

Class3_20231018_DataVisualization_Apichat

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```
#attach the libraries
```

```
library(socviz)
library(ggplot2)
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
```

```
## v dplyr      1.1.0      v readr      2.1.4
## v forcats    1.0.0      v stringr   1.5.0
## v lubridate  1.9.2      v tibble    3.1.8
## v purrr      1.0.1      v tidyr     1.3.0
```

```
## -- Conflicts ----- tidyverse_conflicts() --
```

```
## x dplyr::filter() masks stats::filter()
```

```
## x dplyr::lag()     masks stats::lag()
```

```
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
#install.packages("gapminder")
```

```
library(gapminder)
```

```
#attach the data
```

```
gapminder
```

```
## # A tibble: 1,704 x 6
```

```
##   country      continent  year lifeExp      pop gdpPercap
##   <fct>        <fct>    <int>  <dbl>    <int>    <dbl>
## 1 Afghanistan Asia      1952   28.8  8425333    779.
## 2 Afghanistan Asia      1957   30.3  9240934    821.
## 3 Afghanistan Asia      1962   32.0 10267083    853.
## 4 Afghanistan Asia      1967   34.0 11537966    836.
## 5 Afghanistan Asia      1972   36.1 13079460    740.
## 6 Afghanistan Asia      1977   38.4 14880372    786.
## 7 Afghanistan Asia      1982   39.9 12881816    978.
## 8 Afghanistan Asia      1987   40.8 13867957    852.
## 9 Afghanistan Asia      1992   41.7 16317921    649.
## 10 Afghanistan Asia     1997   41.8 22227415    635.
```

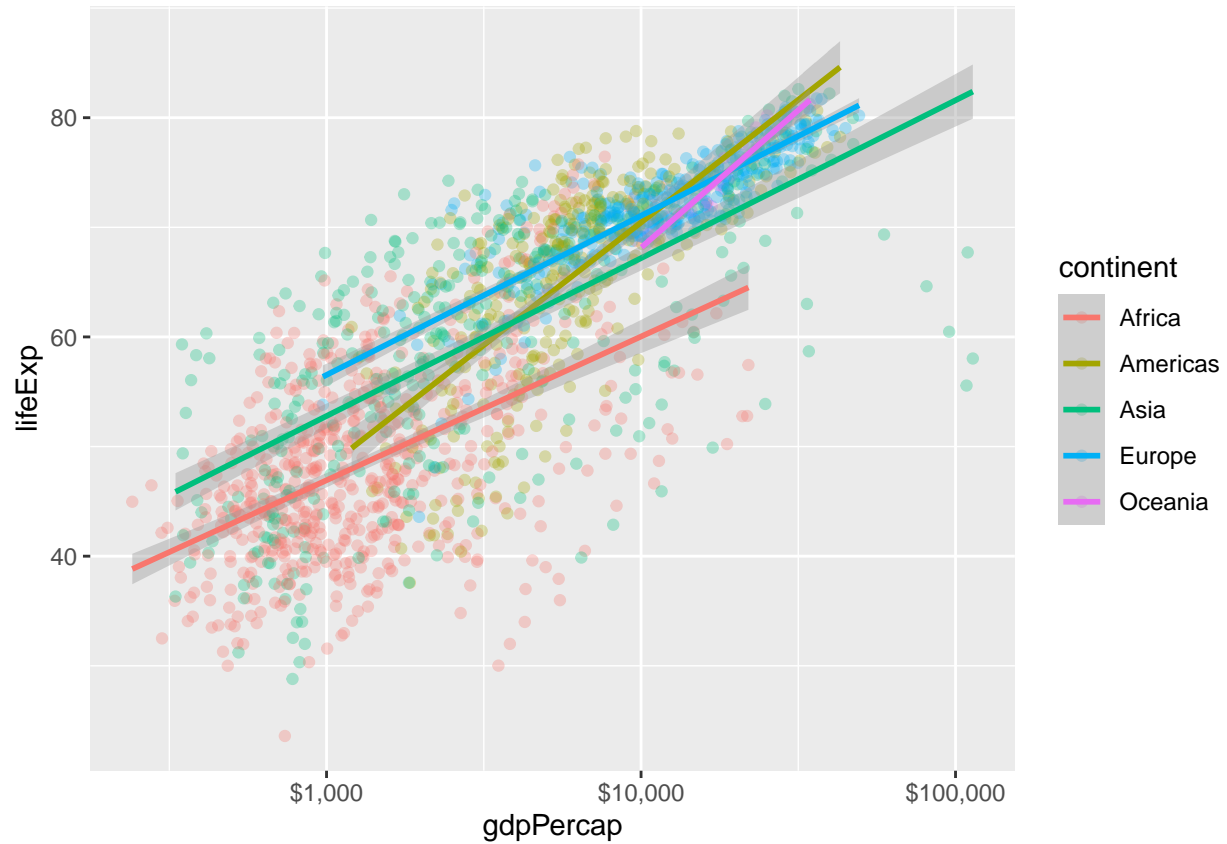
```
## # ... with 1,694 more rows
```

```
#plot the graph of life expectancy over GDPperCap (from last class)
```

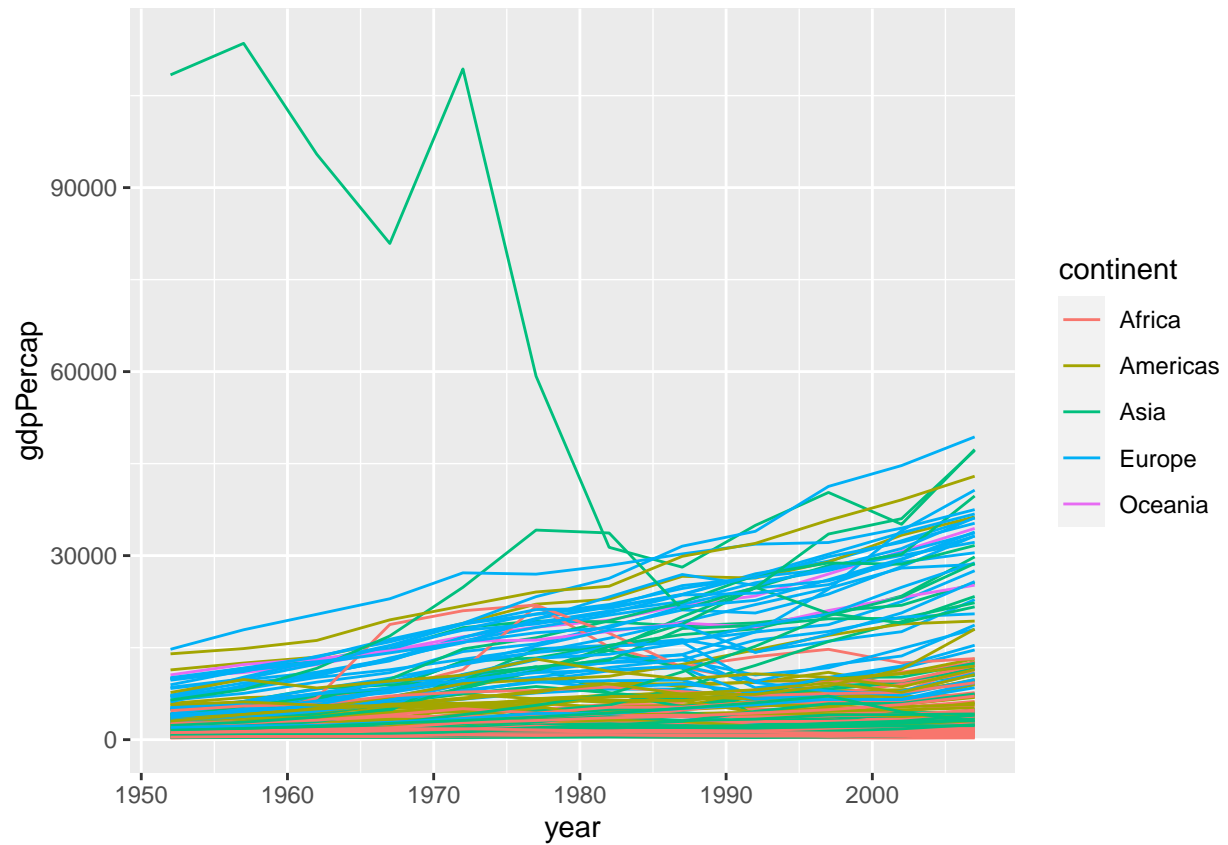
```
p <- ggplot(data = gapminder,
  mapping = aes(x=gdpPercap, y = lifeExp,
    color = continent))
```

```
p + geom_point(alpha = 0.3) + geom_smooth(method = 'lm') + scale_x_log10(labels = scales::dollar)

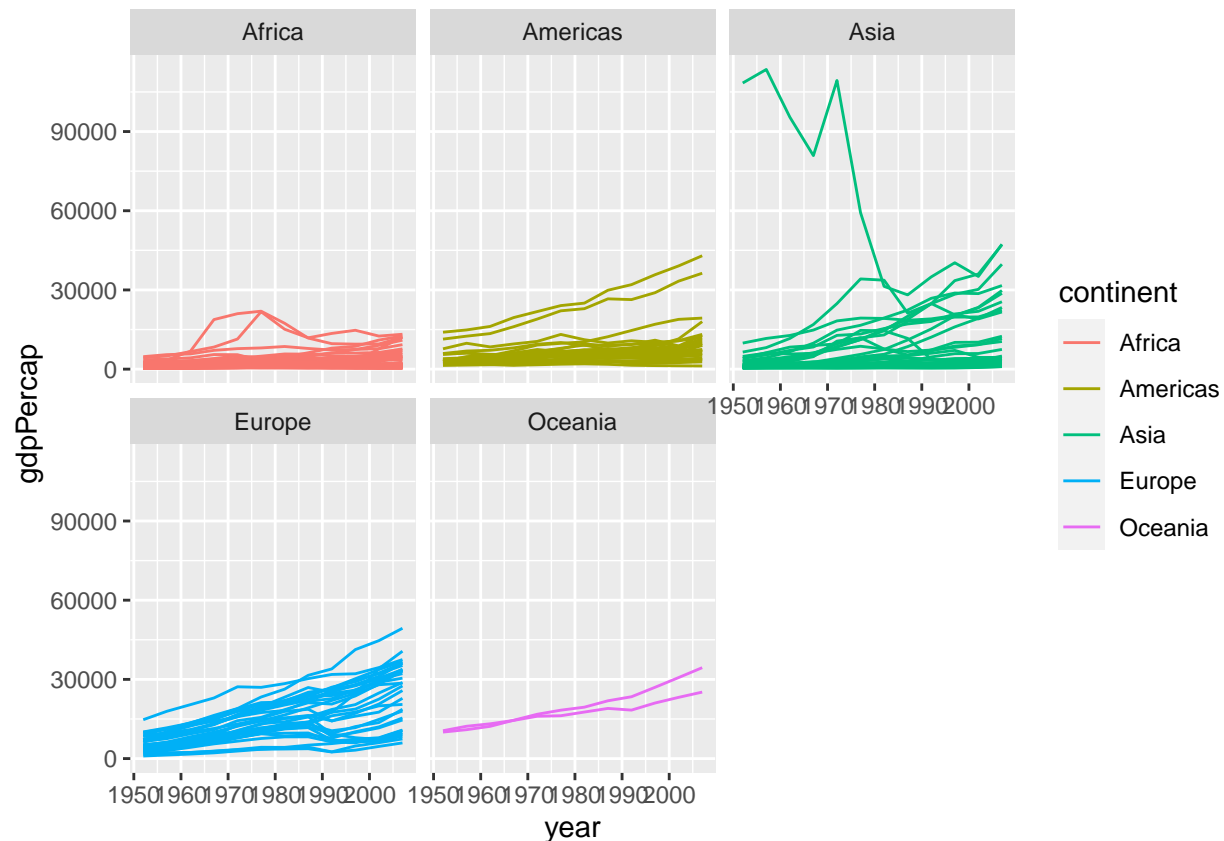
## 'geom_smooth()' using formula = 'y ~ x'
```



```
#plot the graph of GDP over time per country
p <- ggplot(data = gapminder,
            mapping = aes(x= year, y = gdpPercap,
                          color = continent))
p + geom_line(aes(group = country))
```



