Intro to Visualizations & String Data

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Week 2

Agenda

- Visualizing distributions
  - histograms
  - density plots
  - Empirical cumulative density plots
  - QQ plots
- Visualizing amounts
  - bar plots
  - dot plots
  - heatmaps
- Working textual data
  - Splitting into words, n–grams
  - Visualizing word frequencies
- Cleaning string data
  - Substrings, basic transformations
  - Substitutions and quick pattern matching

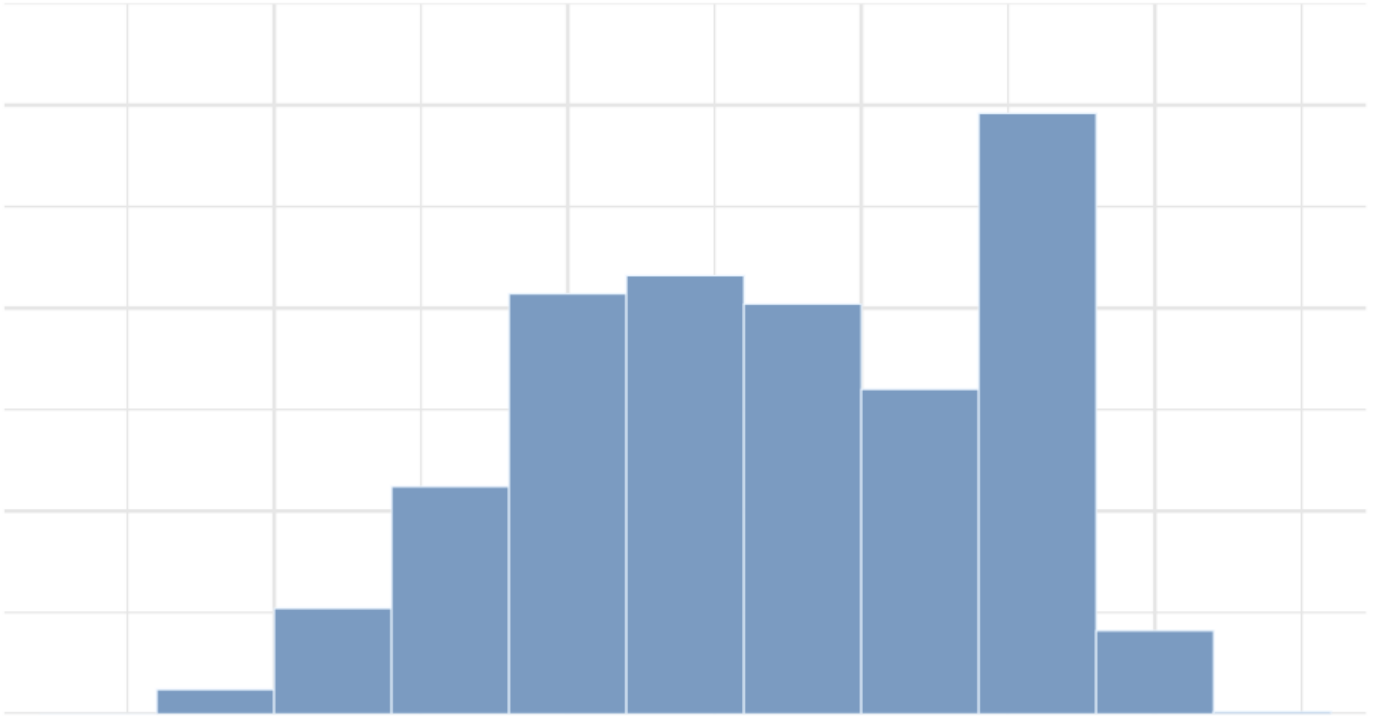
A promise: You will have **at least 30 minutes** for lab, even if we have to pause this lecture early

Learning Objectives

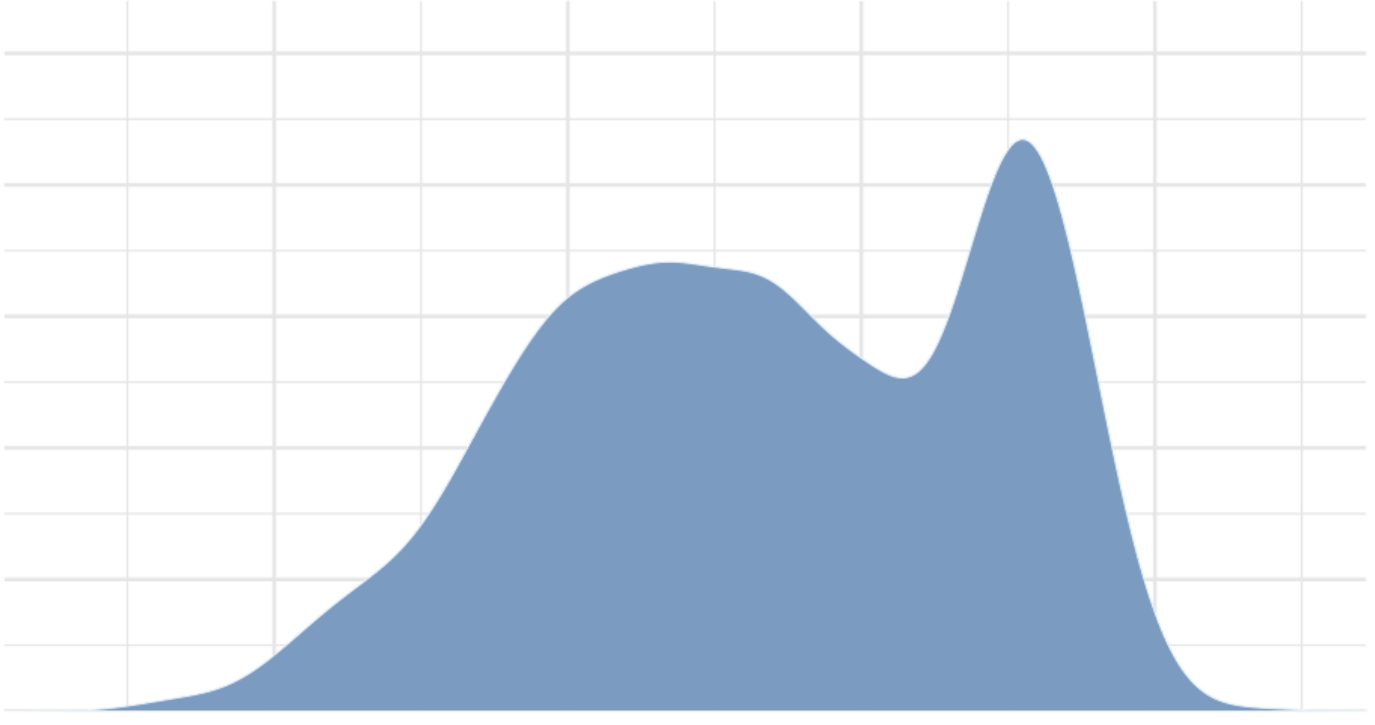
- Understand various ways the same underlying data can be displayed
- Think through pros/cons of each
- Understand the basic structure of the code to produce the various plots
- Create structured data from text and be able to visualize word frequencies
- Be able to replace patterns in strings and understand which character need to be "escaped"

