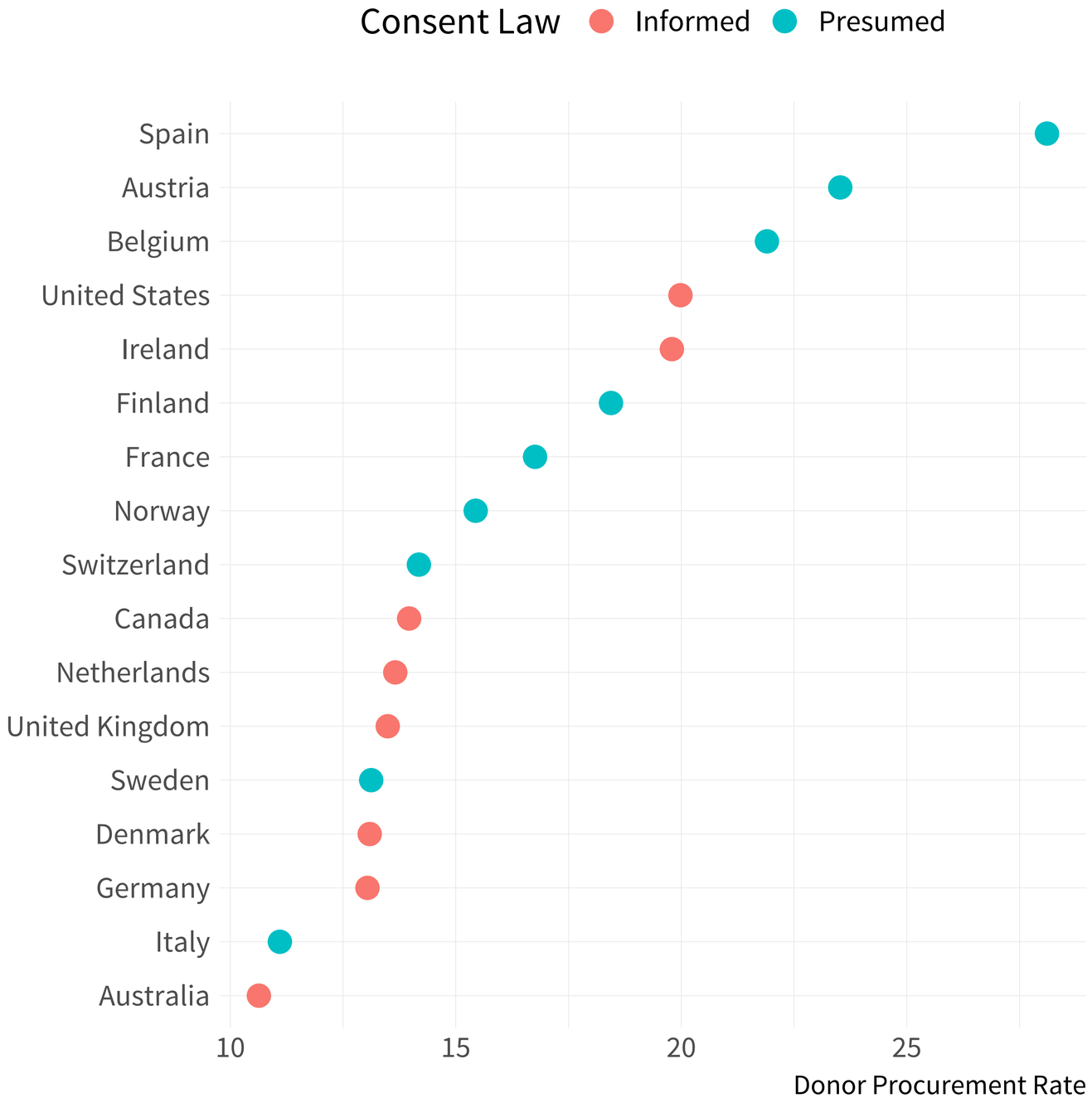
```
by_country <- organdata %>%
  group_by(consent_law, country) %>%
    summarize(across(where(is.numeric),
                     list(mean = mean,
                          sd = sd),
                      na.rm = TRUE,
                      .names = "{col}_{fn}"),
                .groups = "drop")
```

{col} and {fn} are placeholders or templates to name "the specific column currently being summarized" and "the specific function being applied from the list"

```
by_country
```

```
# A tibble: 17 x 28
   consent_law country    donors_mean donors_sd pop_mean pop_sd pop_dens_mean pop_dens_sd
   <chr>       <chr>            <dbl>     <dbl>    <dbl>  <dbl>         <dbl>       <dbl>
 1 Informed    Australia         10.6     1.14    18318. 8.31e2         0.237      0.0107
 2 Informed    Canada            14.0     0.751   29608. 1.19e3         0.297      0.0120
 3 Informed    Denmark           13.1     1.47     5257. 8.06e1        12.2        0.187
 4 Informed    Germany           13.0     0.611   80255. 5.16e3        22.5        1.44
 5 Informed    Ireland           19.8     2.48     3674. 1.32e2         5.23       0.187
 6 Informed    Netherlan…        13.7     1.55    15548. 3.73e2        37.4        0.898
 7 Informed    United Ki…        13.5     0.775   58187. 6.26e2        24.0        0.258
 8 Informed    United St…        20.0     1.33   269330. 1.25e4         2.80       0.130
 9 Presumed    Austria           23.5     2.42     7927. 1.09e2         9.45       0.130
10 Presumed    Belgium           21.9     1.94    10153. 1.09e2        30.7        0.330
11 Presumed    Finland           18.4     1.53     5112. 6.86e1         1.51       0.0203
12 Presumed    France            16.8     1.60    58056. 8.51e2        10.5        0.154
13 Presumed    Italy             11.1     4.28    57360. 4.25e2        19.0        0.141
14 Presumed    Norway            15.4     1.11     4386. 9.73e1         1.35       0.0300
15 Presumed    Spain             28.1     4.96    39666. 9.51e2         7.84       0.188
16 Presumed    Sweden            13.1     1.75     8789. 1.14e2         1.95       0.0253
17 Presumed    Switzerla…        14.2     1.71     7037. 1.70e2        17.0        0.411
# … with 20 more variables: 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>
```

```r
p <- ggplot(data = by_country,
            mapping = aes(x = donors_mean,
                y = reorder(country, donors_mean),
                color = consent_law))

p + geom_point(size = 3) +
    labs(x = "Donor Procurement Rate",
         y = NULL,
         color = "Consent Law") +
    theme(legend.position = "top")
```


Consent Law
Informed
Presumed
Spain
Austria
Belgium
United States
Ireland
Finland
France
Norway
Switzerland
Canada
Netherlands
United Kingdom
Sweden
Denmark
Germany
Italy
Australia
10
15
20
25
Donor Procurement Rate

```r
p <- ggplot(data = by_country,
            mapping = aes(x = donors_mean,
                          y = reorder(country,
                                      donors_mean)))

p + geom_point(size=3) +
    facet_wrap(~ consent_law) +
    labs(x = "Donor Procurement Rate",
         y = NULL)
```