```
#add the facet_wrap to break up the data into pieces too make a small multiple plot
p <- ggplot(data = gapminder,
  mapping = aes(x= year, y = gdpPerCap,
    color = continent))
p + geom_line(aes(group = country)) + facet_wrap(~continent)
```

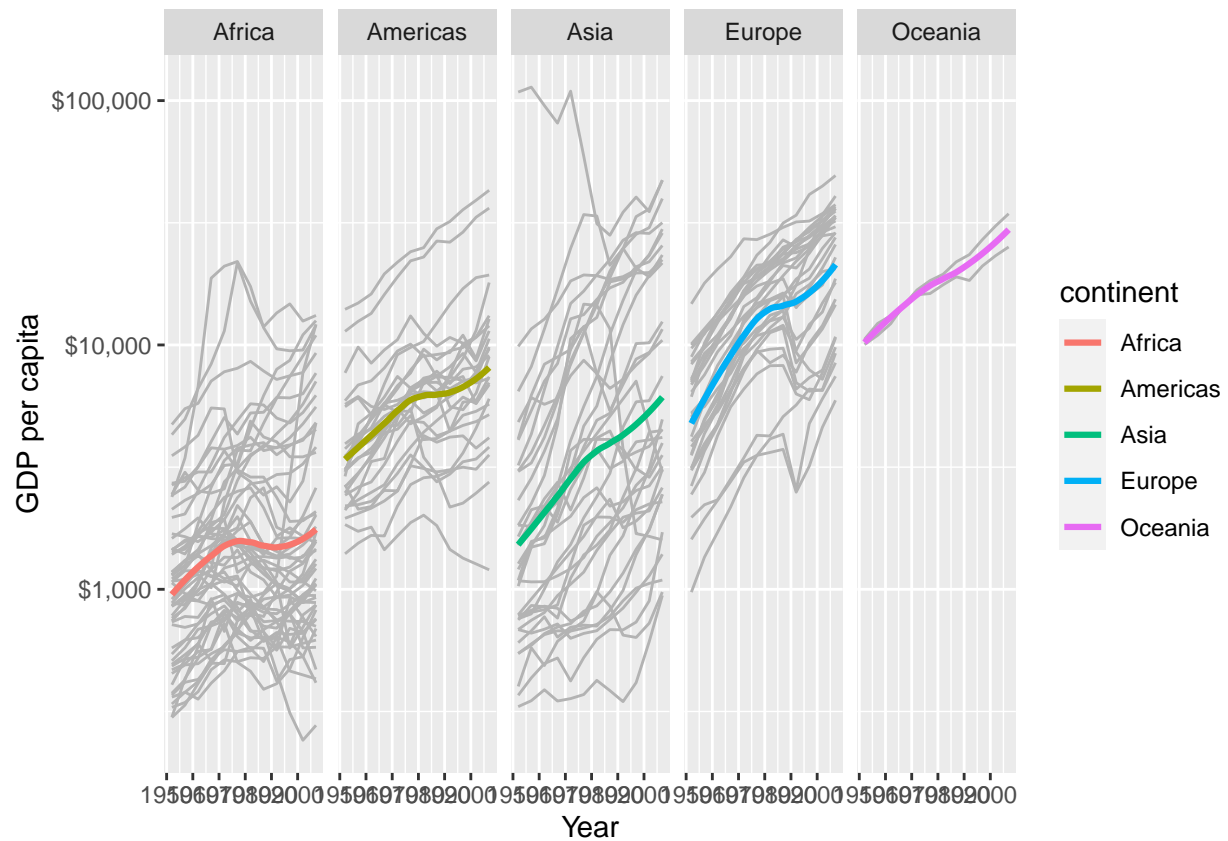


Improving our plot aesthetic, substantive, and perceptual characteristics of our plot: 1. Make country trends light grey colour 2. Add a trend line 3. Make y axis logarithmic and show that values are in dollars 4. Try to fit all five facets on a single row (5 columns) 5. Add axis labels and graph title

```
#add the facet_wrap to break up the data into pieces too make a small multiple plot
p <- ggplot(data = gapminder,
            mapping = aes(x= year, y = gdpPercap,
                          color = continent))
p + geom_line(color = "gray70", aes(group = country)) +
  geom_smooth(size=1.1, method="loess", se = FALSE) +
  scale_y_log10(labels = scales::dollar) +
  facet_wrap(~continent, ncol = 5) +
  labs(x = "Year",
       y = "GDP per capita",
       Title = "GDP per capita on Five Continents")
```

```
## Warning: Using 'size' aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use 'linewidth' instead.
```

```
## 'geom_smooth()' using formula = 'y ~ x'
```



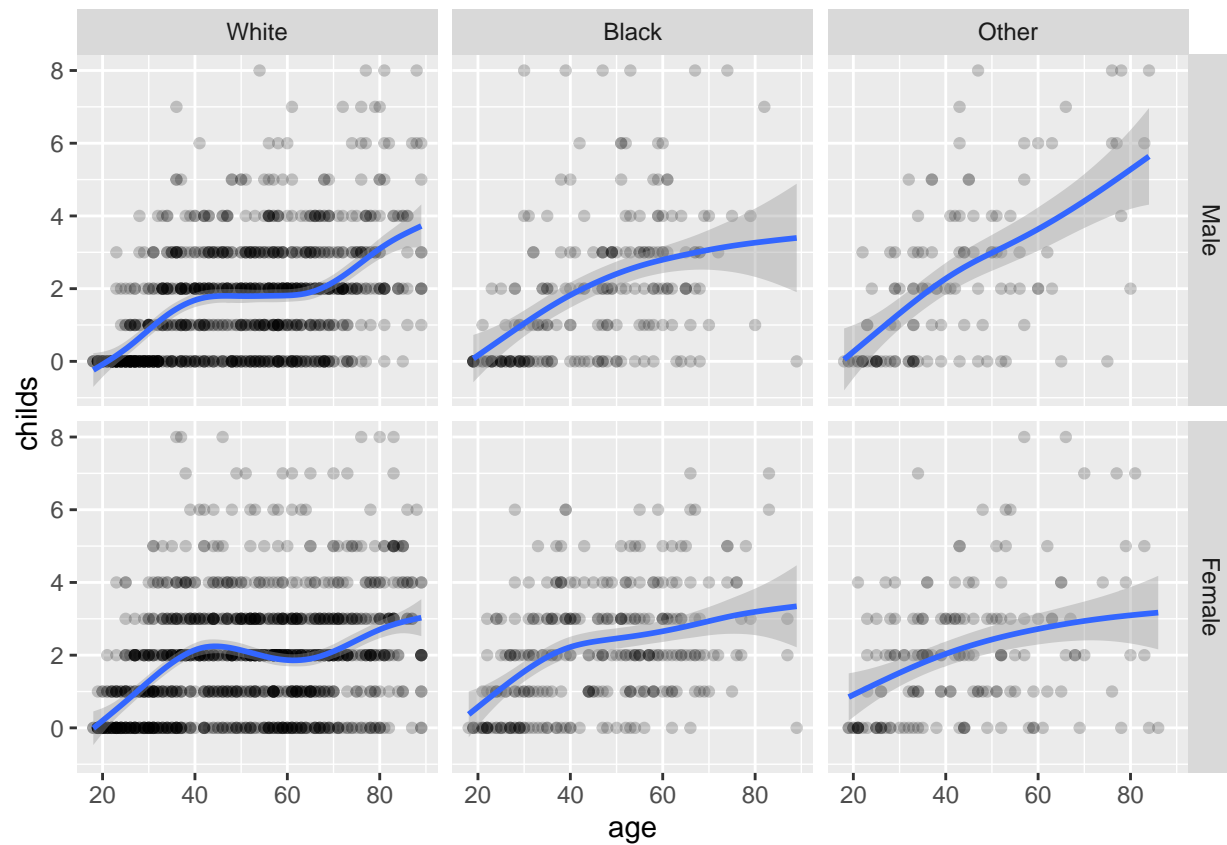
```
#attach new dataset
attach(gss_sm)
#A dataset containing an extract from the 2016 General Social Survey.
#See http://gss.norc.umd.edu/Get-Documentation for full documentation of the variables.

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

```
## 'geom_smooth()' using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```

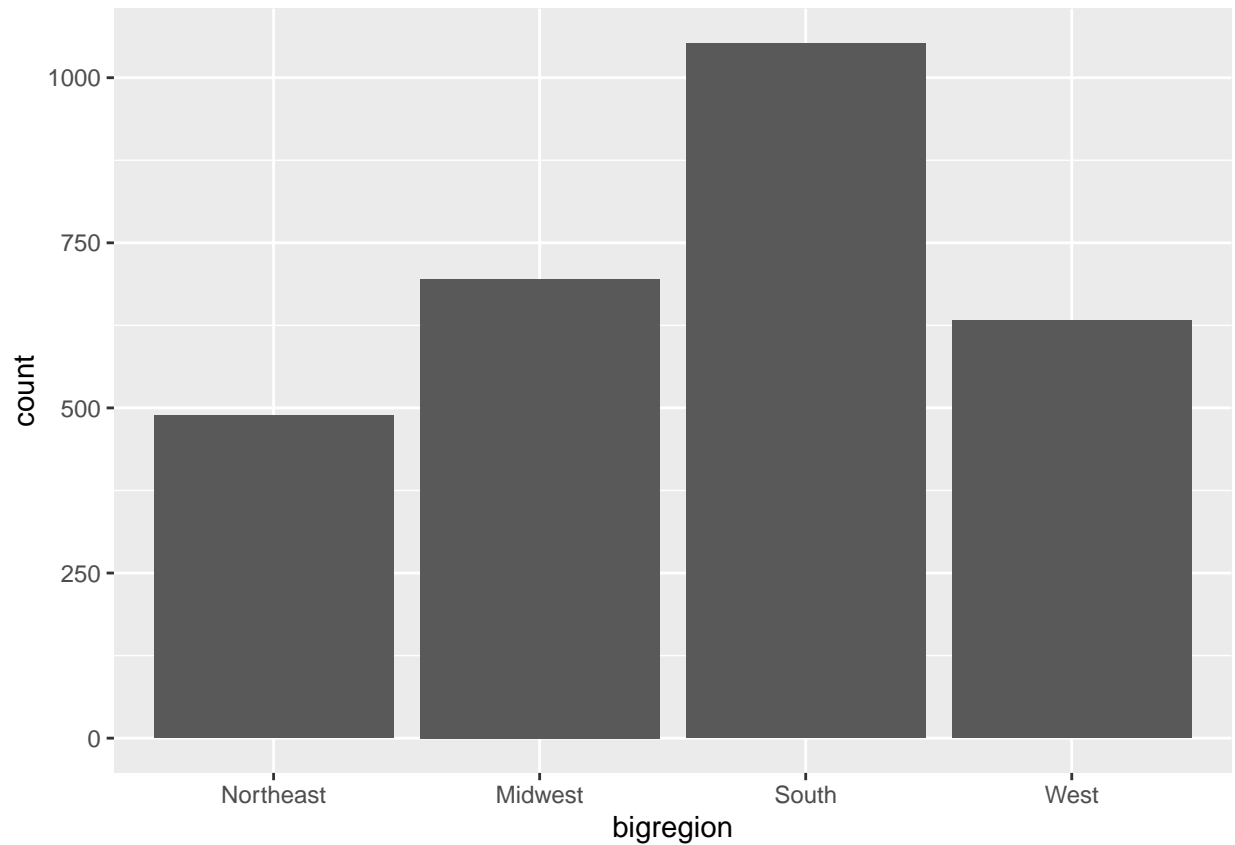
```
## Warning: Removed 18 rows containing non-finite values ('stat_smooth()').
```

```
## Warning: Removed 18 rows containing missing values ('geom_point()').
```



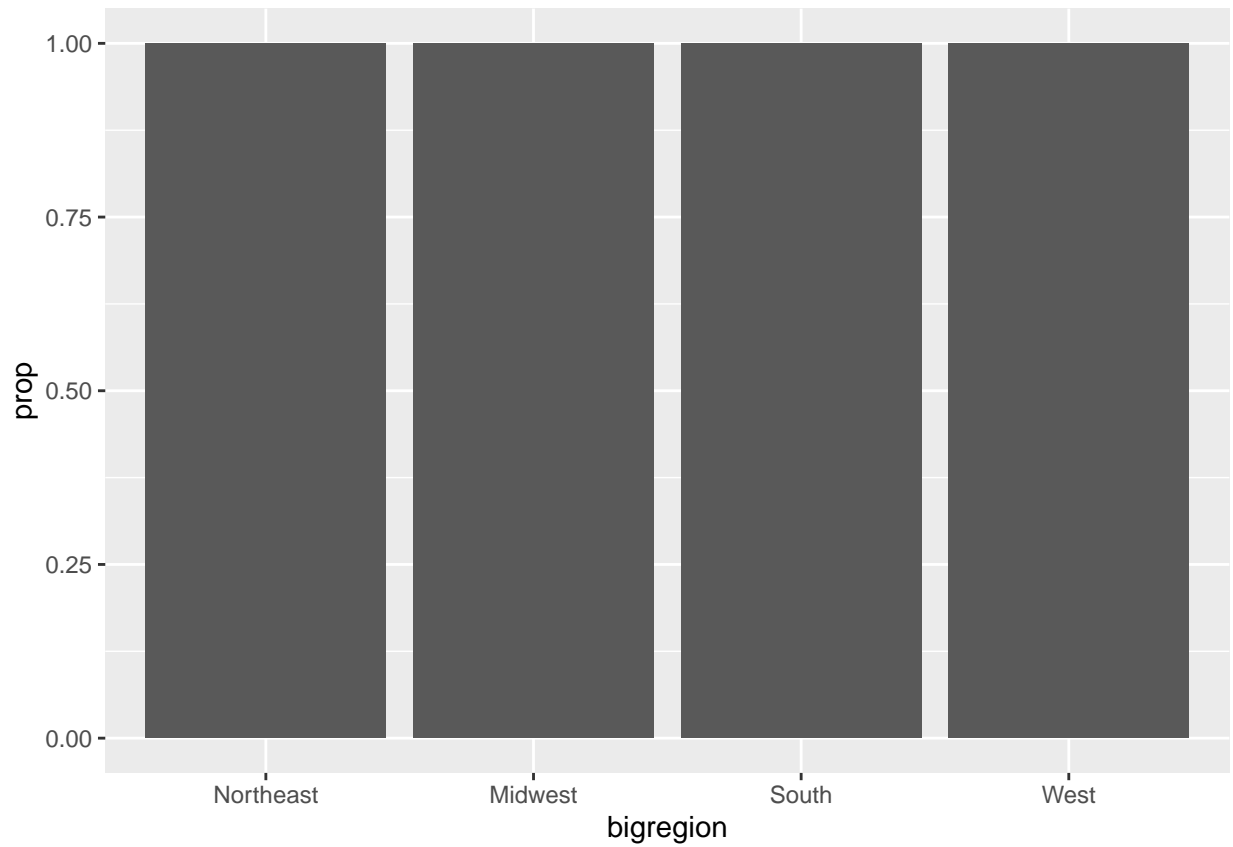
let's try `stat_functions`