One continuous variable

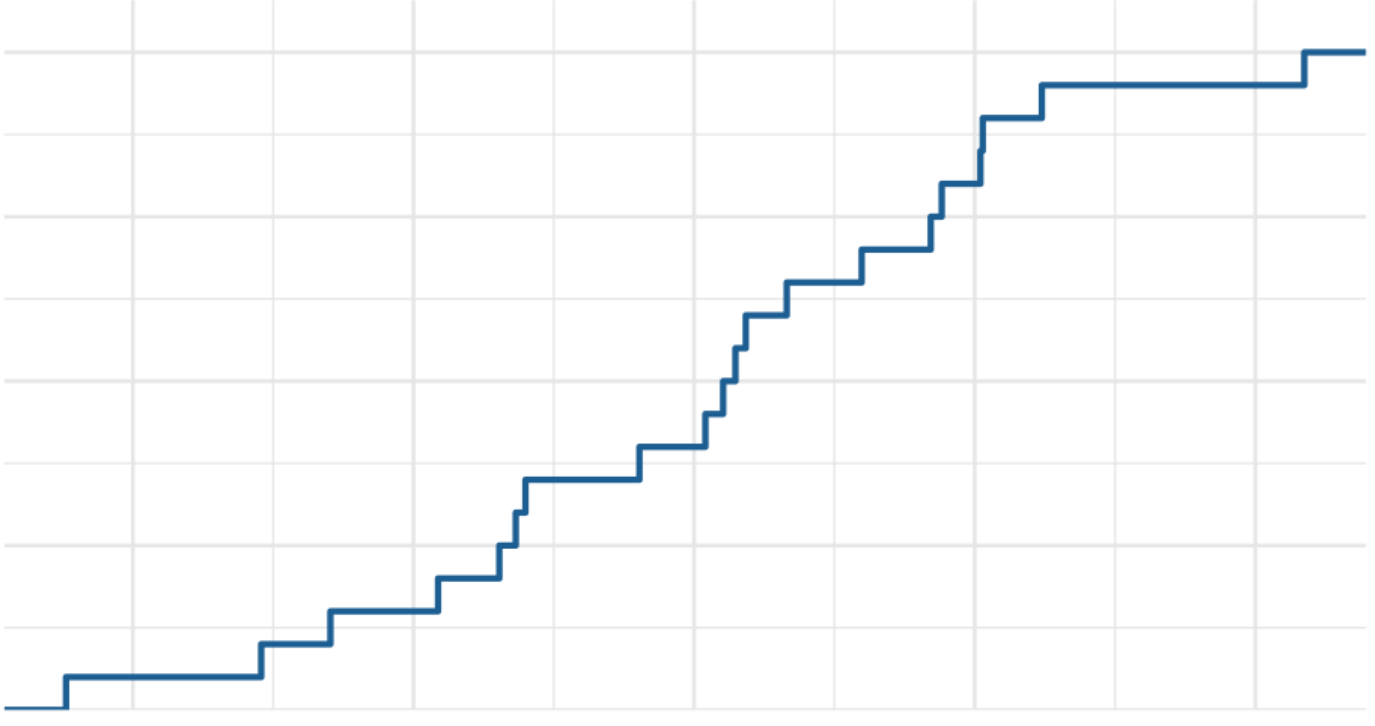
Histogram



Density plot

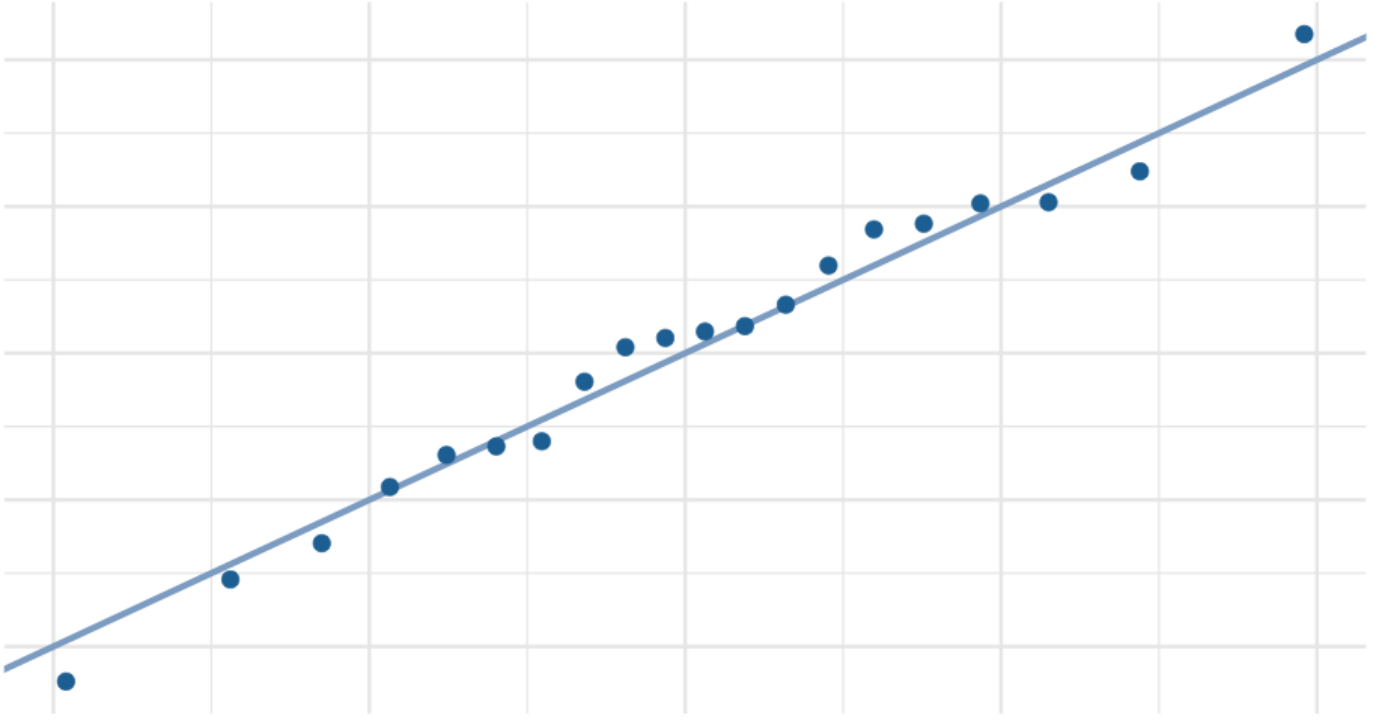


(Empirical) Cumulative Density



QQ Plot