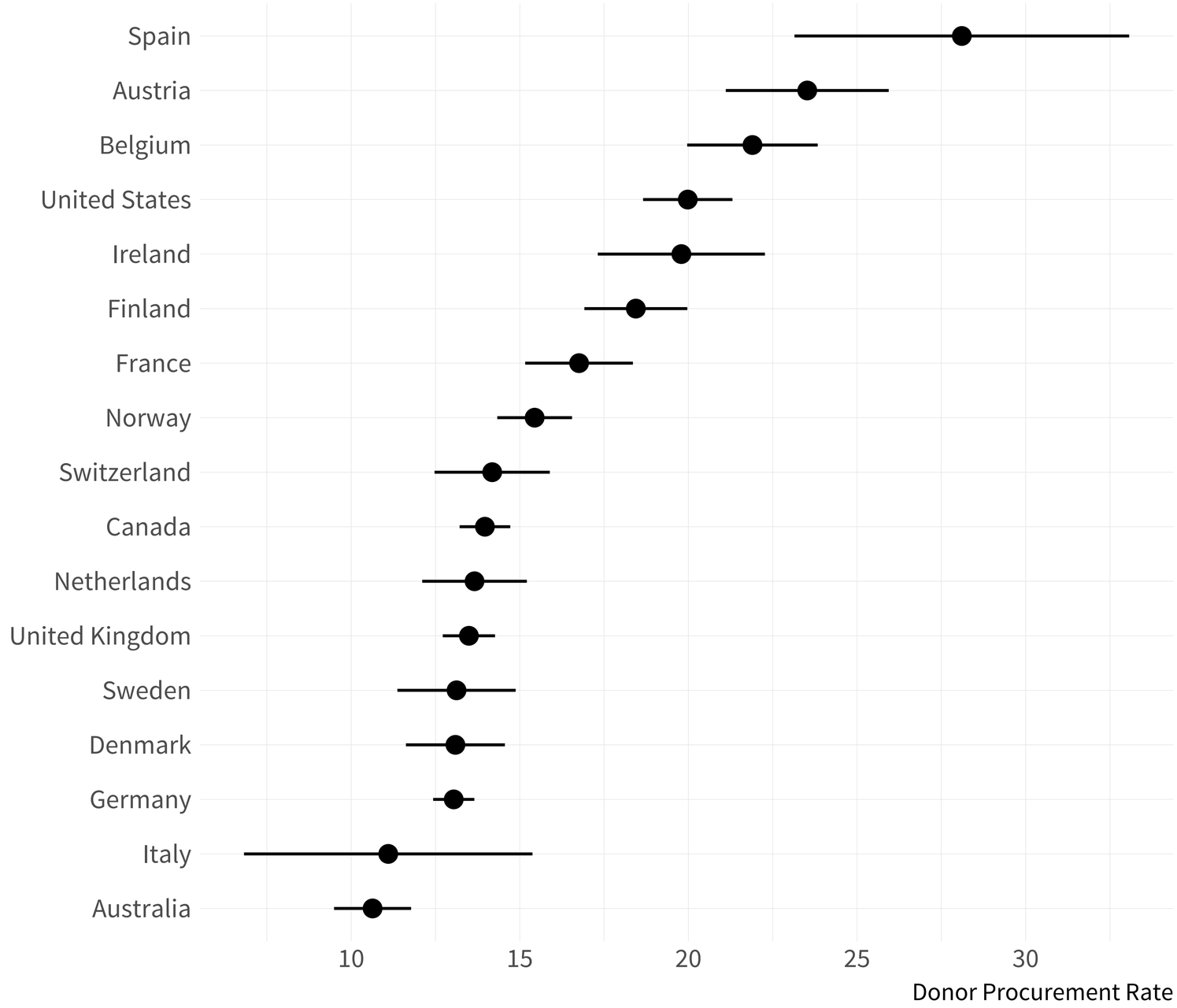
```r
p <- ggplot(data = by_country,
            mapping = aes(x = donors_mean,
                          y = reorder(country,
                                      donors_mean)))
```

```r
p + geom_point(size=3) +
    facet_wrap(~ consent_law, scales = "free_y") +
    labs(x= "Donor Procurement Rate",
         y= NULL)
```

```r
p <- ggplot(data = by_country,
            mapping = aes(x = donors_mean,
                y = reorder(country, donors_mean)))


p + geom_point(size=3) +
    facet_wrap(~ consent_law,
                scales = "free_y", ncol = 1) +
    labs(x = "Donor Procurement Rate",
         y = NULL)
```


Informed
United States
Ireland
Canada
Netherlands
United Kingdom
Denmark
Germany
Australia
Presumed
Spain
Austria
Belgium
Finland
France
Norway
Switzerland
Sweden
Italy
10
15
20
25
Donor Procurement Rate

```r
p <- ggplot(data = by_country,
            mapping = aes(x = reorder(country, donors_mean),
                          y = donors_mean))

p + geom_pointrange(mapping = aes(xmin = donors_mean - donors_sd,
                                  xmax = donors_mean + donors_sd)) +
    labs(x = "Donor Procurement Rate", y = NULL)
```


Spain
Austria
Belgium
United States
Ireland
Finland
France
Norway
Switzerland
Canada
Netherlands
United Kingdom
Sweden
Denmark
Germany
Italy
Australia
10
15
20
25
30
Donor Procurement Rate