```
p <- ggplot(data=gss_sm, mapping = aes(x = bigregion))
p+ geom_bar()
```

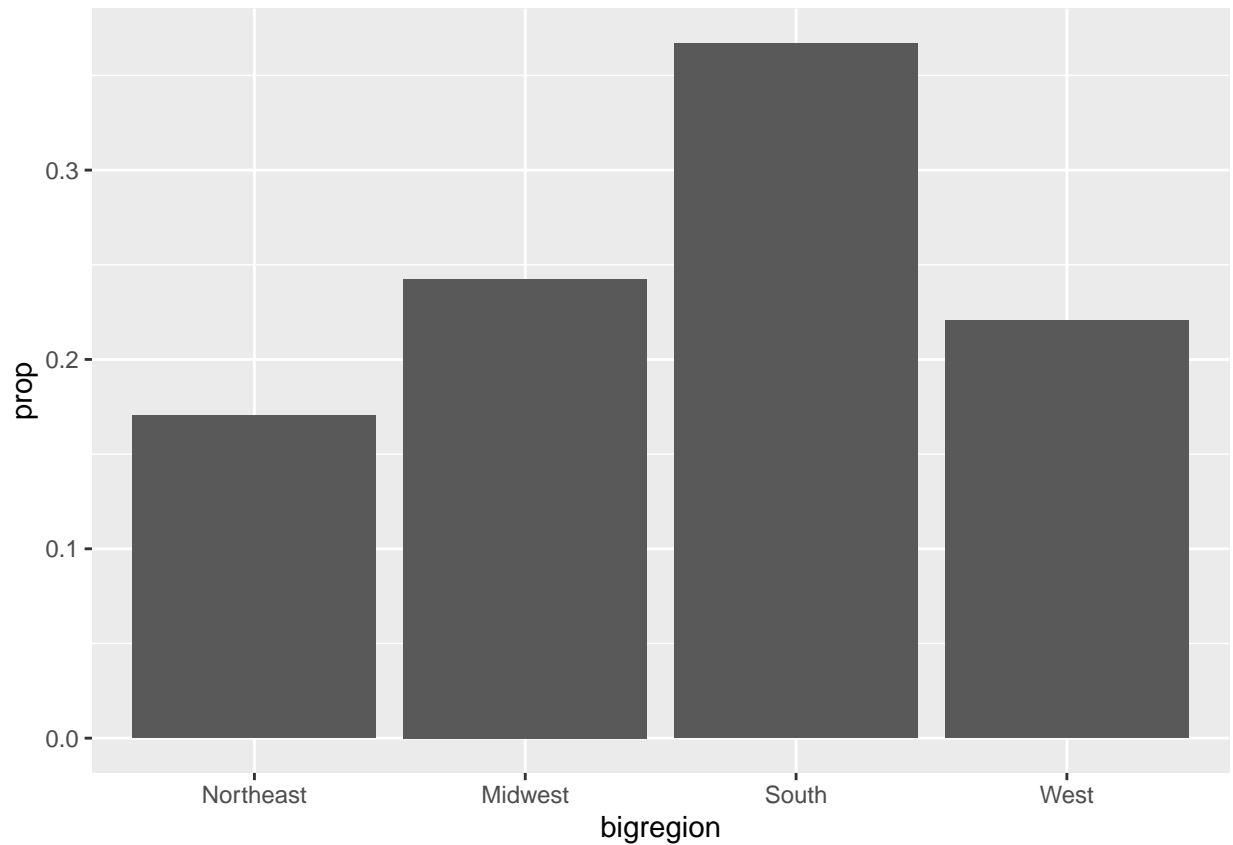


```
#show the relative frequencies rather than counts, we can use the prop (proportion)  
p <- ggplot(data=gss_sm, mapping = aes(x = bigregion))  
p+ geom_bar(mapping = aes(y=..prop..))
```

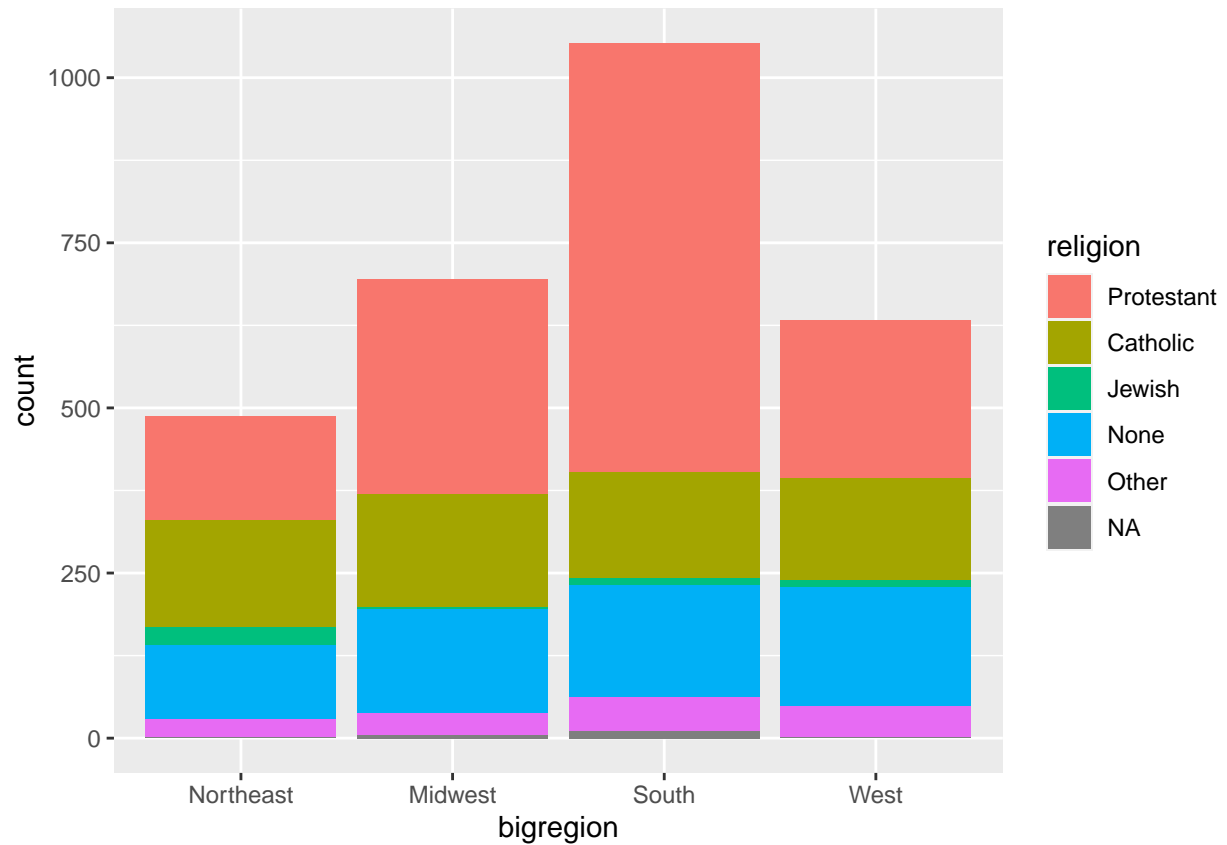
```
## Warning: The dot-dot notation ('..prop..') was deprecated in ggplot2 3.4.0.  
## i Please use 'after_stat(prop)' instead.
```



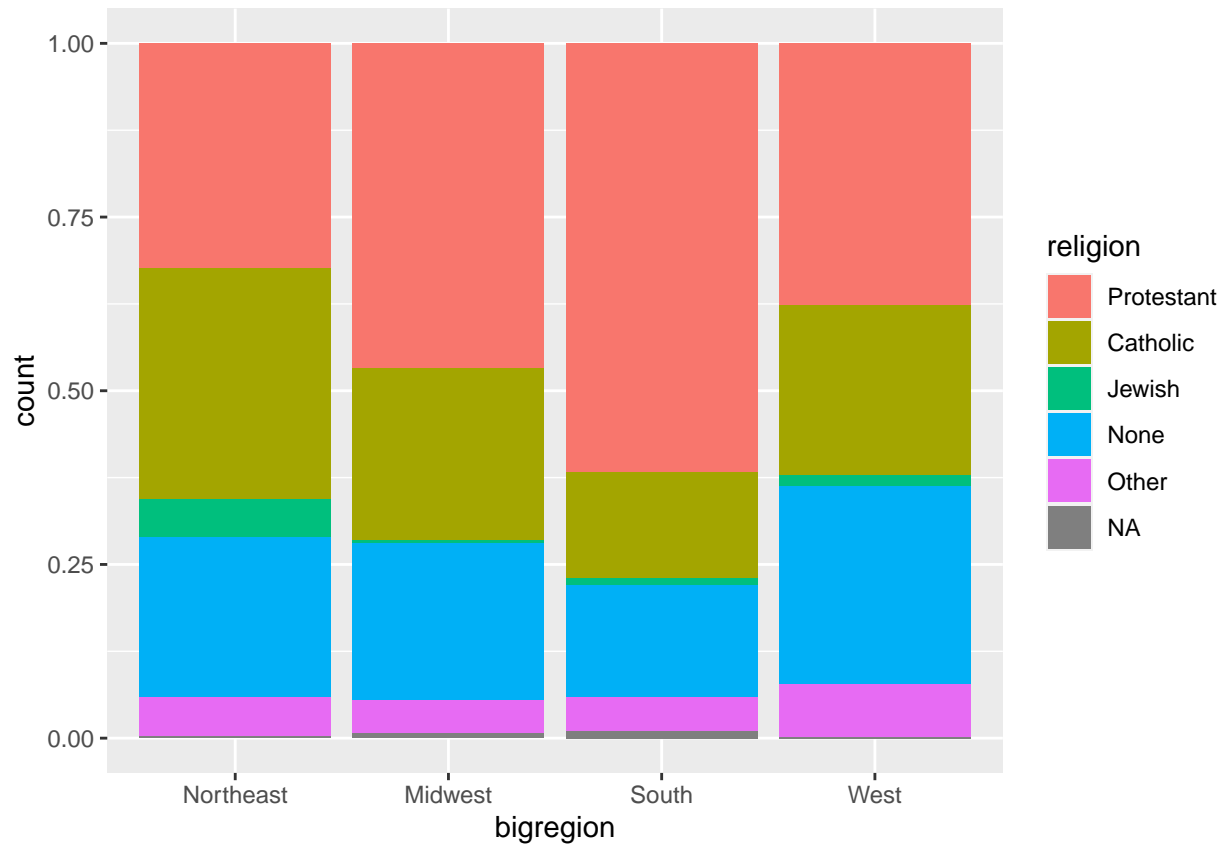
```
#We create a 'dummy group' with group = 1 to tell ggplot to use the whole dataset when establishing the  
p <- ggplot(data=gss_sm, mapping = aes(x = bigregion))  
p+ geom_bar(mapping = aes(y=..prop.., group = 1))
```

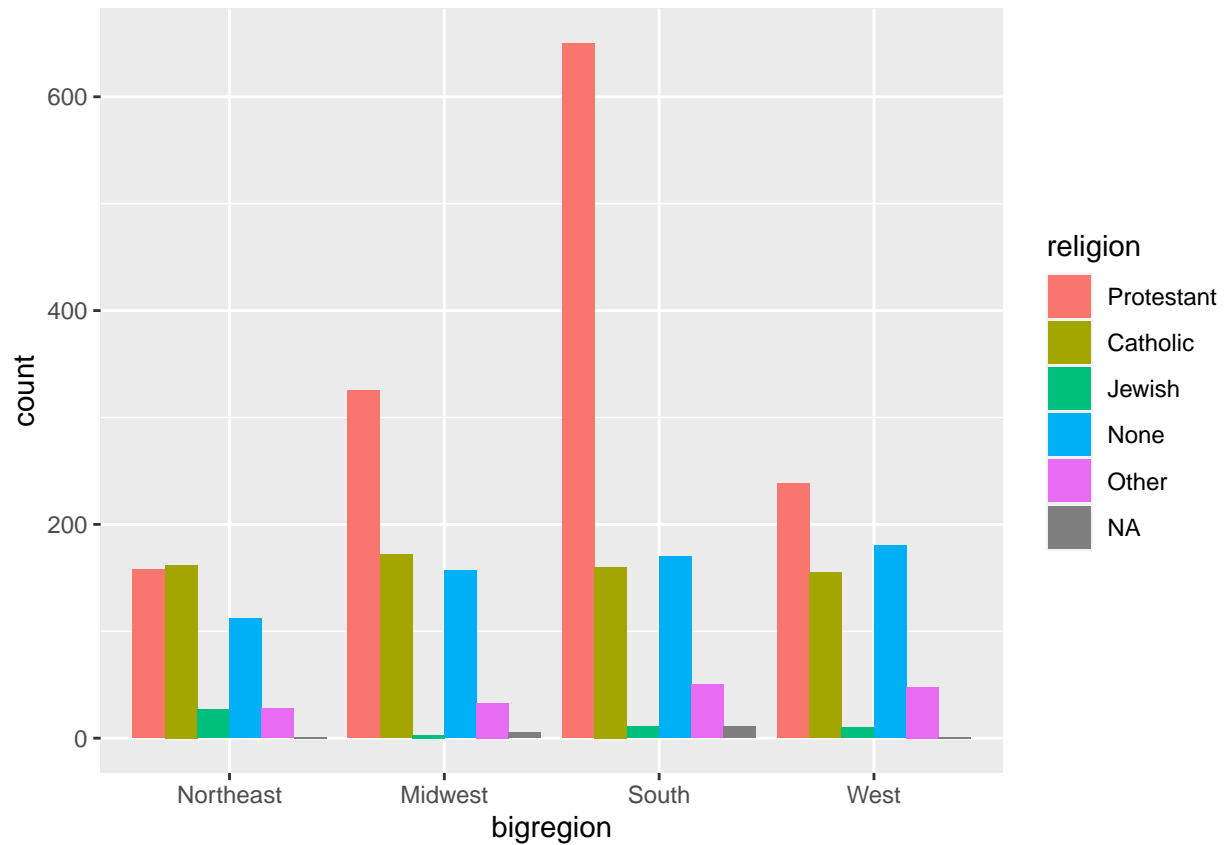
```
#The variable religion is a categorical variable about participants' religious affiliation  
# We can plot religious affiliation by census region as a bar chart, and colour the bars differently for  
p <- ggplot(data=gss_sm, mapping = aes(x = bigregion, fill = religion))  
p+ geom_bar()
```