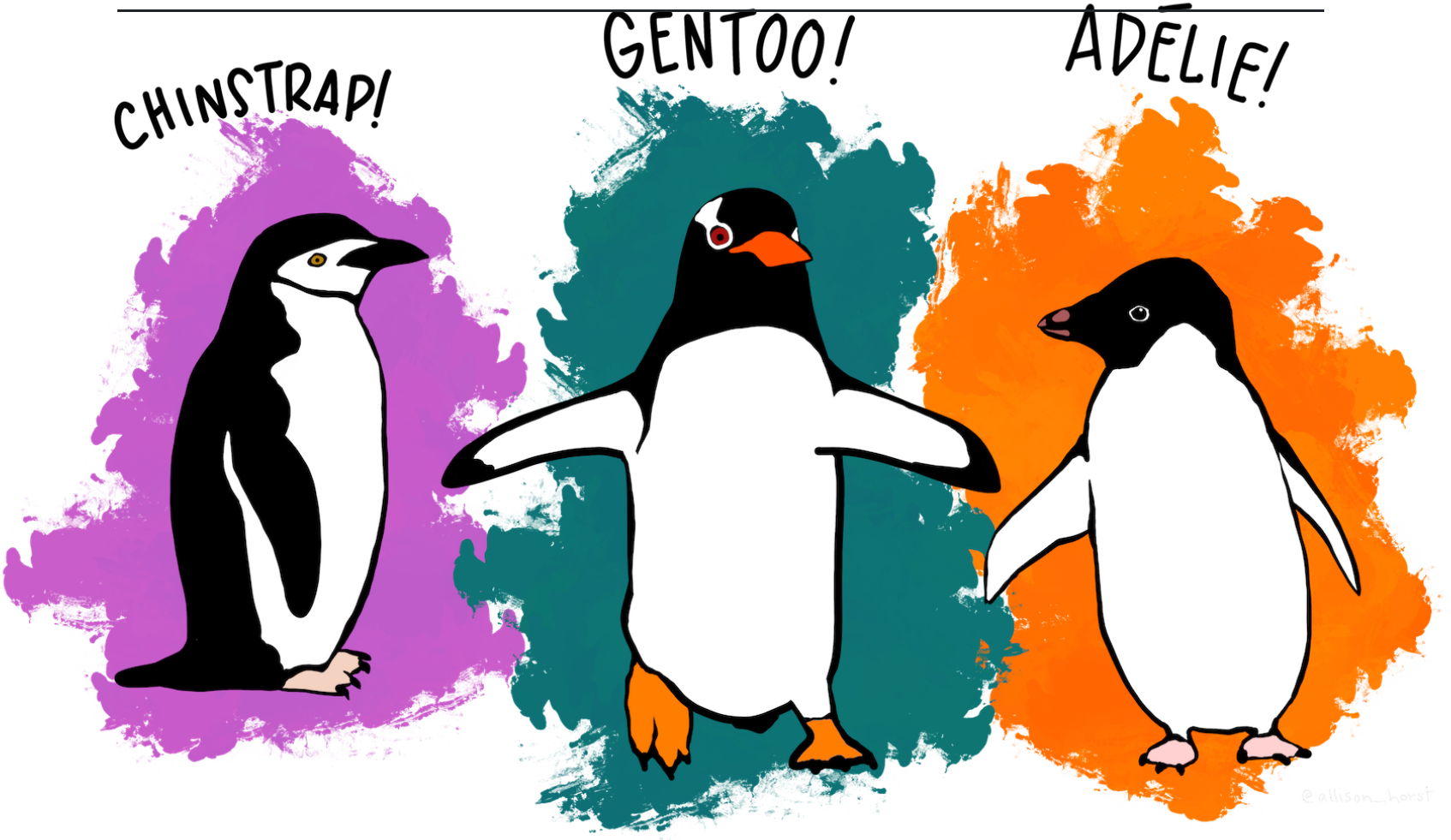
Compare to theoretical quantiles (for normality)



Empirical examples

I'll move fast, but if you want to (try to) follow along, feel free.