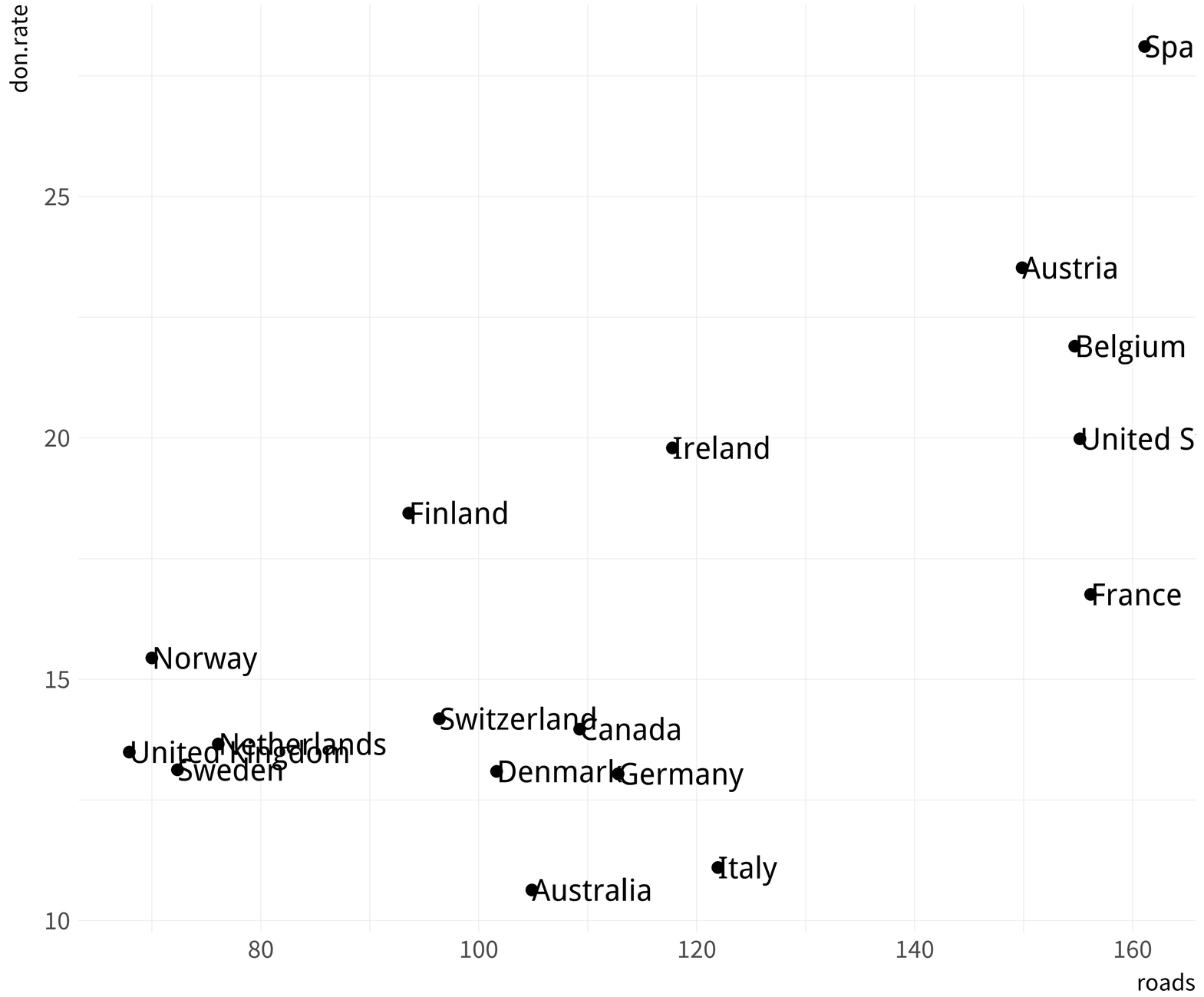
PLOTTING TEXT DIRECTLY

```
geom_text(mapping = aes(label = <VARIABLE>))
```

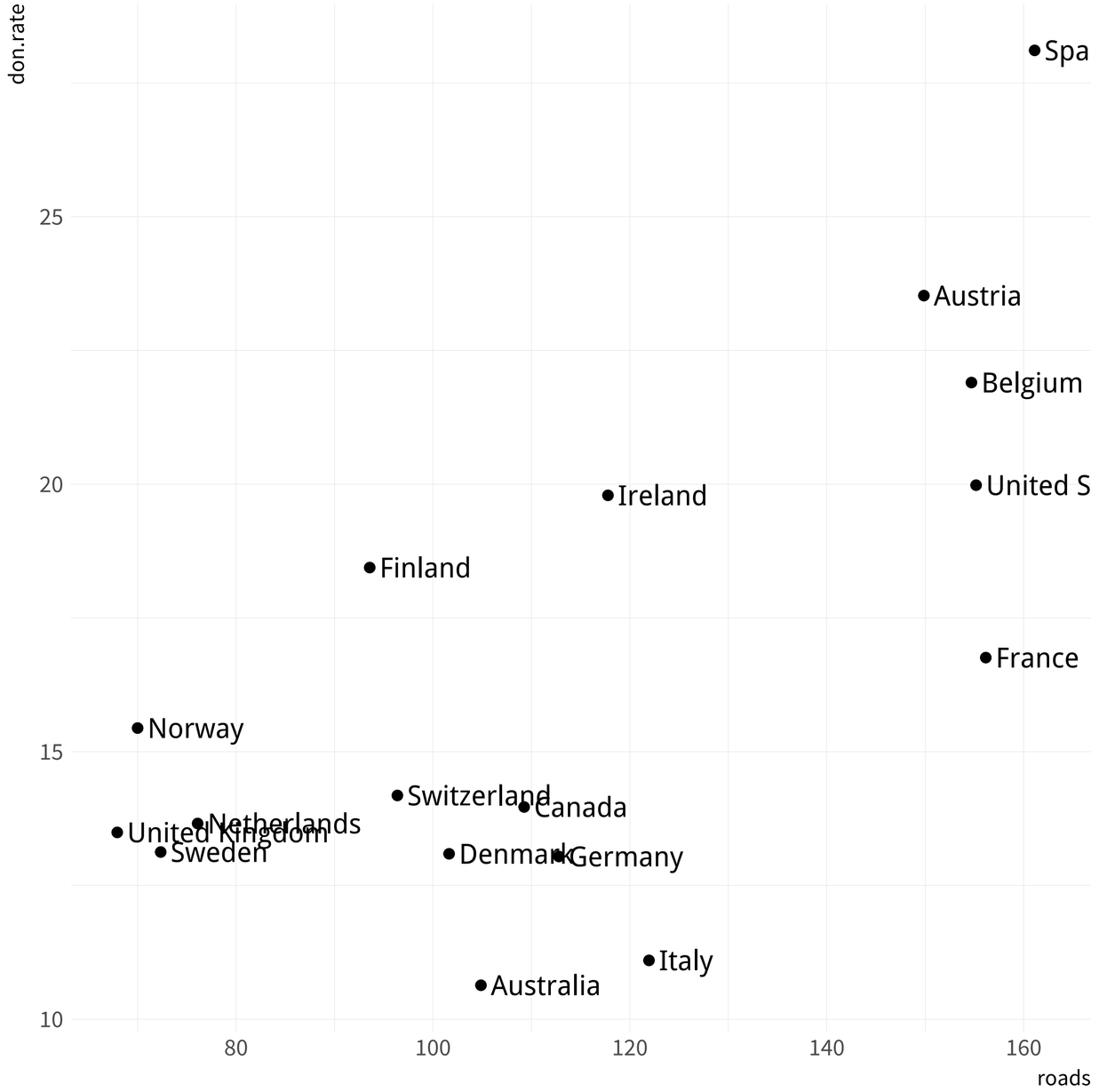
```
p <- ggplot(data = by_country,
            mapping = aes(x = roads_mean, y = donors_mean))

p + geom_point() +
    geom_text(mapping = aes(label = country))
```


don.rate
25
20
15
10
80
100
120
140
160
roads
Spain
Austria
Belgium
United States
Ireland
Finland
France
Norway
Switzerland
Canada
Netherlands
ed Kingdom
Sweden
Denmark
Germany
Italy
Australia

```
p <- ggplot(data = by_country,
            mapping = aes(x = roads_mean,
                          y = donors_mean))

p + geom_point() + geom_text(mapping = aes(label = country),
                             hjust = 0)
```


don.rate
25
20
15
10
80
100
120
140
160
roads
Spa
Austria
Belgium
United S
Ireland
Finland
France
Norway
Switzerland
Canada
Netherlands
United Kingdom
Sweden
Denmark
Germany
Italy
Australia

```
p <- ggplot(data = by_country,
            mapping = aes(x = roads_mean, y = donors_mean))

p + geom_point() +
    geom_text(mapping = aes(x = roads_mean + 1, label = country),
              hjust = 0)
```


don.rate
25
20
15
10
Spa
Austria
Belgium
United S
Ireland
Finland
France
Norway
Switzerland
Canada
Netherlands
United Kingdom
Sweden
Denmark
Germany
Italy
Australia
80
100
120
140
160
roads

```
library(ggrepel)
```