```
#Now we can compare proportions across groups  
# BUT we cannot see the relative size of each cut with respect to the overall total  
# Our frequency chart can benefit from faceting!  
p <- ggplot(data=gss_sm, mapping = aes(x = bigregion, fill = religion))  
p+ geom_bar(position = "fill")
```

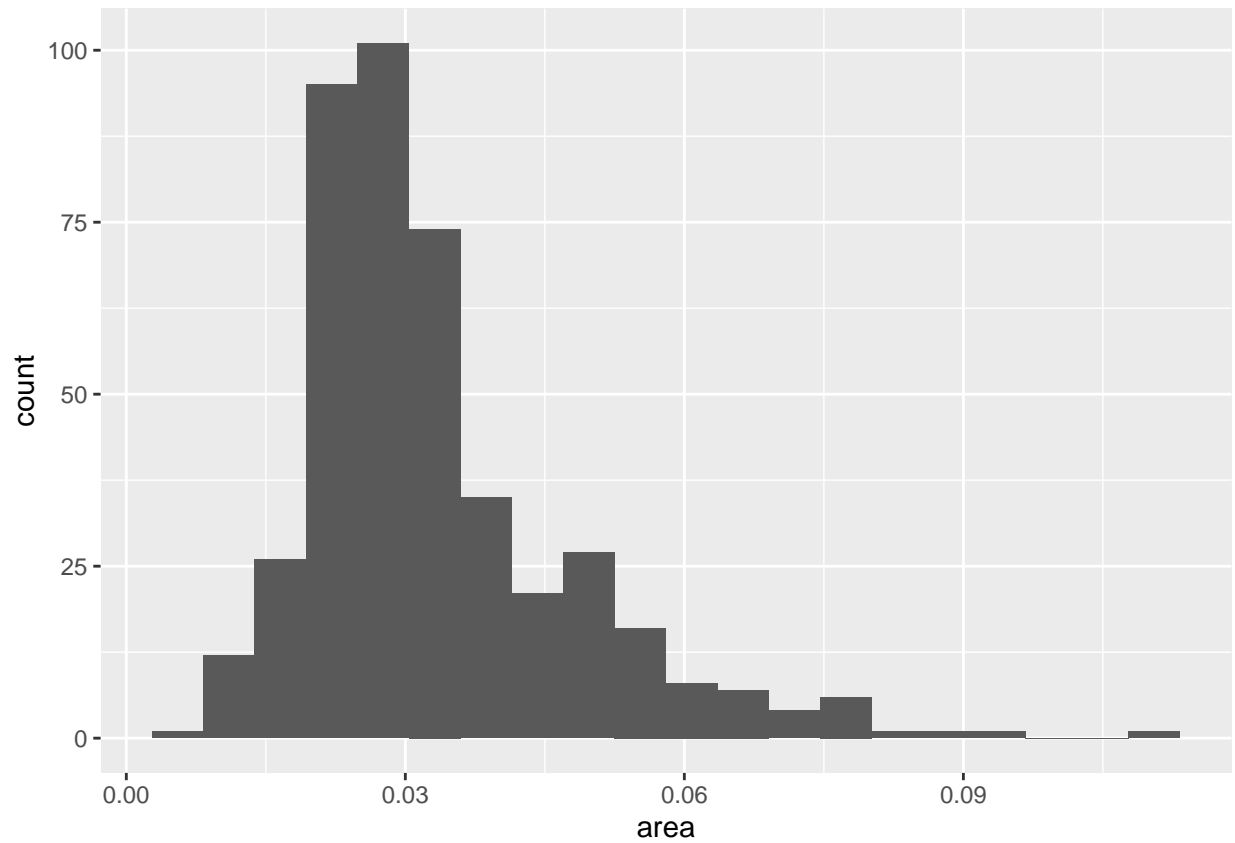


```
#Now we can compare proportions across groups
# BUT we cannot see the relative size of each cut with respect to the overall total
# Our frequency chart can benefit from faceting!
p <- ggplot(data=gss_sm, mapping = aes(x = bigregion, fill = religion))
p+ geom_bar(position = "dodge", mapping = aes(y = ..prop.., group = bigregion) +
            facet_wrap(~bigregion, ncol = 1))
```



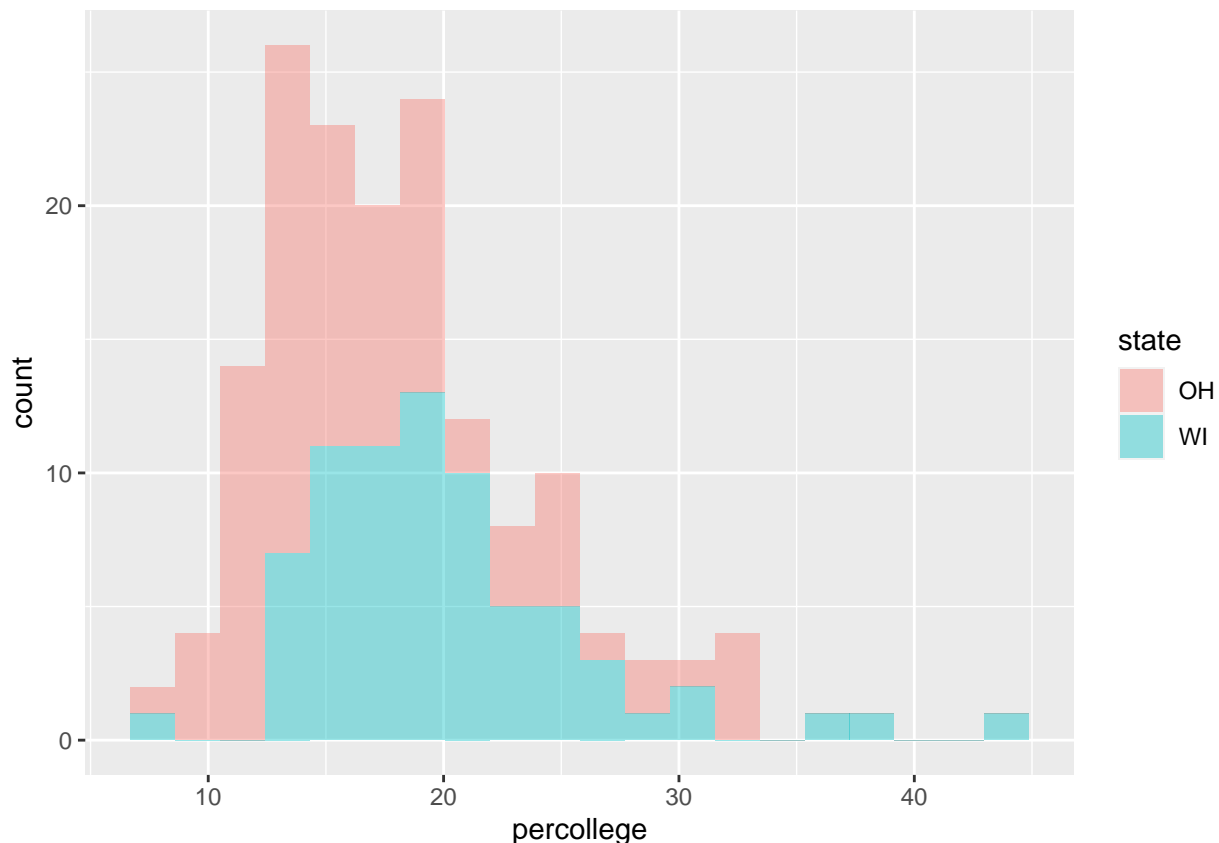
Histograms - Choosing bins

```
attach(midwest)
p <- ggplot(data=midwest, mapping = aes(x = area))
p + geom_histogram(bins = 20)
```



```
# comparing histograms
oh_wi <- c("OH", "WI")

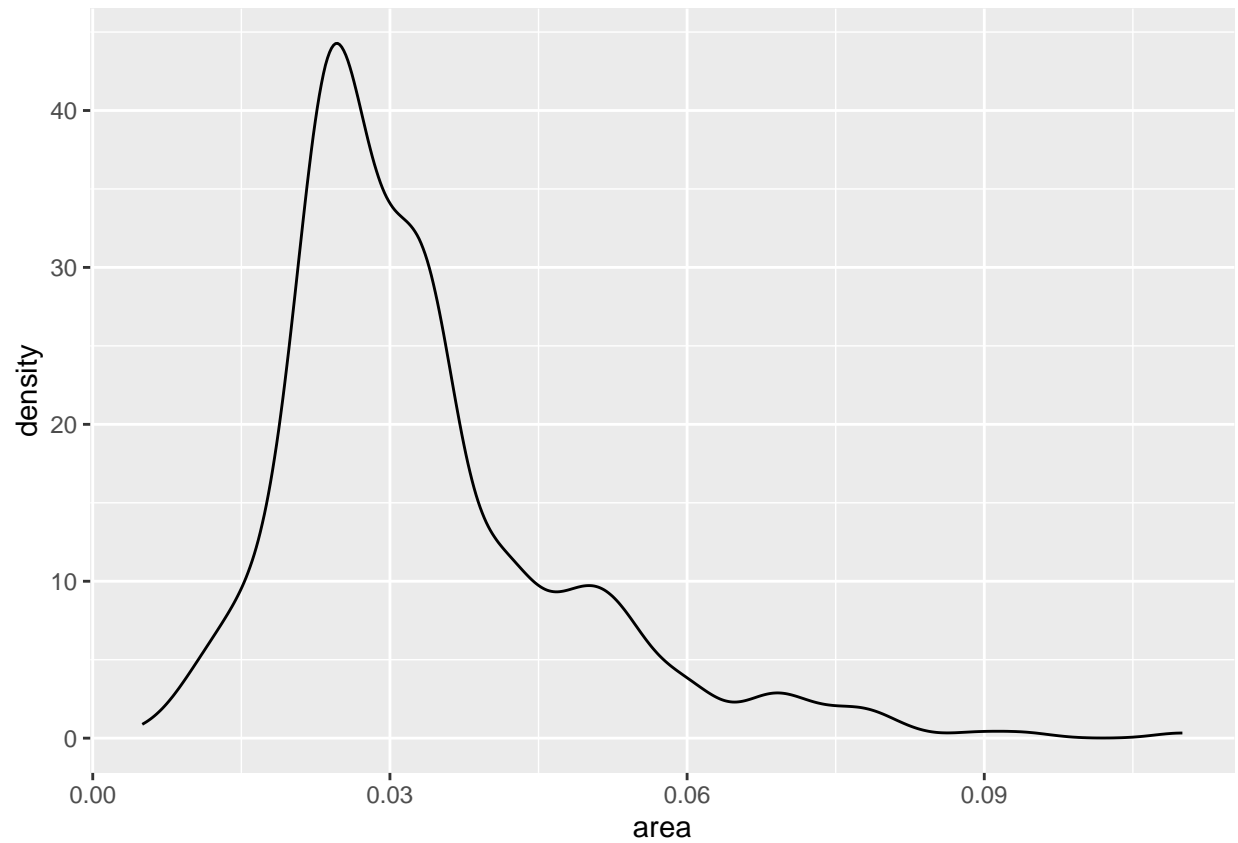
p <- ggplot(data = subset(midwest, subset = state %in% oh_wi),
            mapping = aes(x = percollege, fill = state))
p + geom_histogram(alpha = 0.4, bins = 20)
```



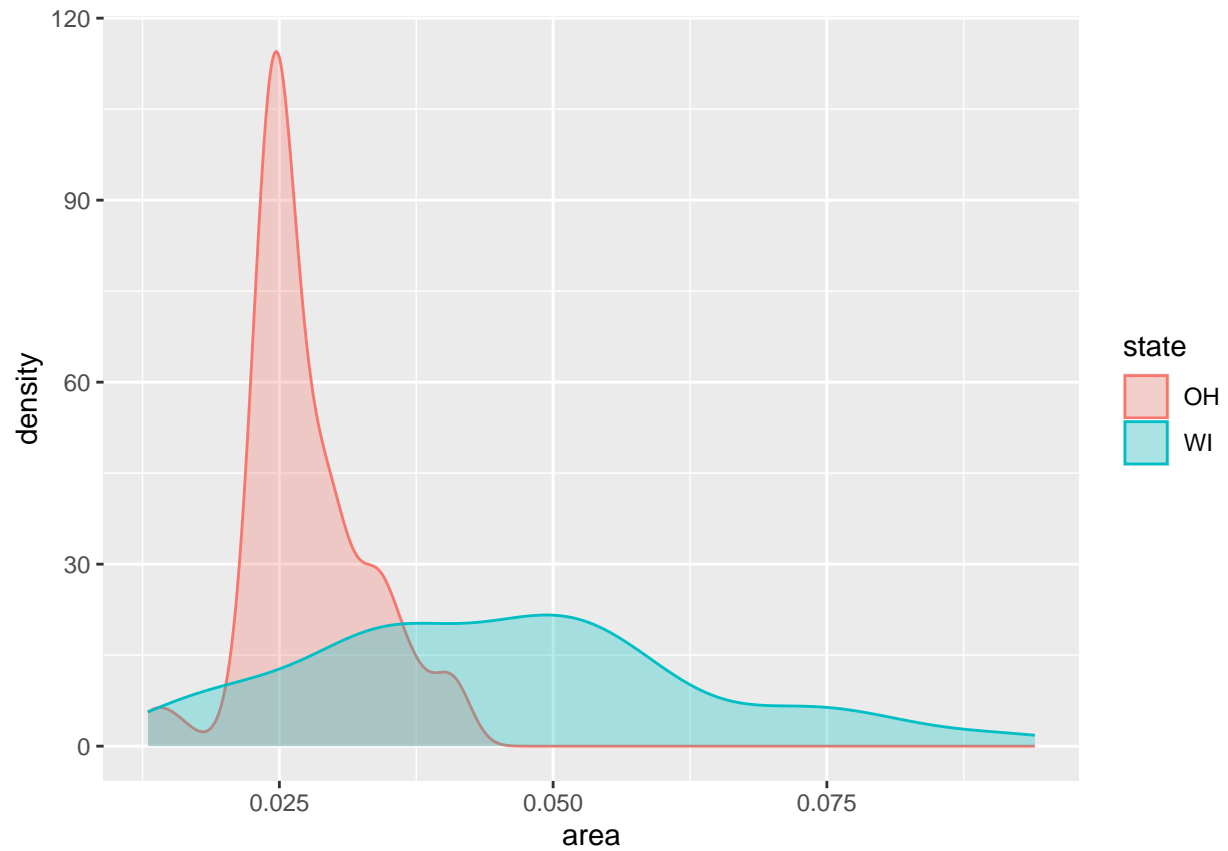
```
midwest
```