Penguin data



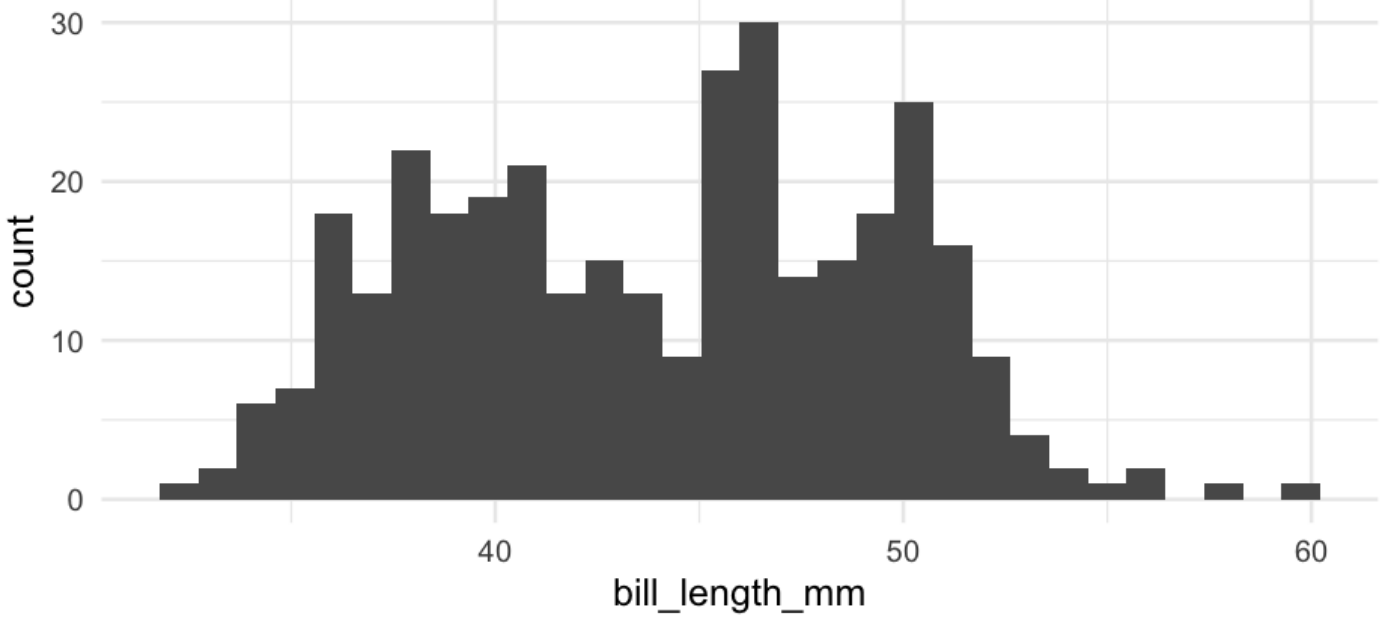
```r
library(palmerpenguins)
penguins
```

```
## # A tibble: 344 × 8
##    species island    bill_length_mm bill_depth_mm
##    <fct>   <fct>              <dbl>         <dbl>
##  1 Adelie  Torgersen           39.1          18.7
##  2 Adelie  Torgersen           39.5          17.4
##  3 Adelie  Torgersen           40.3          18
##  4 Adelie  Torgersen           NA            NA
##  5 Adelie  Torgersen           36.7          19.3
##  6 Adelie  Torgersen           39.3          20.6
##  7 Adelie  Torgersen           38.9          17.8
##  8 Adelie  Torgersen           39.2          19.6
##  9 Adelie  Torgersen           34.1          18.1
## 10 Adelie  Torgersen           42            20.2
## # … with 334 more rows, and 4 more variables:
## #   flipper_length_mm <int>, body_mass_g <int>,
## #   sex <fct>, year <int>
```

Basic histogram

```
ggplot(penguins, aes(x = bill_length_mm)) +
  geom_histogram()
```

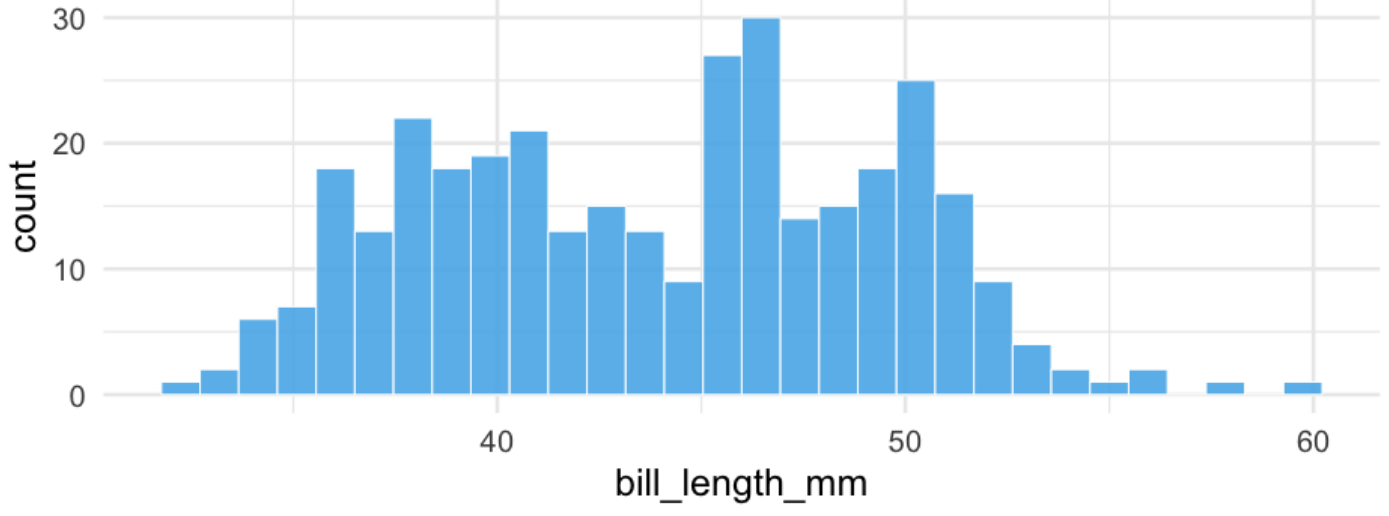
```
## `stat_bin()` using `bins = 30`. Pick better
## value with `binwidth`.
```