This package provides geom_text_repel() and geom_label_repel()

```
elections_historic %>% select(2:7)
```

US Elections Data

```
## # A tibble: 49 x 6
##     year                winner win_party ec_pct popular_pct popular_margin
##    <int>                 <chr>     <chr>  <dbl>       <dbl>          <dbl>
##  1  1824      John Quincy Adams     D.-R.  0.322       0.309        -0.1044
##  2  1828         Andrew Jackson      Dem.  0.682       0.559         0.1225
##  3  1832         Andrew Jackson      Dem.  0.766       0.547         0.1781
##  4  1836       Martin Van Buren      Dem.  0.578       0.508         0.1420
##  5  1840 William Henry Harrison      Whig  0.796       0.529         0.0605
##  6  1844             James Polk      Dem.  0.618       0.495         0.0145
##  7  1848         Zachary Taylor      Whig  0.562       0.473         0.0479
##  8  1852        Franklin Pierce      Dem.  0.858       0.508         0.0695
##  9  1856         James Buchanan      Dem.  0.588       0.453         0.1220
## 10  1860        Abraham Lincoln      Rep.  0.594       0.397         0.1013
## # ... with 39 more rows
```

Presidential Elections: Popular & Electoral College Margins

1824-2016

Data for 2016 are provisional.

```
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"
```

Put labels in objects to keep your code tidy

```
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"

theme_set(theme_minimal())
```

Set a theme

Put labels in objects to keep your code tidy

```
 p <- ggplot(data = elections_historic,
             mapping = aes(x = popular_pct,
                           y = ec_pct,
                           label = winner_label))
p + geom_hline(yintercept = 0.5, size = 1.4, color = "gray70") +
    geom_vline(xintercept = 0.5, size = 1.4, color = "gray70") +
    geom_point()
```

Base Layer, Grid Lines, Points

```
p + geom_hline(yintercept = 0.5, size = 1.4, color = "gray70") +
    geom_vline(xintercept = 0.5, size = 1.4, color = "gray70") +
    geom_point() +
    geom_text_repel()
```

Add the textual labels

```r
p + geom_hline(yintercept = 0.5, size = 1.4, color = "gray70") +
    geom_vline(xintercept = 0.5, size = 1.4, color = "gray70") +
    geom_point() +
    geom_text_repel() +
    scale_x_continuous(labels = scales::percent) +
    scale_y_continuous(labels = scales::percent)
```

Add the scale adjustments

```
p + geom_hline(yintercept = 0.5, size = 1.4, color = "gray70") +
    geom_vline(xintercept = 0.5, size = 1.4, color = "gray70") +
    geom_point() +
    geom_text_repel() +
    scale_x_continuous(labels = scales::percent) +
    scale_y_continuous(labels = scales::percent) +
    labs(x = x_label,
         y = y_label,
         title = p_title,
         subtitle = p_subtitle,
         caption = p_caption)
```

Add the scale and guide labels

Presidential Elections: Popular & Electoral College Margins

1824-2016

Data for 2016 are provisional.

Use ggsave

```r
ggsave()

ggsave("my_figure.png")

ggsave("my_figure.pdf")

ggsave("my_figure.pdf",
       plot = p5,
       scale = 1.2)

ggsave("figures/my-figure.pdf",
       plot = p5,
       width = 8,
       height = 5)
```

With pdf() or other graphics devices

```
pdf(file = "plot.pdf", height = 5in,
    width = 5in)
```

Open device ...

```
print(p5)

dev.off()
```

... and close when done

Within an Rmd file using knitr's options

```
```{r electionplot, fig.cap="Popular and Electoral College Margins.",
    out.width="100%", fig.width=9, fig.height=8, fig.fullwidth=TRUE,
    warning=FALSE, echo=FALSE}
 p + geom_hline(yintercept = 0.5, size = 1.4, color = "gray70") +
     geom_vline(xintercept = 0.5, size = 1.4, color = "gray70") +
     geom_point() +
     geom_text_repel() +
     scale_x_continuous(labels = scales::percent) +
     scale_y_continuous(labels = scales::percent) +
     labs(x = x_label,
          y = y_label,
          title = p_title,
          subtitle = p_subtitle,
          caption = p_caption)
```
```

Labeling Points of Interest

```r
p <- ggplot(data = by_country,
            mapping = aes(x = gdp, y = health))
```

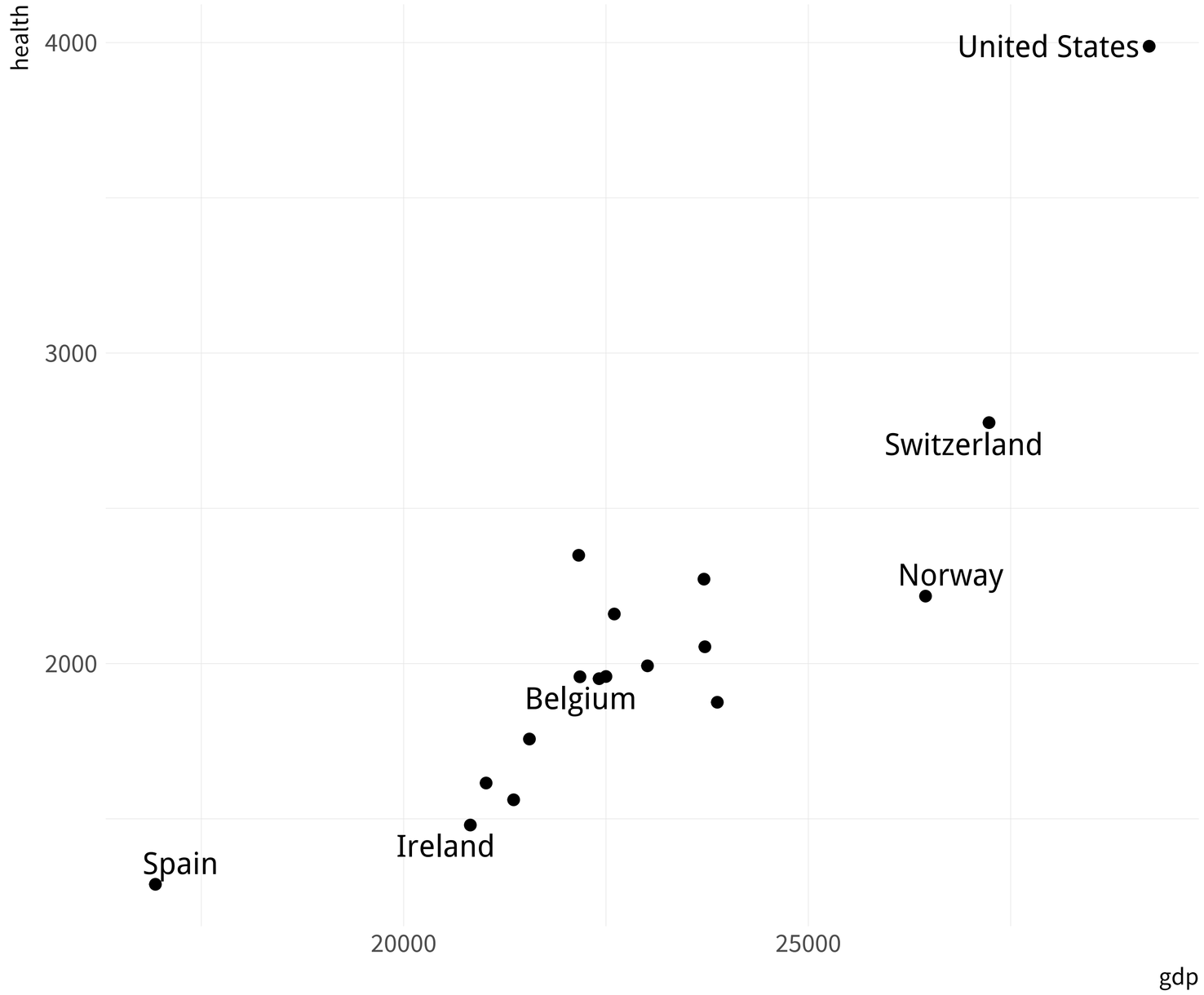
```r
p + geom_point() +
    geom_text_repel(data = subset(by_country, gdp > 25000),
                    mapping = aes(label = country))
```

```r
p <- ggplot(data = by_country,
            mapping = aes(x = gdp, y = health))

p + geom_point() +
    geom_text_repel(data = subset(by_country,
                     gdp > 25000 | health < 1500 | country %in% "Belgium"),
                    mapping = aes(label = country))
```