```
## # A tibble: 437 x 28
##   PID county state area poptotal popden-1 popwh-2 popbl-3 popam-4 popas-5
##   <int> <chr> <chr> <dbl> <int> <dbl> <int> <int> <int> <int>
## 1 561 ADAMS IL 0.052 66090 1271. 63917 1702 98 249
## 2 562 ALEXANDER IL 0.014 10626 759 7054 3496 19 48
## 3 563 BOND IL 0.022 14991 681. 14477 429 35 16
## 4 564 BOONE IL 0.017 30806 1812. 29344 127 46 150
## 5 565 BROWN IL 0.018 5836 324. 5264 547 14 5
## 6 566 BUREAU IL 0.05 35688 714. 35157 50 65 195
## 7 567 CALHOUN IL 0.017 5322 313. 5298 1 8 15
## 8 568 CARROLL IL 0.027 16805 622. 16519 111 30 61
## 9 569 CASS IL 0.024 13437 560. 13384 16 8 23
## 10 570 CHAMPAIGN IL 0.058 173025 2983. 146506 16559 331 8033
## # ... with 427 more rows, 18 more variables: popother <int>, percwhite <dbl>,
## # percblack <dbl>, percamerindan <dbl>, percasian <dbl>, percother <dbl>,
## # popadults <int>, perchsd <dbl>, percollege <dbl>, percprof <dbl>,
## # poppovertyknown <int>, percpovertyknown <dbl>, percbelowpoverty <dbl>,
## # percchildbelowpovert <dbl>, percadultpoverty <dbl>,
## # percelderlypoverty <dbl>, inmetro <int>, category <chr>, and abbreviated
## # variable names 1: popdensity, 2: popwhite, 3: popblack, ...
```

```
#Density plot
p <- ggplot(data = midwest, mapping = aes(x = area))
p+ geom_density()
```



```
#create a subset  
oh_wi <- c("OH", "WI")  
p <- ggplot(data = subset(midwest, subset = state %in% oh_wi),  
mapping = aes(x = area, fill = state, color = state))  
p+ geom_density(alpha = 0.3)
```



Part2

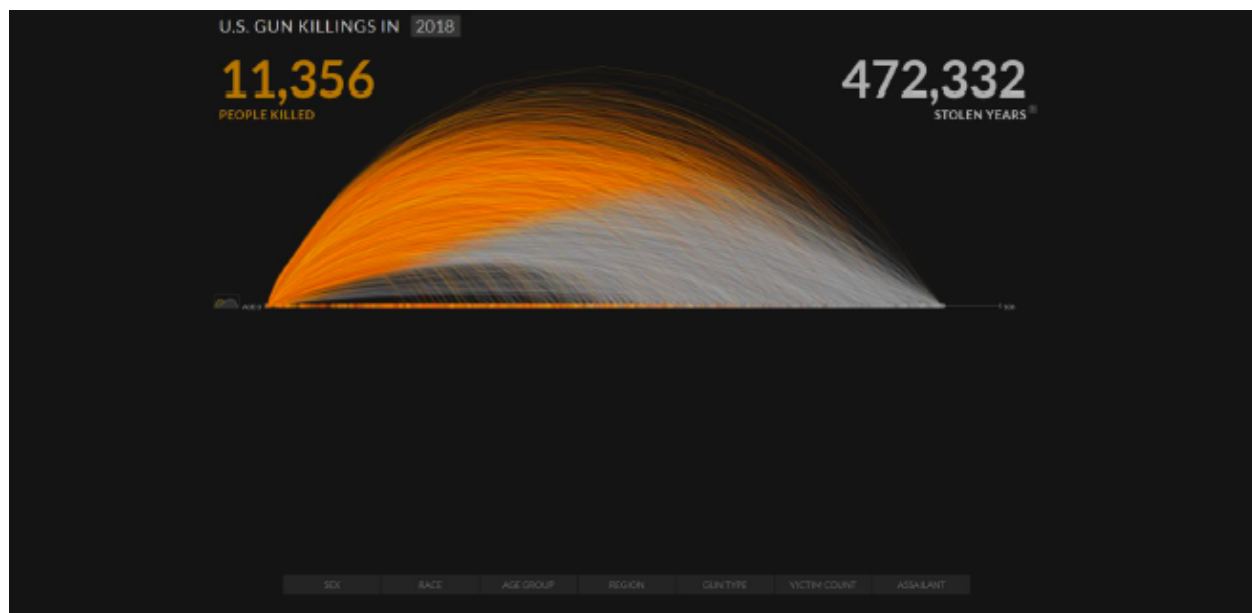


Figure 1: Resource picture

- What information can we learn from this visualization?

Answer Relationship between the stolen guns and the people killed # people killed, # of projected years cut short; not objective as projected years are speculative (assuming based on statistical likelihood)

- Is this an example of objective, neutral data visualization? Why or why not?

Answer It shows only the numbers.

What we want our data viz to do?

Intended purpose - Persuading - Comparison - Evaluation - Exploring

Intended audience - Age - Education - Expertise - Accessibility

Intended medium - Print - Web - Poster - Presentation

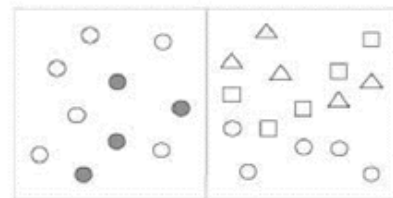
How is our data visualization perceived?

Gestalt principles



Proximity

Objects that are close together are perceived as belonging to a group



Similarity

Similar objects are grouped, regardless of proximity

Figure 2: Gestalt#1

Cognitive load can be divided into: Intrinsic (the intrinsic complexity of the new Germane (the audience's familiarity with the Extraneous (complexity from how the information is presented)

To find the useful dataviz catalogue, visit the DataViz catalogue

Interactive version

Stationary version

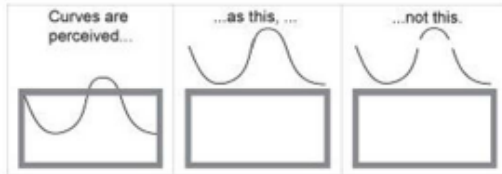
Part3

```
organdata
```

```
## # A tibble: 238 x 21
```

```
##   country year      donors  pop pop_d~1  gdp gdp_lag health healt~2 pubhe~3
```

Gestalt principles



Continuity

Aligned objects or objects that appear to continue are perceived as a group

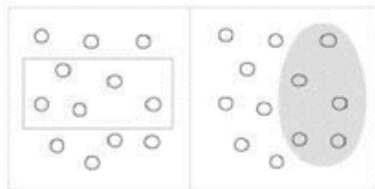


Closure

Open structures are perceived as closed/complete (our brains fill in the gaps)

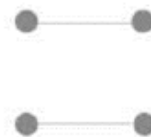
Figure 3: Gestalt#2

Gestalt principles



Enclosure

Objects with a boundary around them are perceived as a group



Connection

Connected objects are perceived as related/as a group

Figure 4: Gestalt#3

Cognitive load

- Elements of a visualization that can affect cognitive load include:
 - **Familiar vs. Rare chart types** → rare types increase cognitive load
 - **Accurate vs. Approximate interpretation** → relational values or areas (approximate) increase cognitive load compared to absolute values or position (accurate)
 - **Concise vs. Detailed composition** → more visual elements increases cognitive load
 - **Explanatory vs. Exploratory composition** → a chart that the audience navigates alone increases cognitive load compared to a chart that they are guided through step-by-step

(Sibinga & Waldron, 2021)

Figure 5: Cognitive load

```
##      <chr>      <date>      <dbl> <int>      <dbl> <int>      <int> <dbl>      <dbl>      <dbl>
## 1 Austral~ NA              NA      17065  0.220 16774  16591  1300      1224      4.8
## 2 Austral~ 1991-01-01    12.1  17284  0.223 17171  16774  1379      1300      5.4
## 3 Austral~ 1992-01-01    12.4  17495  0.226 17914  17171  1455      1379      5.4
## 4 Austral~ 1993-01-01    12.5  17667  0.228 18883  17914  1540      1455      5.4
## 5 Austral~ 1994-01-01    10.2  17855  0.231 19849  18883  1626      1540      5.4
## 6 Austral~ 1995-01-01    10.2  18072  0.233 21079  19849  1737      1626      5.5
## 7 Austral~ 1996-01-01    10.6  18311  0.237 21923  21079  1846      1737      5.6
## 8 Austral~ 1997-01-01    10.3  18518  0.239 22961  21923  1948      1846      5.7
## 9 Austral~ 1998-01-01    10.5  18711  0.242 24148  22961  2077      1948      5.9
## 10 Austral~ 1999-01-01    8.67 18926  0.244 25445  24148  2231      2077      6.1
## # ... with 228 more rows, 11 more variables: 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>,
## #   and abbreviated variable names 1: pop_dens, 2: health_lag, 3: pubhealth
```

#A dataset containing data on rates of organ donation for seventeen OECD countries between 1991 and 2000.

```
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 Germany  2002-01-01  12.2  82489  23.1  25843
## 2 Denmark  1996-01-01   14   5263  12.2  23548
## 3 France    NA         NA     NA    NA     NA
## 4 Finland  NA         NA    4986  1.47  18025
```

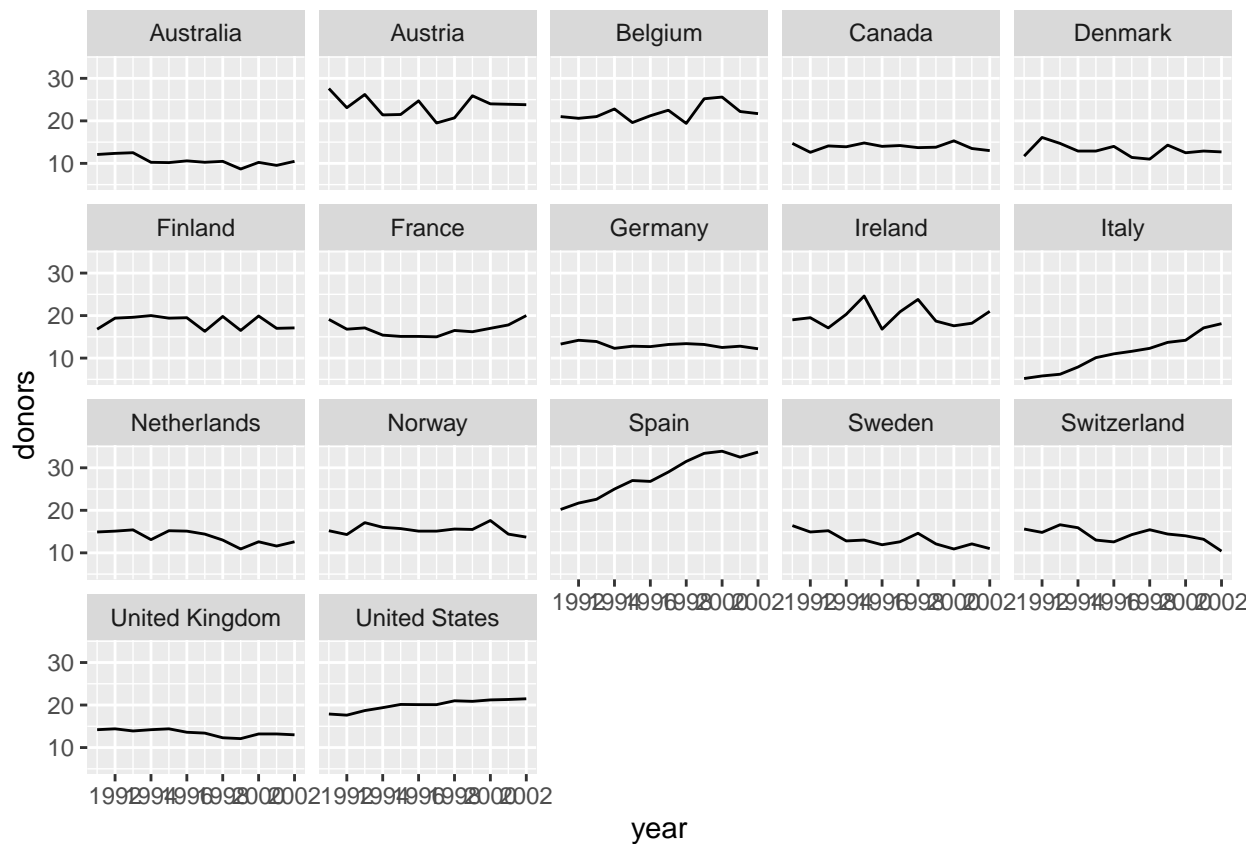
```
## 5 Canada      1994-01-01  13.9 29036  0.291 21428
## 6 United States 1992-01-01  17.6 256514  2.66 24411
## 7 Australia    1992-01-01  12.4 17495  0.226 17914
## 8 Germany      1993-01-01  13.9 81156  22.7 19983
## 9 Switzerland  1993-01-01  16.6 6938  16.8 25316
## 10 United States 1991-01-01  17.9 252981  2.63 23443
```