Make it a little prettier

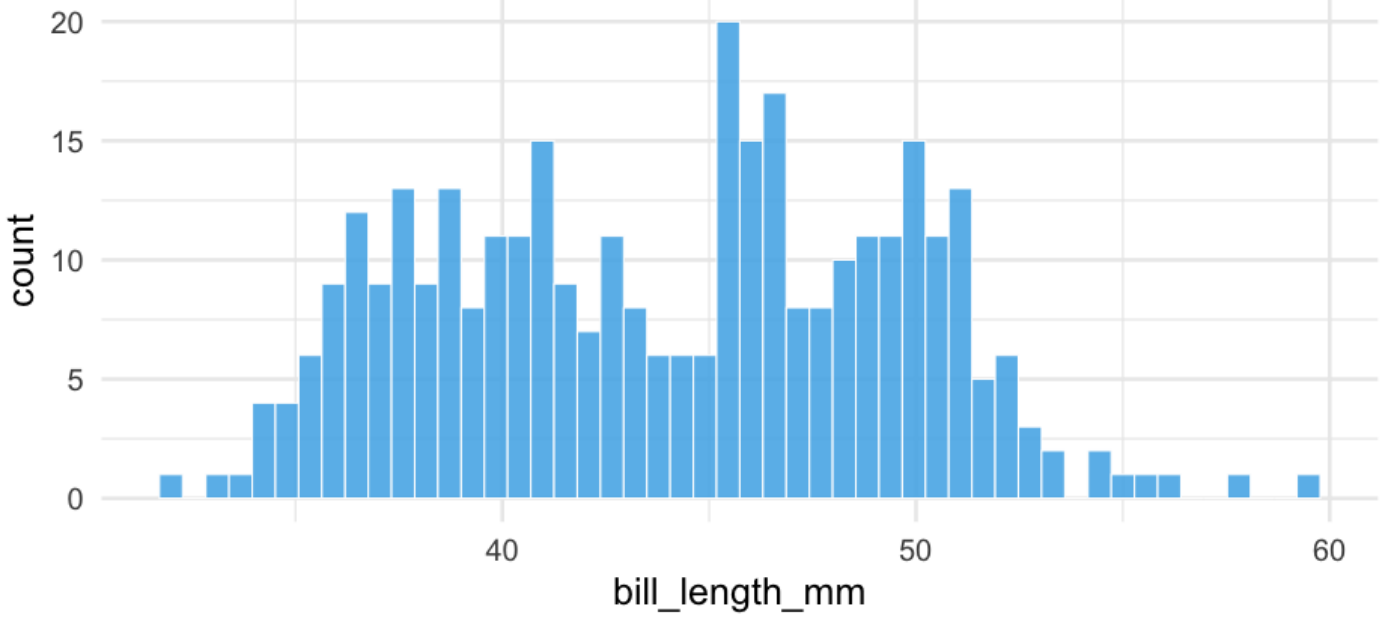
```
ggplot(penguins, aes(x = bill_length_mm)) +
  geom_histogram(fill = "#56B4E9",
                 color = "white",
                 alpha = 0.9)
```

```
## `stat_bin()` using `bins = 30`. Pick better
## value with `binwidth`.
```