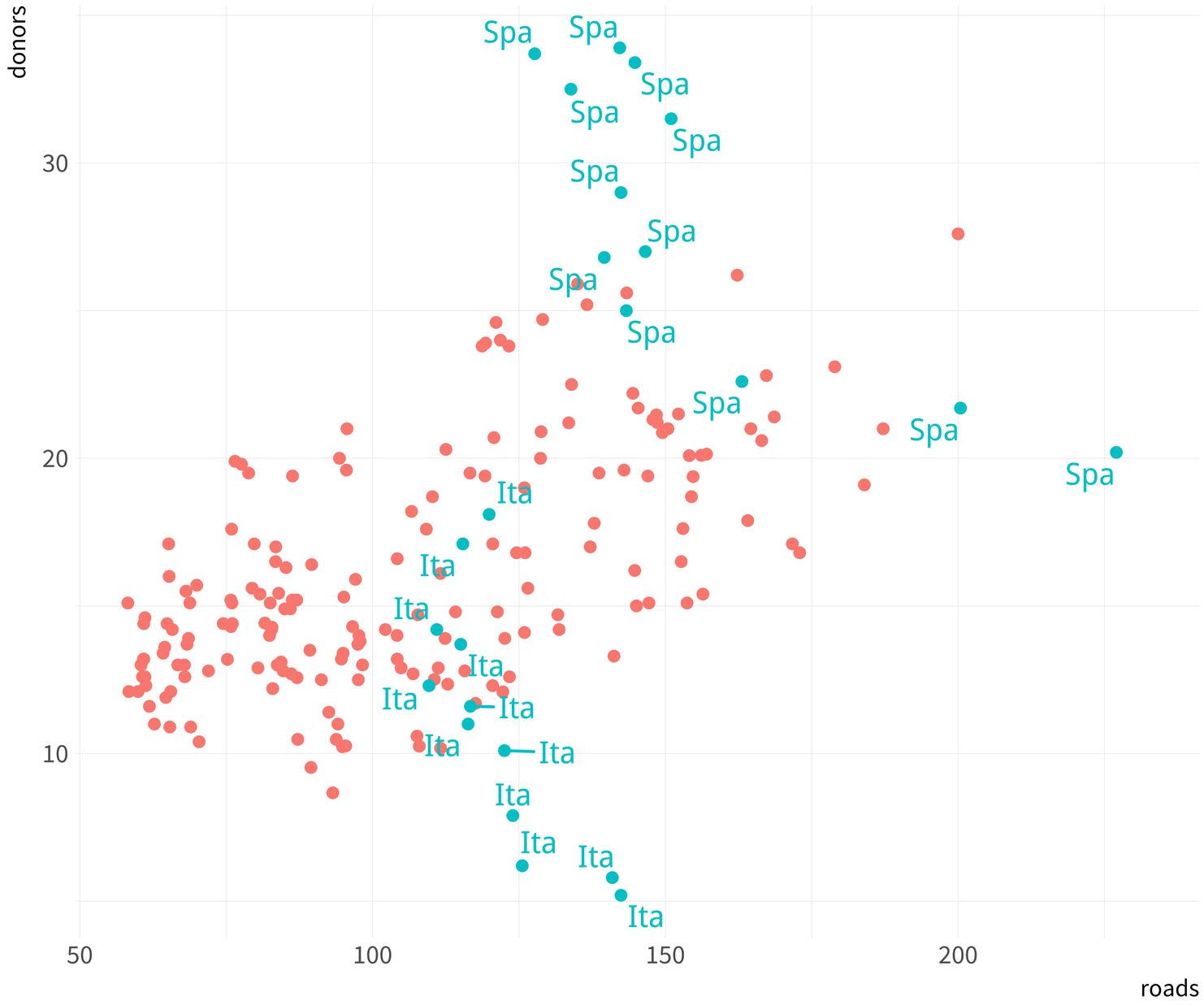
```r
p <- ggplot(data = by_country,
            mapping = aes(x = gdp, y = health))
```

```r
p + geom_point() +
    geom_text_repel(data = subset(by_country, gdp > 25000),
                    mapping = aes(label = country))
```

```r
p <- ggplot(data = by_country,
            mapping = aes(x = gdp, y = health))

p + geom_point() +
    geom_text_repel(data = subset(by_country,
                     gdp > 25000 | health < 1500 | country %in% "Belgium"),
                    mapping = aes(label = country))
```