```
#select from col 1 to 6
#random sample for 10 rows
```

```
#continuous variables by group or category
p <- ggplot(data = organdata, mapping = aes(x = year, y = donors))

p + geom_line(aes(group = country)) + facet_wrap(~country)
```

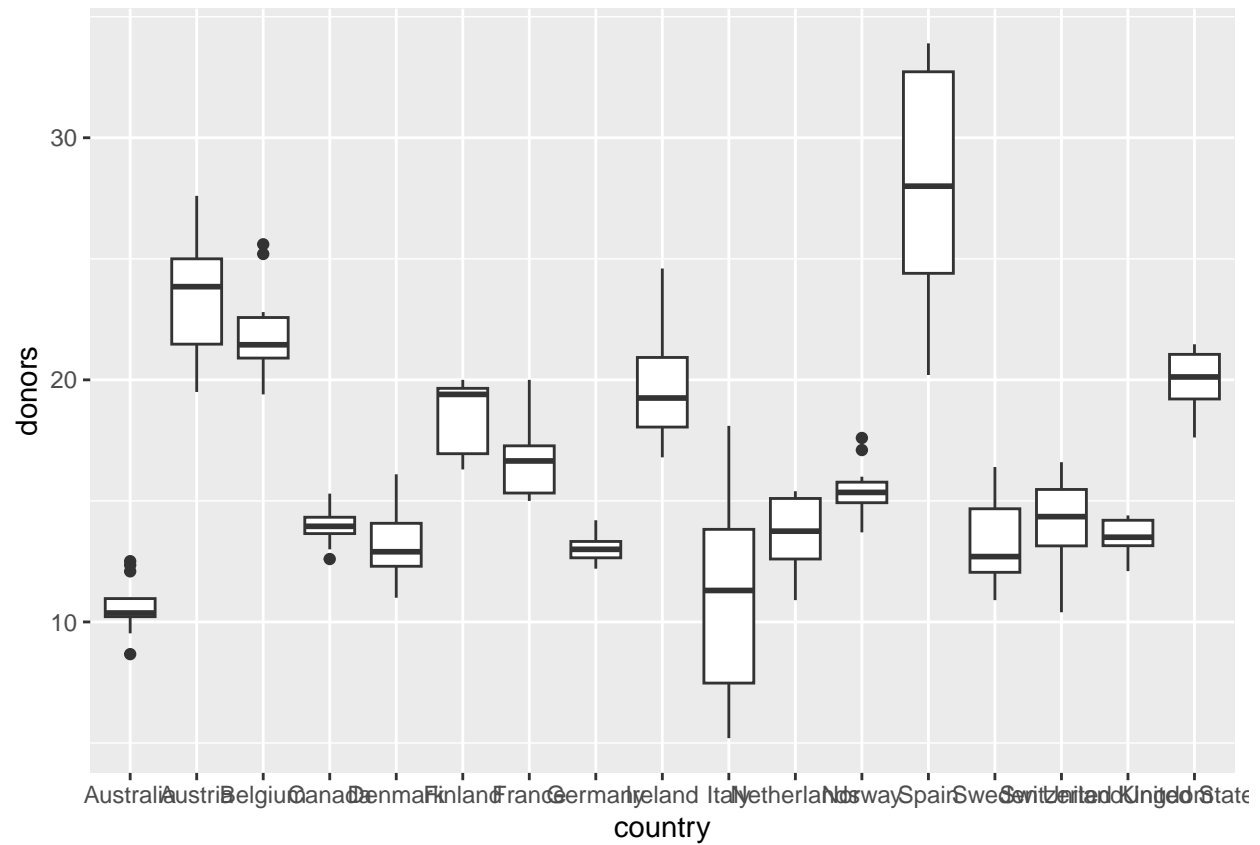
```
## Warning: Removed 34 rows containing missing values ('geom_line()').
```



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

p + geom_boxplot()
```

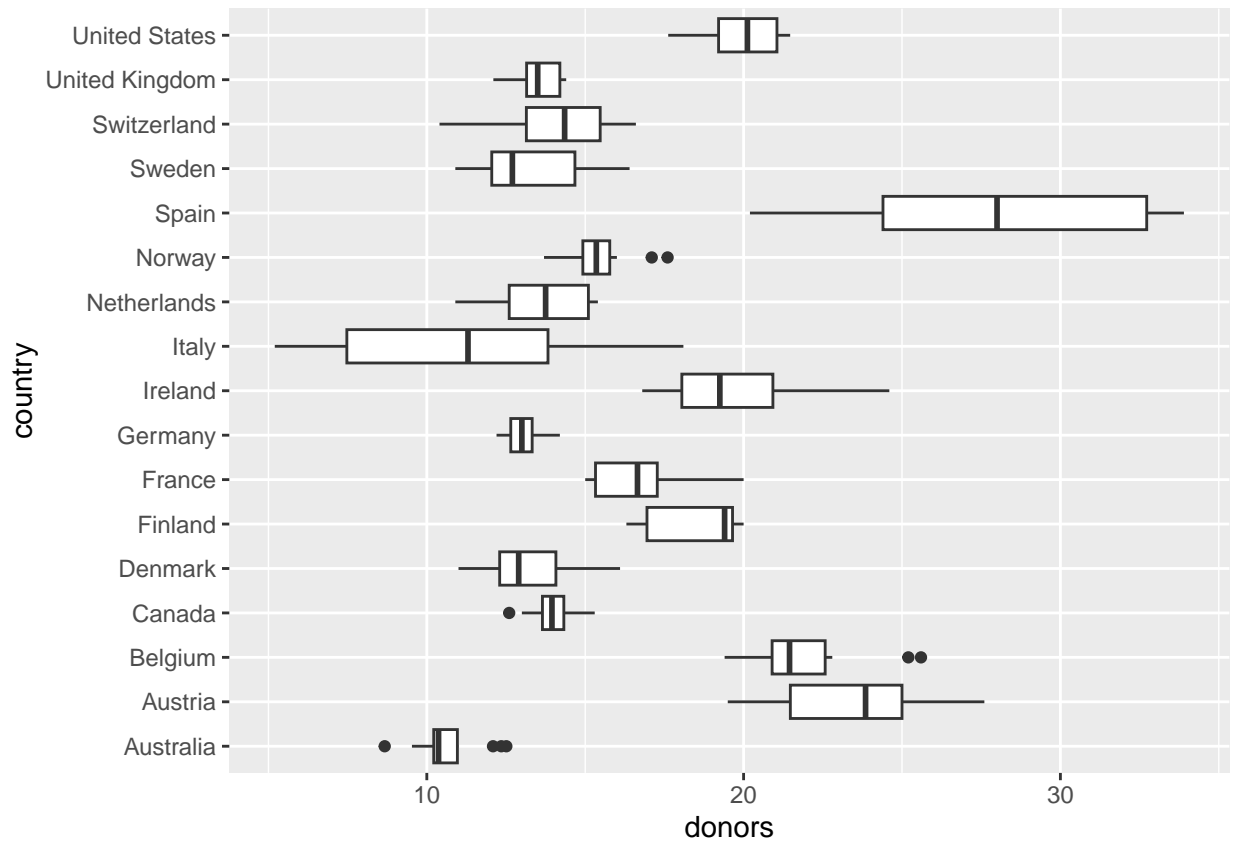
```
## Warning: Removed 34 rows containing non-finite values ('stat_boxplot()').
```



```
#improving the boxplot by adding coord_flip()
p <- ggplot(data = organdata, mapping = aes(x = country, y = donors))

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

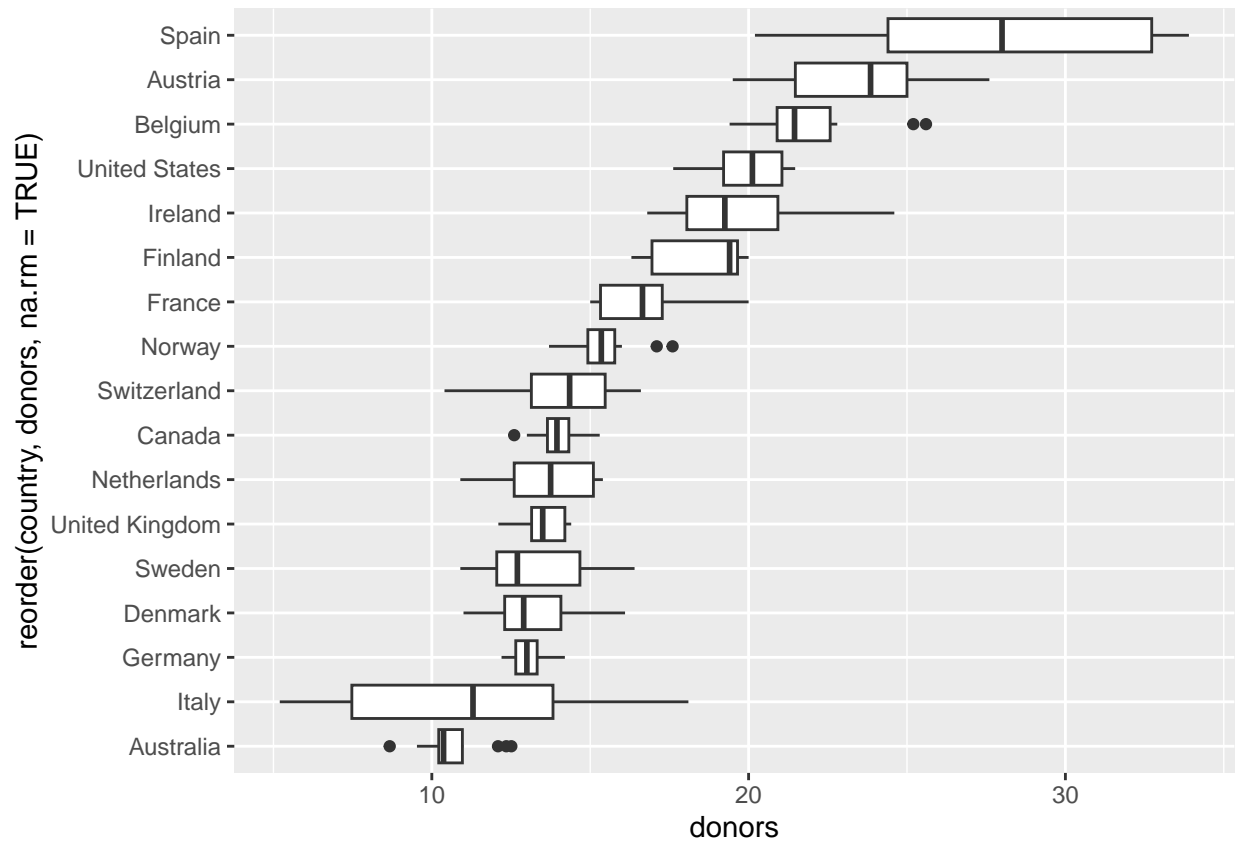
```
## Warning: Removed 34 rows containing non-finite values ('stat_boxplot()').
```



```
#improving the boxplot by reordering
p <- ggplot(data = organdata, mapping = aes(x = reorder(country, donors, na.rm = TRUE), y = donors))

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

```
## Warning: Removed 34 rows containing non-finite values ('stat_boxplot()').
```



```
#improving the boxplot by reordering alphabetically
p <- ggplot(data = organdata, mapping = aes(x = reorder(country, country, na.rm = TRUE), y = donors))
p + geom_boxplot() + coord_flip()
```

```
## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA
```

```
## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA
```

```
## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA
```

```
## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA
```

```
## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA
```

```
## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA
```

```
## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA
```