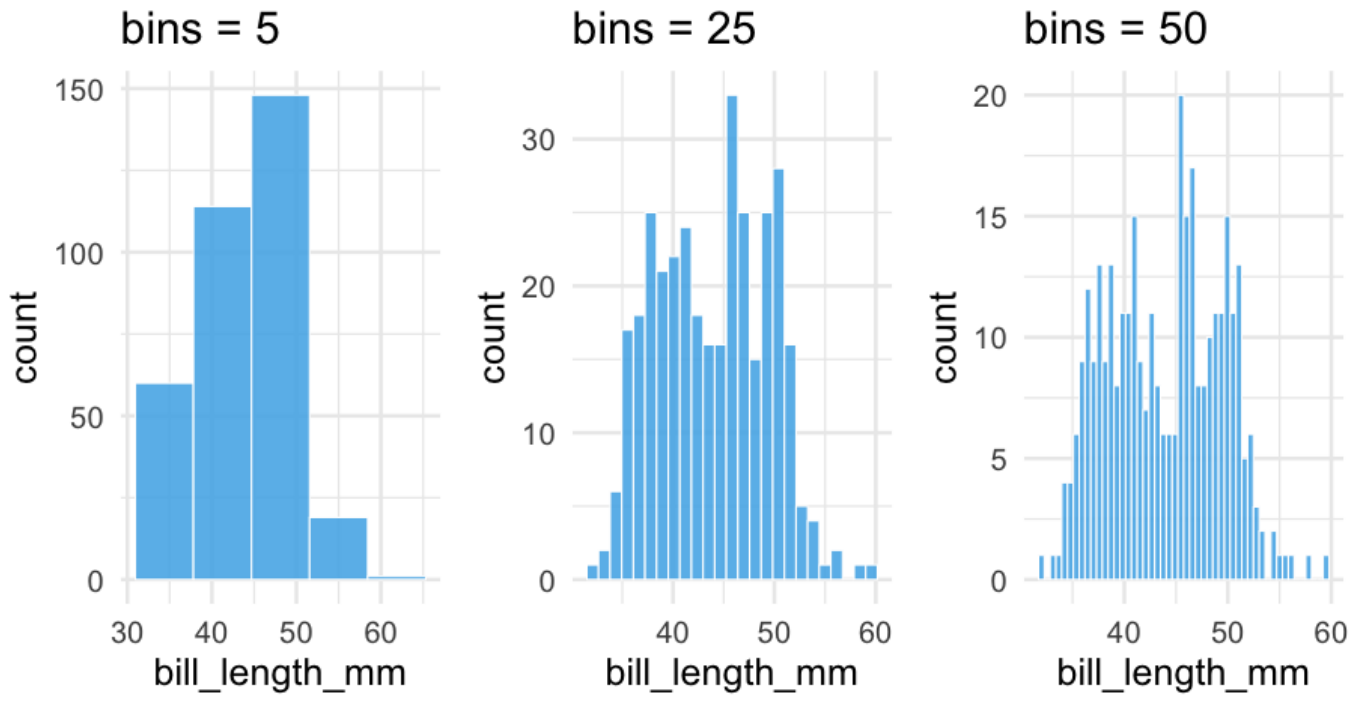


Change the number of bins

```
ggplot(penguins, aes(x = bill_length_mm)) +
  geom_histogram(fill = "#56B4E9",
                 color = "white",
                 alpha = 0.9,
                 bins = 50)
```