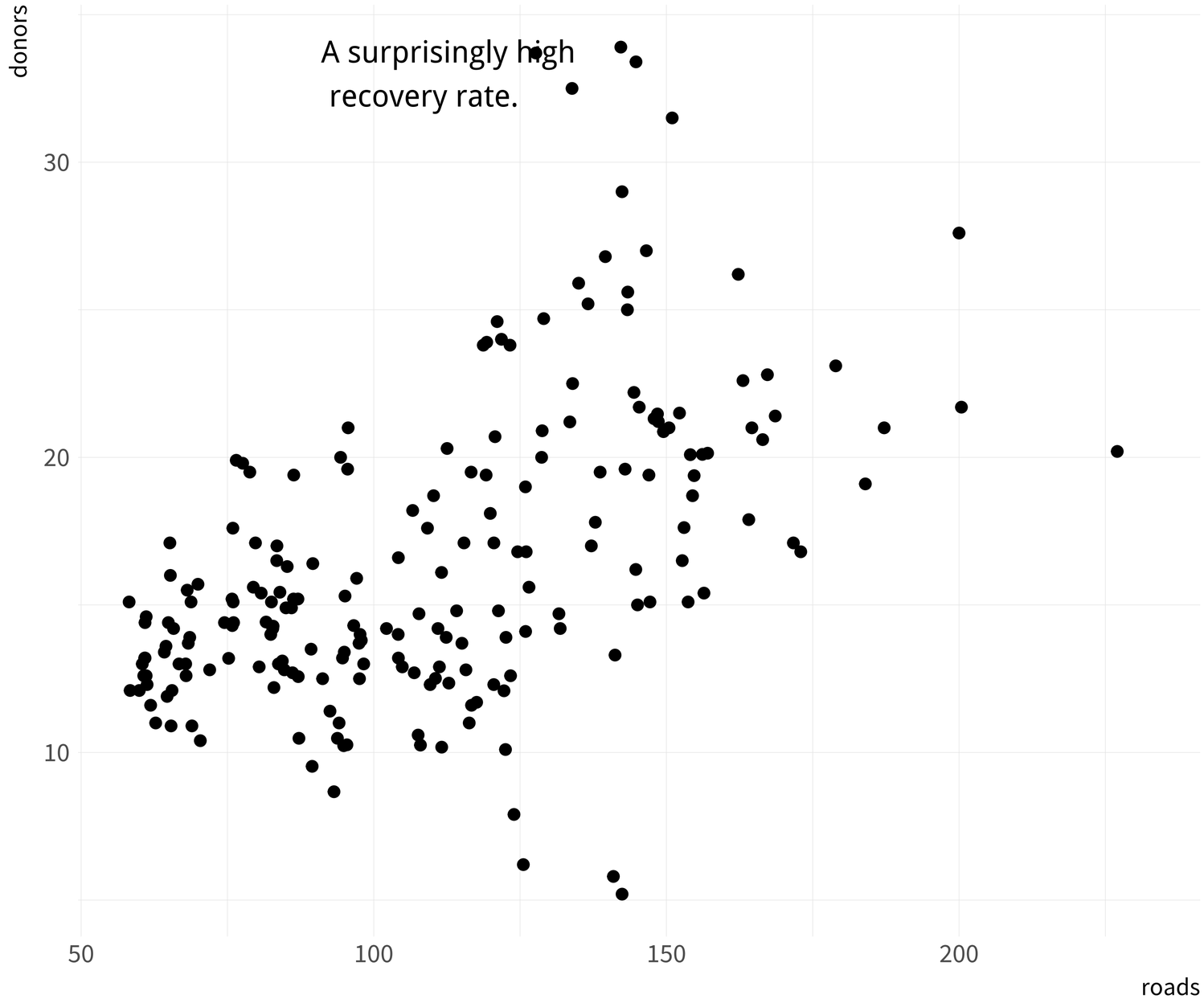

health
4000
3000
2000
United States
Switzerland
Norway
Belgium
Ireland
Spain
20000
25000
gdp

```r
organdata <- organdata %>%
       mutate(ind = ccode %in% c("Ita", "Spa") &
                    year > 1998)

p <- ggplot(data = organdata,
            mapping = aes(x = roads,
                          y = donors, color = ind))
p + geom_point() +
    geom_text_repel(data = subset(organdata, ind),
                    mapping = aes(label = ccode)) +
    guides(label = FALSE, color = FALSE)
```


donors
30
20
10
50
100
150
200
roads
Spa
Spa
Spa
Spa
Spa
Spa
Spa
Spa
Spa
Spa
Spa
Spa
Ita
Ita
Ita
Ita
Ita
Ita
Ita
Ita
Ita
Ita
Ita
Ita

Write and Draw in the Plot Area

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

p + geom_point() +
    annotate(geom = "text", x = 91, y = 33,
    label = "A surprisingly high \n recovery rate.",
    hjust = 0)
```


A surprisingly high
recovery rate.
donors
30
20
10
50
100
150
200
roads

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

p + 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,
             label = "A surprisingly high \n recovery rate.", hjust = 0)
```


donors
30
20
10
50
100
150
200
roads
A surprisingly high
recovery rate.

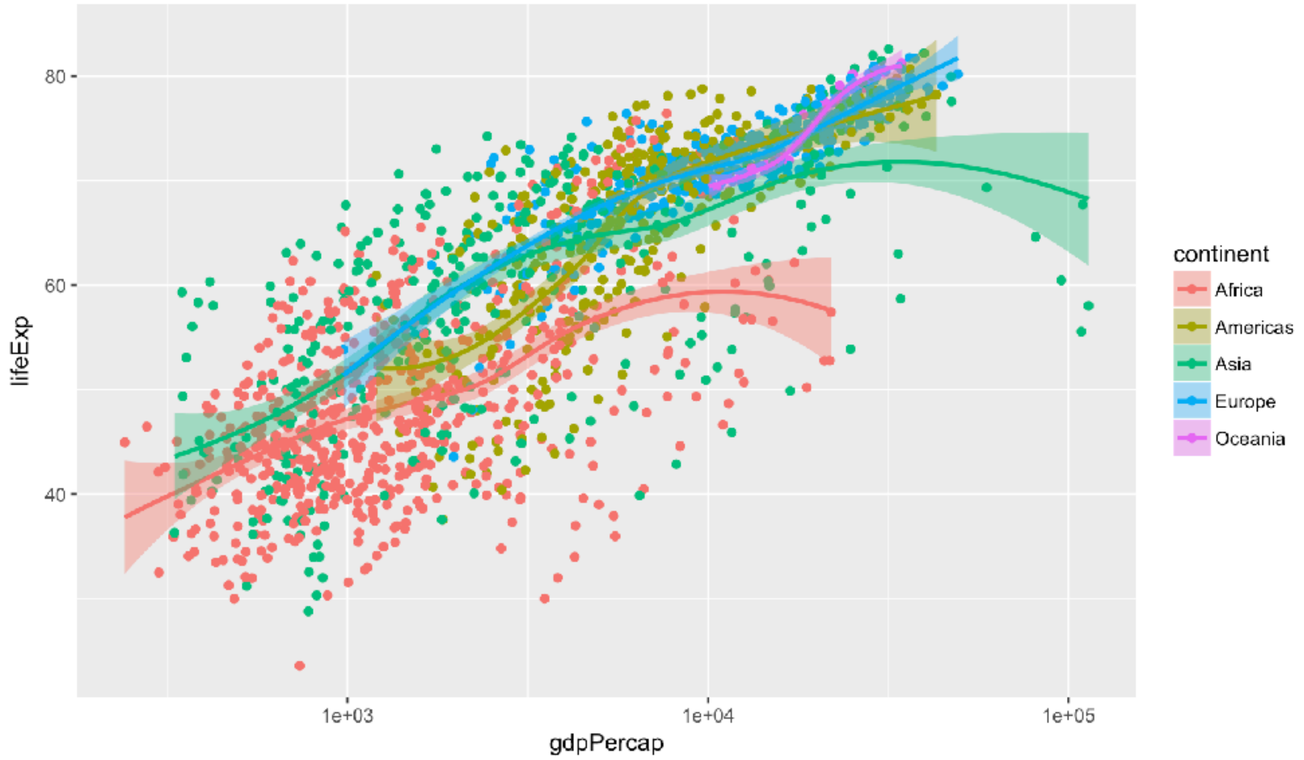
SCALES, GUIDES, and THEMES

Presidential Elections: Popular & Electoral College Margins

1824-2016

Data for 2016 are provisional.

```r
p <- ggplot(data = gapminder,
            mapping =
             aes(x = gdpPercap,
                 y = lifeExp,
                 color = continent,
                 fill = continent))
p + geom_point() +
    geom_smooth(method = "loess") +
    scale_x_log10()
```



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, and size are scales.