[illegible]


```
## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA

## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA

## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA

## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA

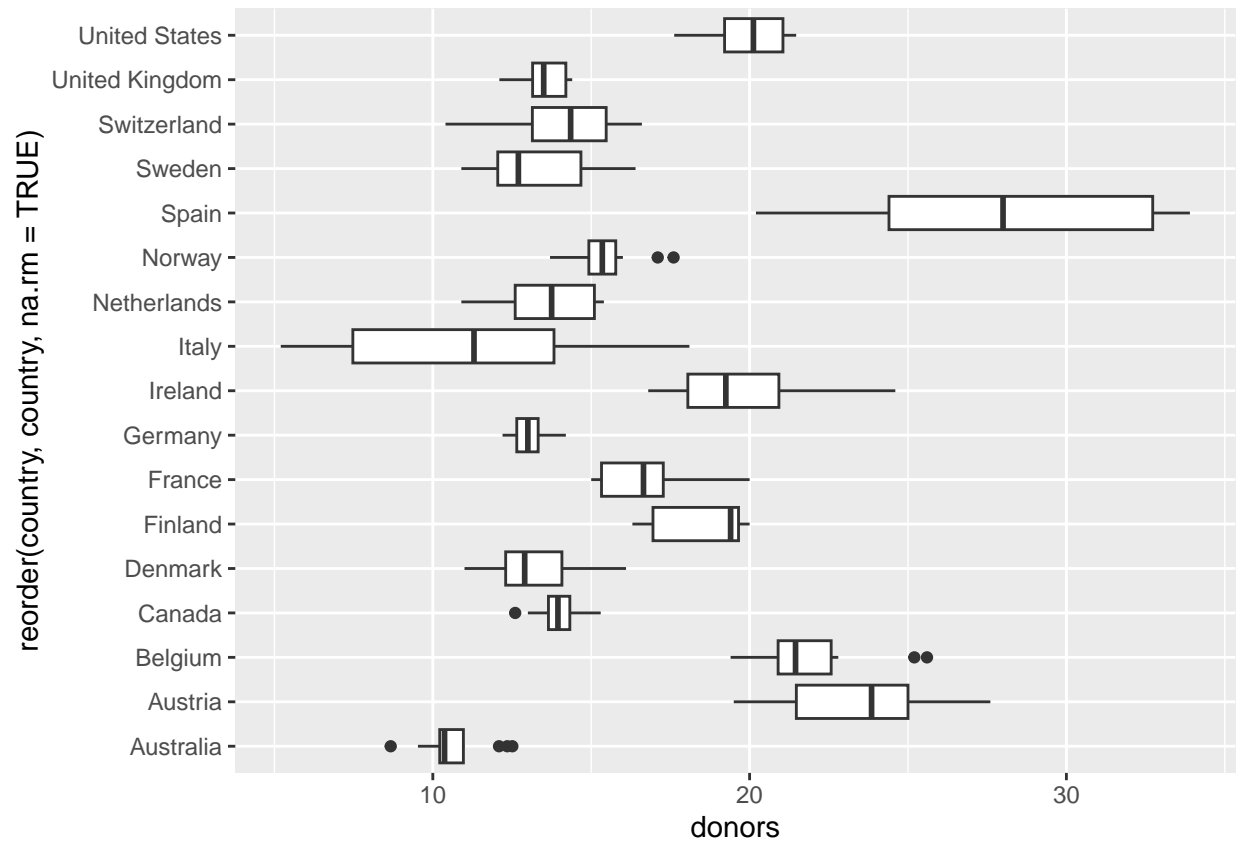
## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA

## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA

## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA

## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA

## Warning: Removed 34 rows containing non-finite values ('stat_boxplot()').
```

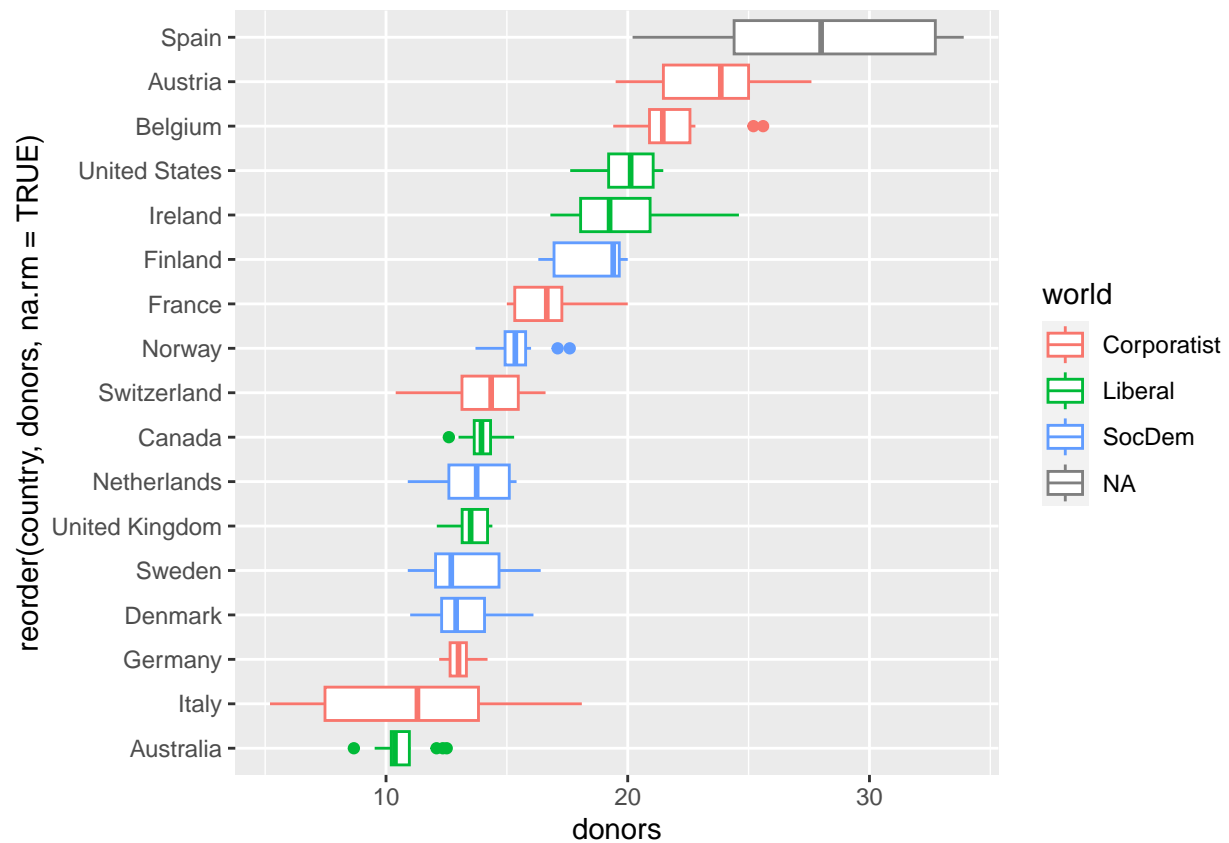


#improving the boxplot by coloring the world variable

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

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

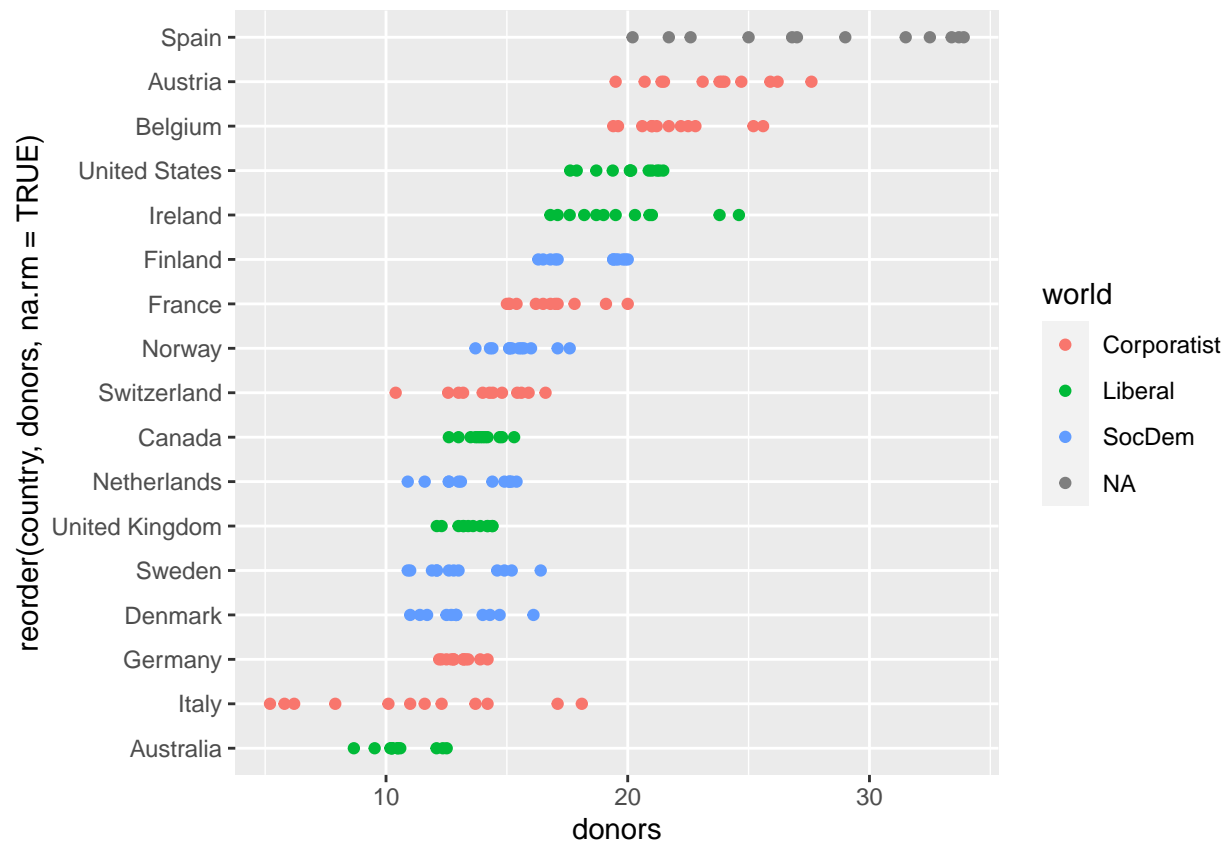
```
## Warning: Removed 34 rows containing non-finite values ('stat_boxplot()').
```



#improving the boxplot by changing into a point plot

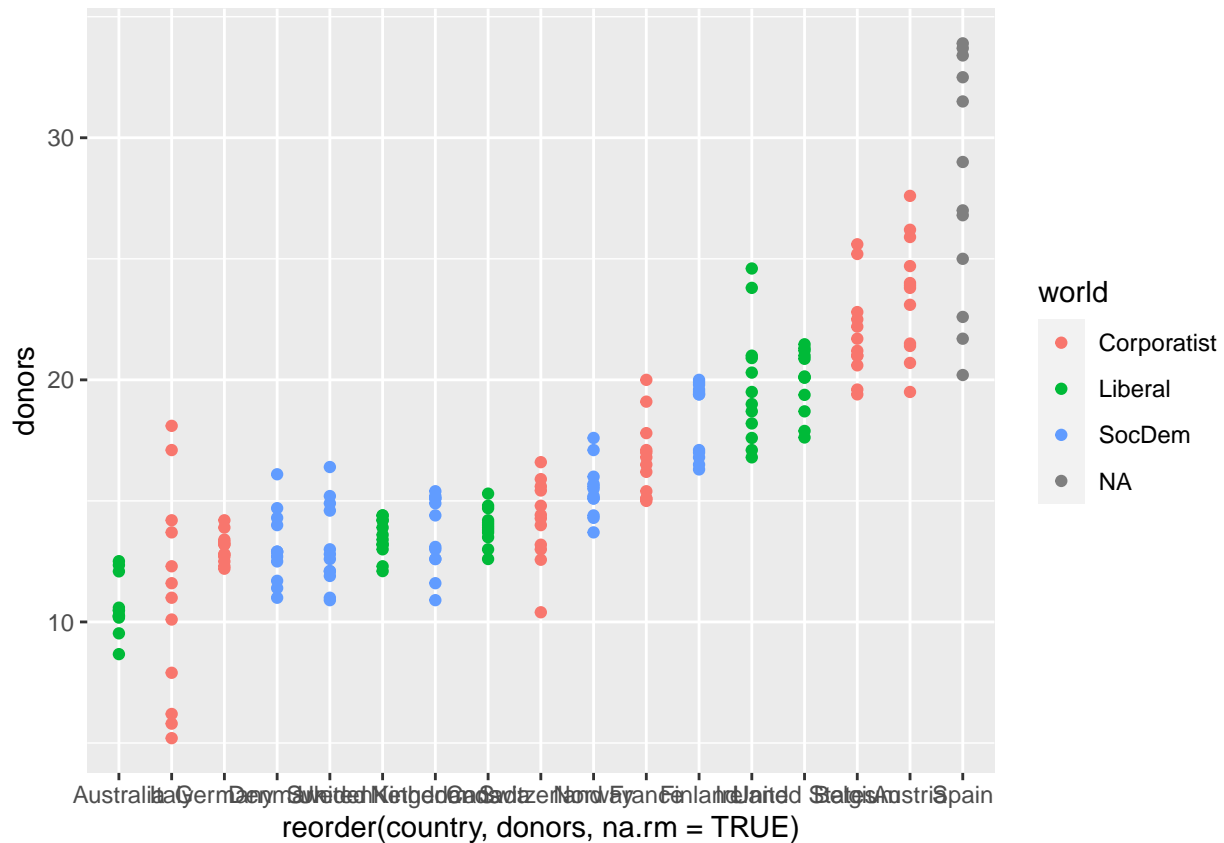
```
p <- ggplot(data = organdata, mapping = aes(x = reorder(country, donors, na.rm = TRUE), y = donors, color = world))
p + geom_point() + coord_flip()
```

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



```
#improving the boxplot by changing into a point plot and remove coord_flip()
p <- ggplot(data = organdata, mapping = aes(x = reorder(country, donors, na.rm = TRUE), y = donors, color = world))
p + geom_point()
```