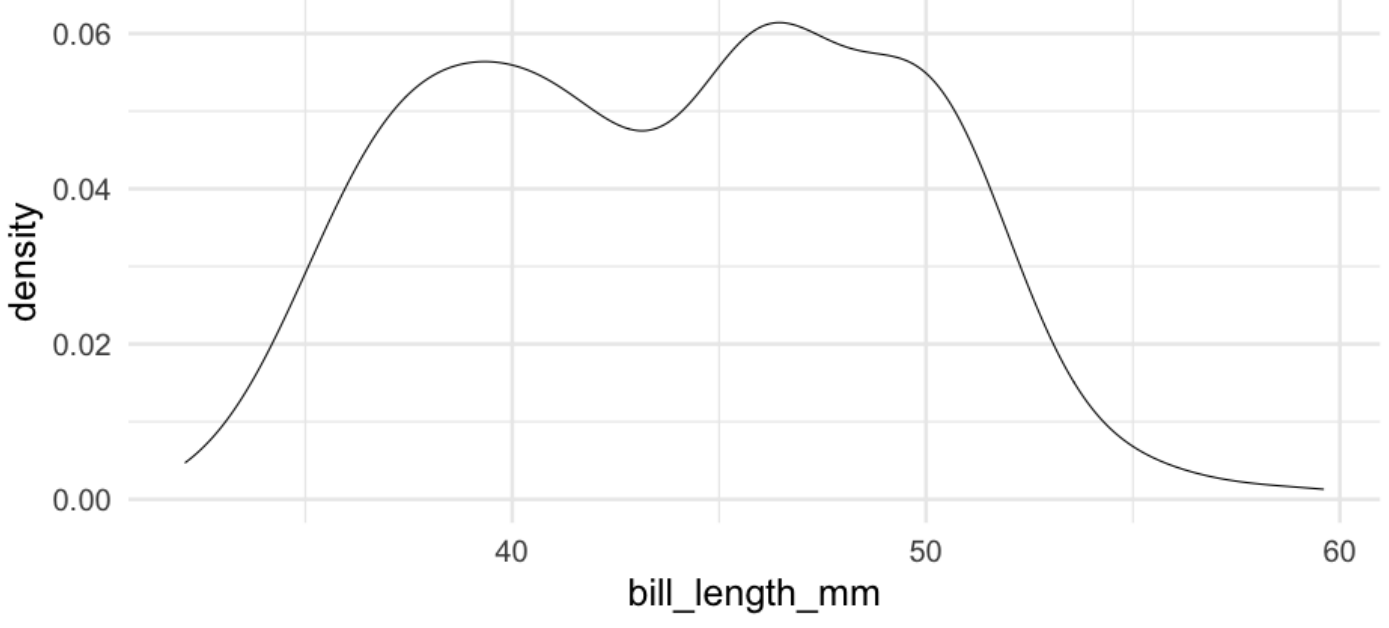
Vary the number of bins



Denisty plot

ugly 😫

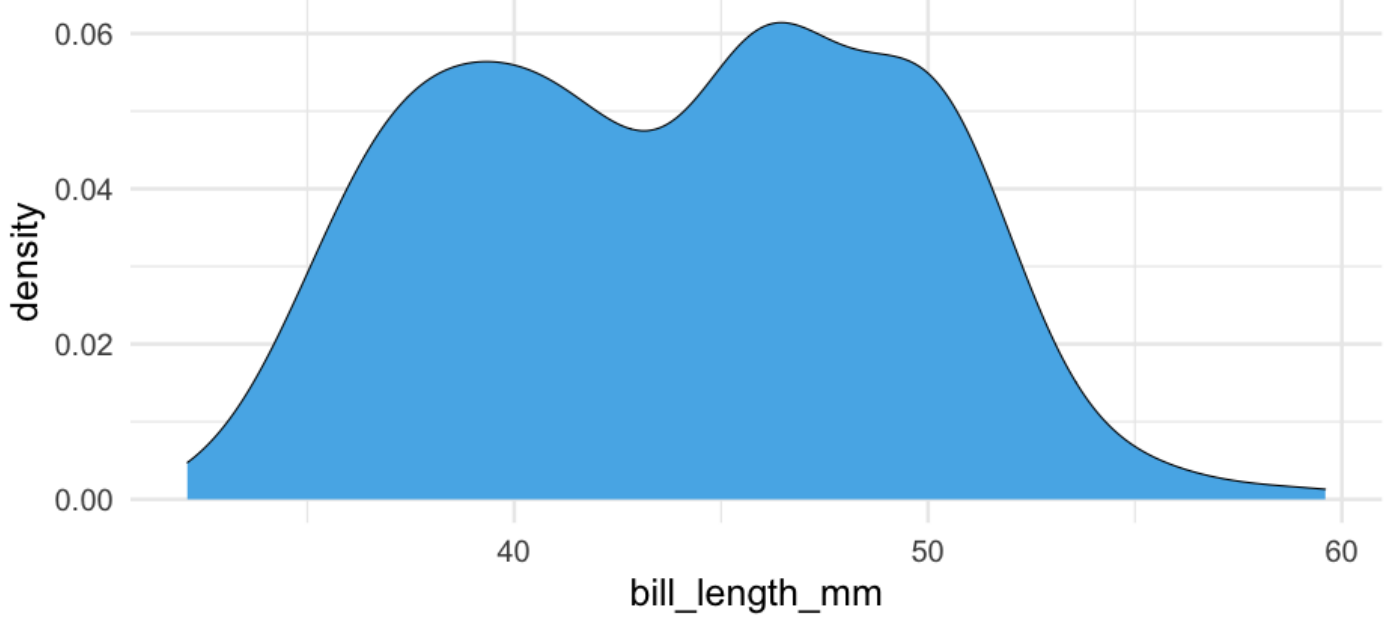
```
ggplot(penguins, aes(bill_length_mm)) +
  geom_density()
```



Denisty plot

Change the fill 😌

```
ggplot(penguins, aes(bill_length_mm)) +
  geom_density(fill = "#56B4E9")
```