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

```
scale_<MAPPING>_<KIND>()
```

Scale functions are consistently named, by mapping and kind

```
scale_<MAPPING>_<KIND>()
```

```
scale_x_continuous()
```

```
scale_y_continuous()
```

```
scale_x_discrete()
```

```
scale_y_discrete()
```

```
scale_x_log10()
```

```
scale_x_sqrt()
```

```
scale_<MAPPING>_<KIND>()
```

```
scale_color_gradient()
```

```
scale_color_gradient2()
```

```
scale_color_hue()
```

```
scale_fill_gradient()
```

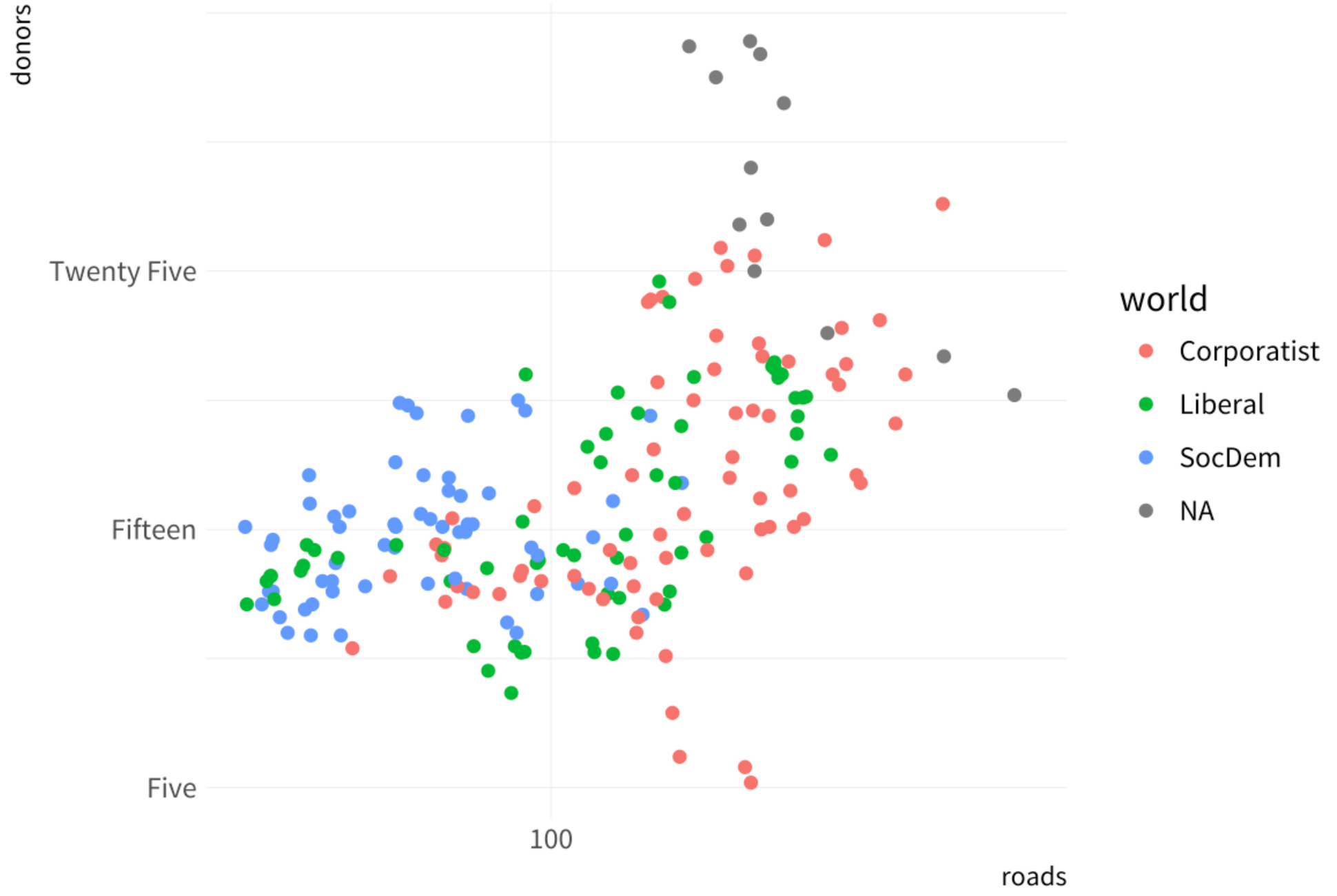
```
scale_fill_gradient2()
```

```
scale_fill_gradient()
```