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



Summarizing the data

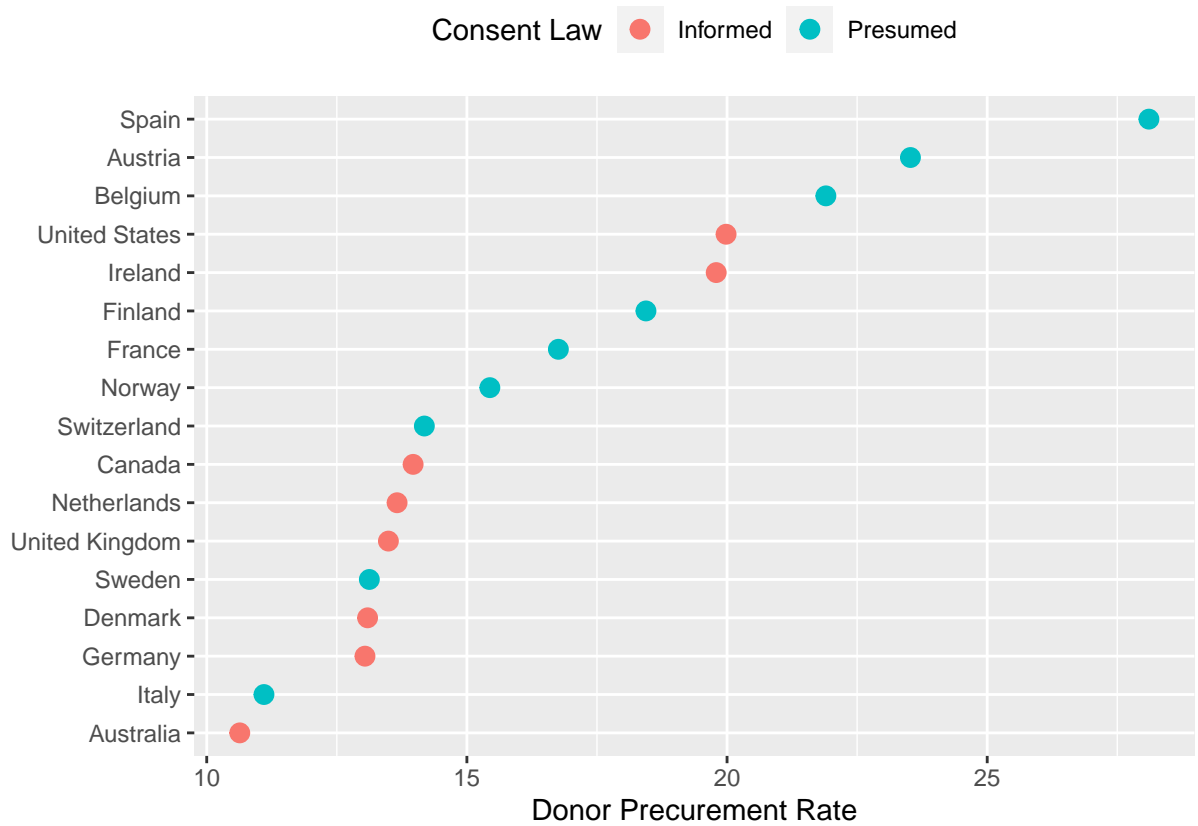
```
by_country <- organdata |> group_by(consent_law, country) |> summarize_if(is.numeric, funs(mean, sd), na.rm = TRUE)
```

```
## Warning: 'funs()' was deprecated in dplyr 0.8.0.
## i Please use a list of either functions or lambdas:
##
## # Simple named list: list(mean = mean, median = median)
##
## # Auto named with 'tibble::lst()': tibble::lst(mean, median)
##
## # Using lambdas list(~ mean(., trim = .2), ~ median(., na.rm = TRUE))
```

```
#if our col is a numeric, it will calculate the mean and SD
#exclude NA data by using na.rm = TRUE
```

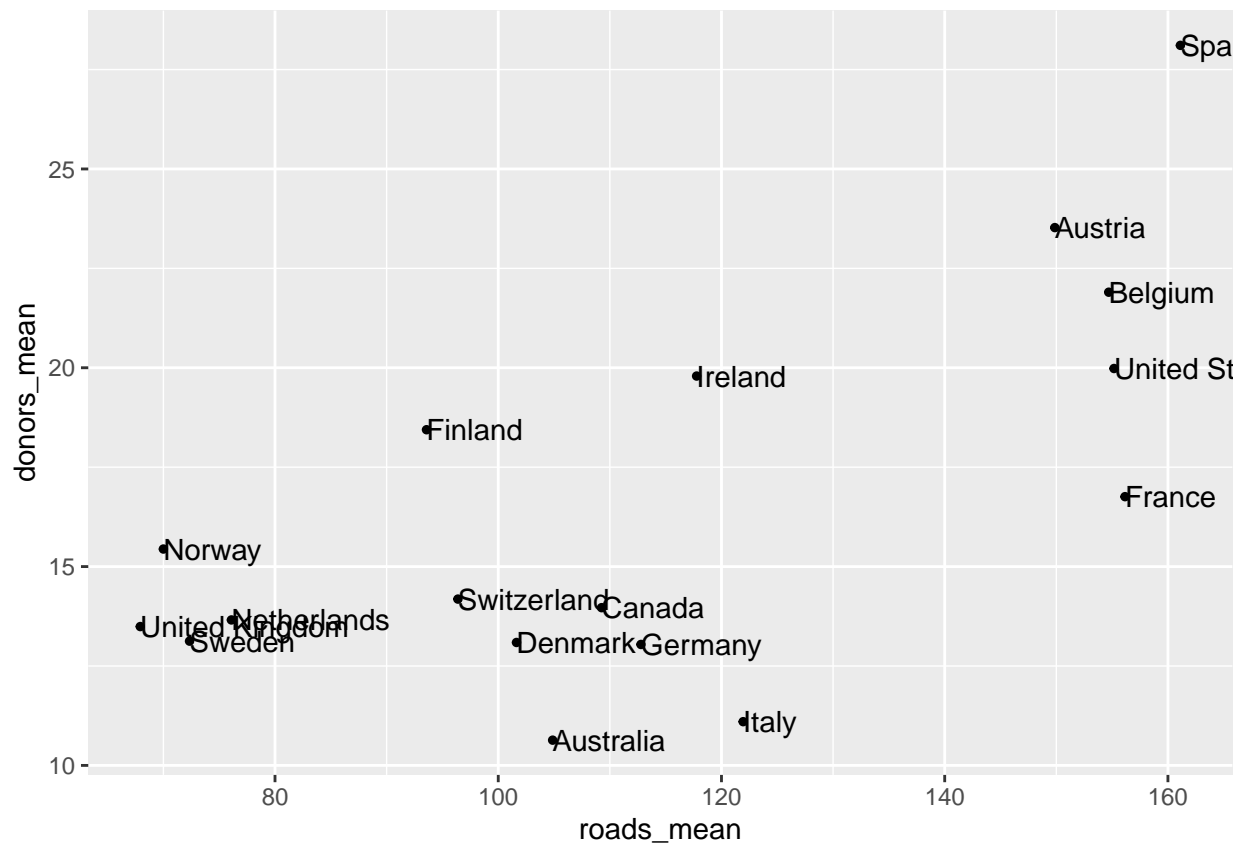
Categorical variables with a single point Now that we have summarized our data, we can make our Cleveland dotplot using `geom_point()`. We will also - Colour our results by the consent law for each country - Move our legend to the top of our plot

```
p <- ggplot(data = by_country, mapping = aes(x = donors_mean, y = reorder(country, donors_mean), color = consent_law)) +
  geom_point(size = 3) +
  labs(x = "Donor Procurement Rate",
       y = "", color = "Consent Law") +
  theme(legend.position = "top")
```



##Adding text labels to data points

```
p <- ggplot(data = by_country, mapping = aes(x = roads_mean, y = donors_mean))
p + geom_point(size = 1) + geom_text(mapping = aes(label = country), hjust = 0)
```



```
#load the library ggrepel
```

```
library(ggrepel)
```

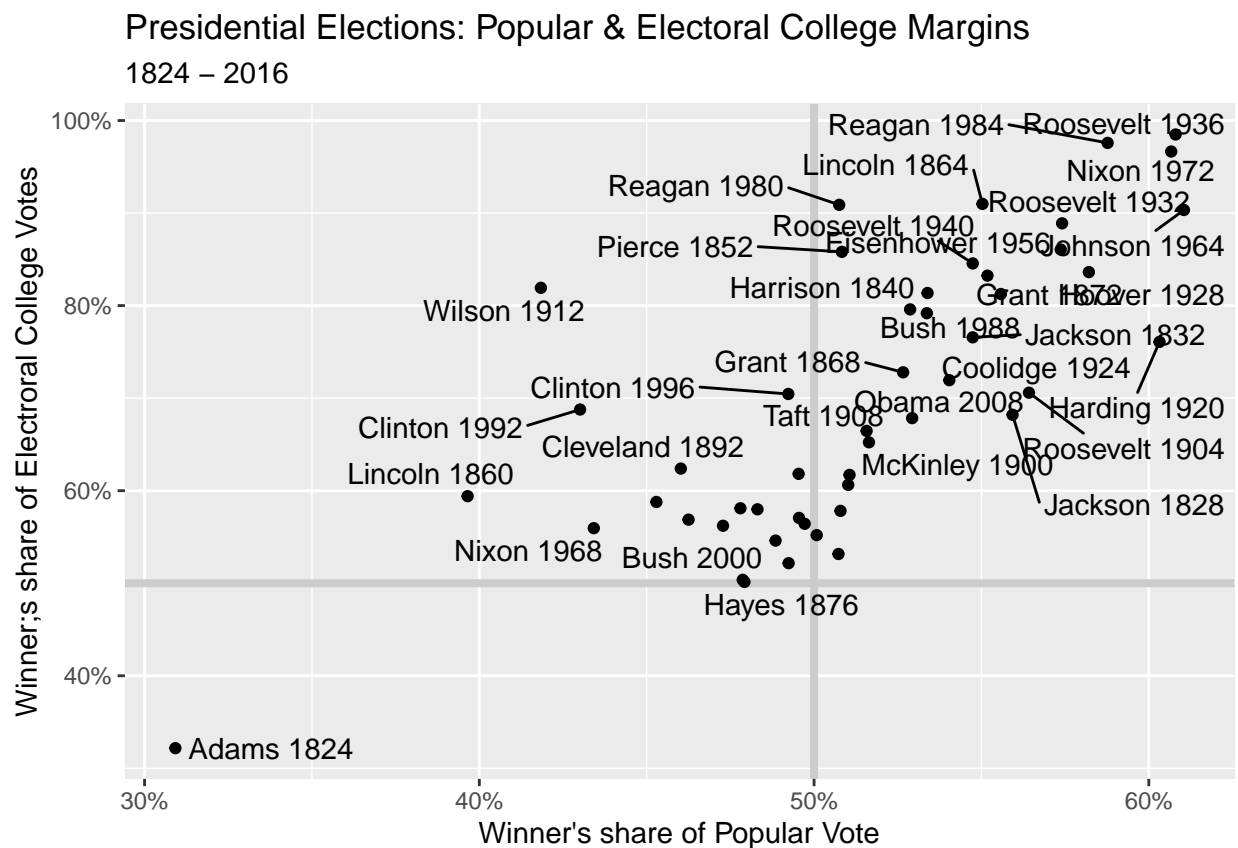
```
elections_historic
```

```
## # A tibble: 49 x 19
##   election year winner   win_p~1 ec_pct popul~2 popul~3 votes margin runne~4
##   <int> <int> <chr>   <chr>   <dbl>   <dbl>   <dbl>   <int>   <int> <chr>
## 1      10  1824 John Qui~ D.-R.    0.322   0.309 -0.104  1.13e5 -38221 Andrew~
## 2      11  1828 Andrew J~ Dem.     0.682   0.559  0.122  6.43e5 140839 John Q~
## 3      12  1832 Andrew J~ Dem.     0.766   0.547  0.178  7.03e5 228628 Henry ~
## 4      13  1836 Martin V~ Dem.     0.578   0.508  0.142  7.63e5 213384 Willia~
## 5      14  1840 William ~ Whig    0.796   0.529  0.0605 1.28e6 145938 Martin~
## 6      15  1844 James Po~ Dem.     0.618   0.495  0.0145 1.34e6  39413 Henry ~
## 7      16  1848 Zachary ~ Whig    0.562   0.473  0.0479 1.36e6 137882 Lewis ~
## 8      17  1852 Franklin~ Dem.     0.858   0.508  0.0695 1.61e6 219525 Winfie~
## 9      18  1856 James Bu~ Dem.     0.588   0.453  0.122  1.84e6 494472 John F~
## 10     19  1860 Abraham ~ Rep.     0.594   0.396  0.101  1.86e6 474049 John B~
## # ... with 39 more rows, 9 more variables: 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>, and abbreviated variable
## #   names 1: win_party, 2: popular_pct, 3: popular_margin, 4: runner_up
```

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

p + geom_hline(yintercept = 0.5, size = 1.4, color = "gray80") +
  #We add reference lines so we can see the 50% threshold of votes on each axis.by geom_hline
  geom_vline(xintercept = 0.5, size = 1.4, color = "gray80") +
  geom_point() +
  #geom_text_repel() will ensure that our data labels do not overlap.
  geom_text_repel() +
  #Vote shares are stored as proportions rather than percents, so we adjust the labels of the scales.
  scale_x_continuous(labels = scales::percent) +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "Winner's share of Popular Vote", y = "Winner;s share of Electroral College Votes", title = "Presidential Elections: Popular & Electoral College Margins")

## Warning: ggrepel: 17 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



Reference