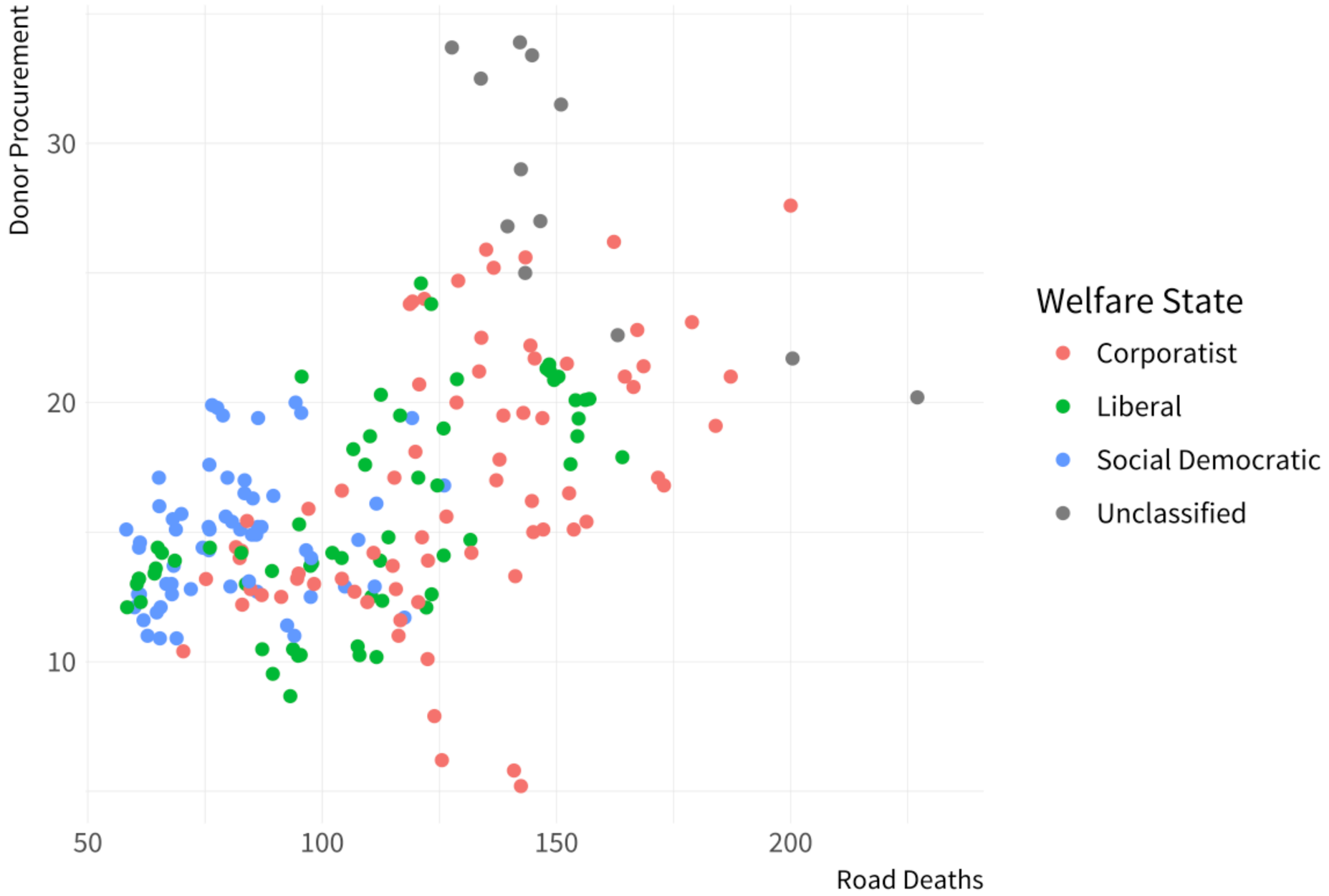
```
scale_<MAPPING>_<KIND>(<ARGUMENTS>)
```

```
p <- ggplot(data = organdata,
            mapping = aes(x = roads_mean,
                          y = donors,
                          color = world))
p + geom_point() +
    scale_x_log10() +
    scale_y_continuous(breaks = c(5, 15, 25),
                       labels = c("Five", "Fifteen", "Twenty Five"))
```

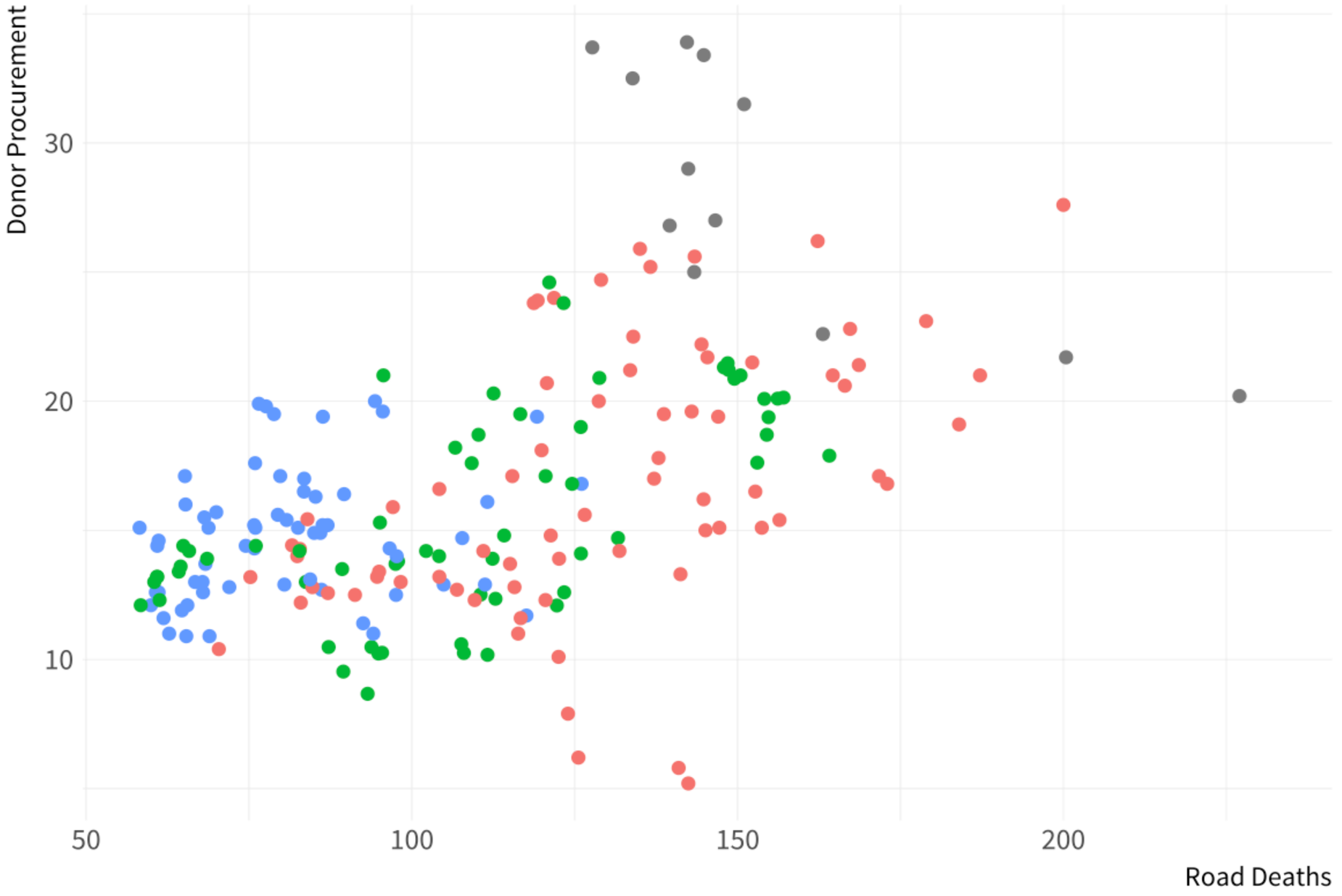
E.g., labels, breaks, and limits


donors
Twenty Five
Fifteen
Five
100
roads
world
Corporatist
Liberal
SocDem
NA

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


Donor Procurement
30
20
10
50
100
150
200
Road Deaths
Welfare State
Corporatist
Liberal
Social Democratic
Unclassified

```
p <- ggplot(data = organdata,
            mapping = aes(x = roads,
                          y = donors,
                          color = world))

p + geom_point() +
    labs(x = "Road Deaths",
         y = "Donor Procurement") +
    guides(color = FALSE)
```


Donor Procurement
30
20
10
50
100
150
200
Road Deaths

```
scale_<MAPPING>_<KIND>()
```