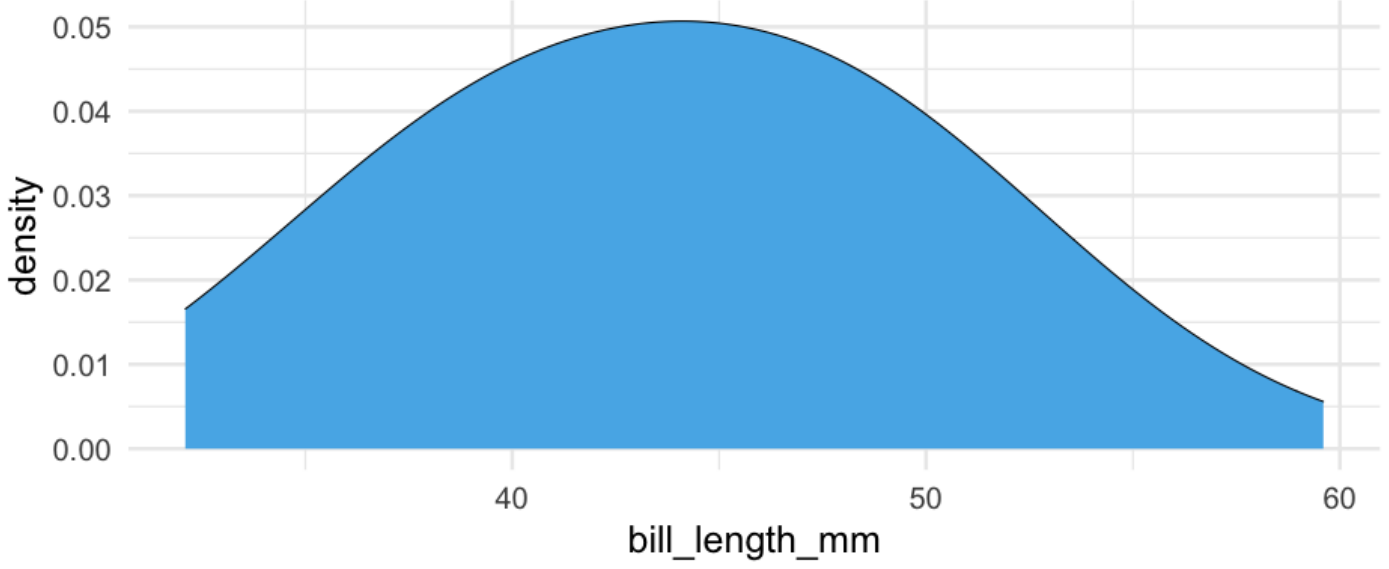
Density plot estimation

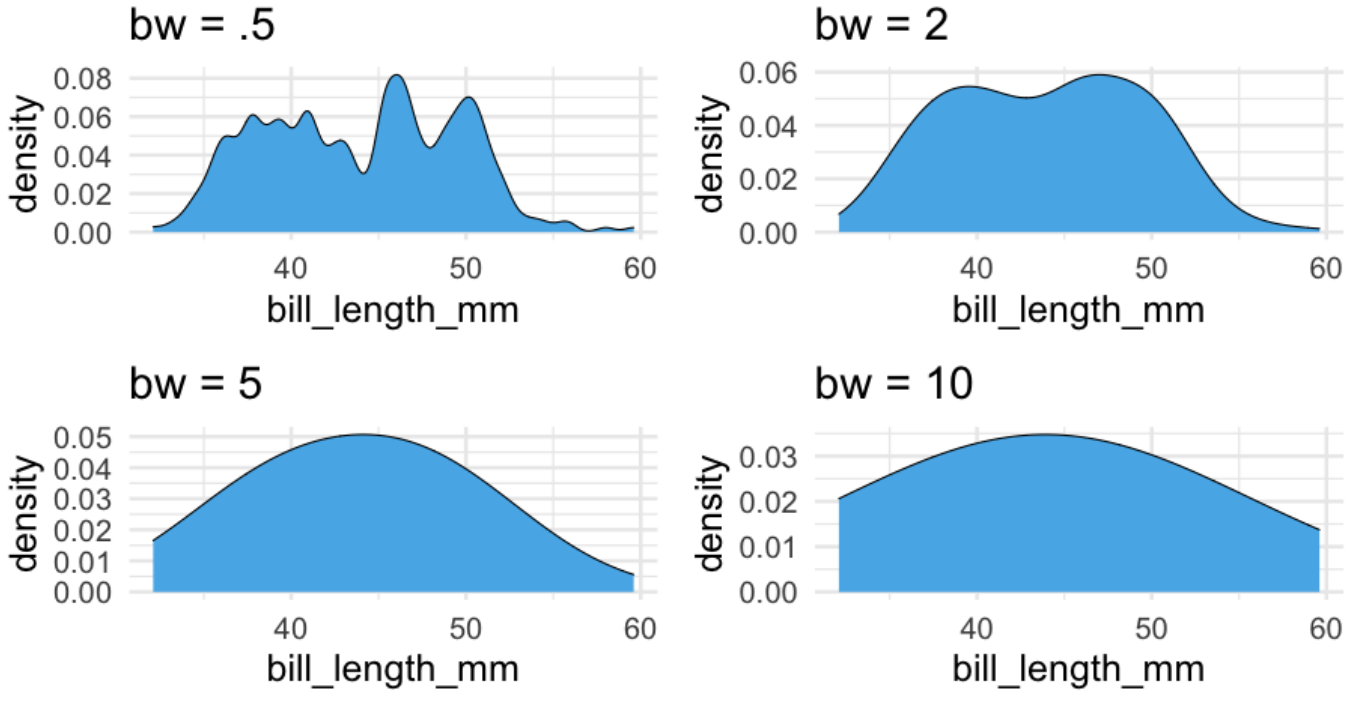
- Kernal density estimation
    - Different kernal shapes can be selected
    - Bandwidth matters most
    - Smaller bands = bend more to the data
- Approximation of the underlying continuous probability function
    - Integrates to 1.0 (y–axis is somewhat difficult to interpret)

Denisty plot

change the bandwidth

```
ggplot(penguins, aes(bill_length_mm)) +
  geom_density(fill = "#56B4E9",
               bw = 5)
```

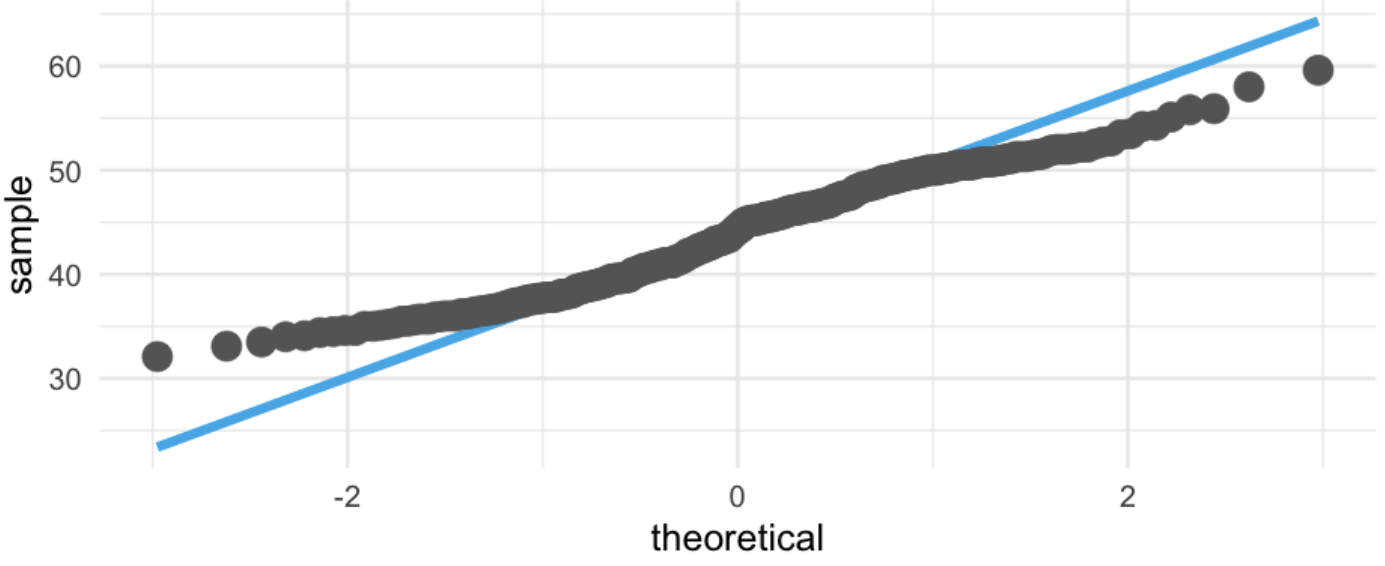



bw = .5
density
0.08
0.06
0.04
0.02
0.00
40
50
60
bill_length_mm
bw = 2
density
0.06
0.04
0.02
0.00
40
50
60
bill_length_mm
bw = 5
density
0.05
0.04
0.03
0.02
0.01
0.00
40
50
60
bill_length_mm
bw = 10
density
0.03
0.02
0.01
0.00
40
50
60
bill_length_mm

Quickly

How well does it approximate a normal distribution?

```
ggplot(penguins, aes(sample = bill_length_mm)) +
  stat_qq_line(color = "#56B4E9") +
  geom_qq(color = "gray40")
```

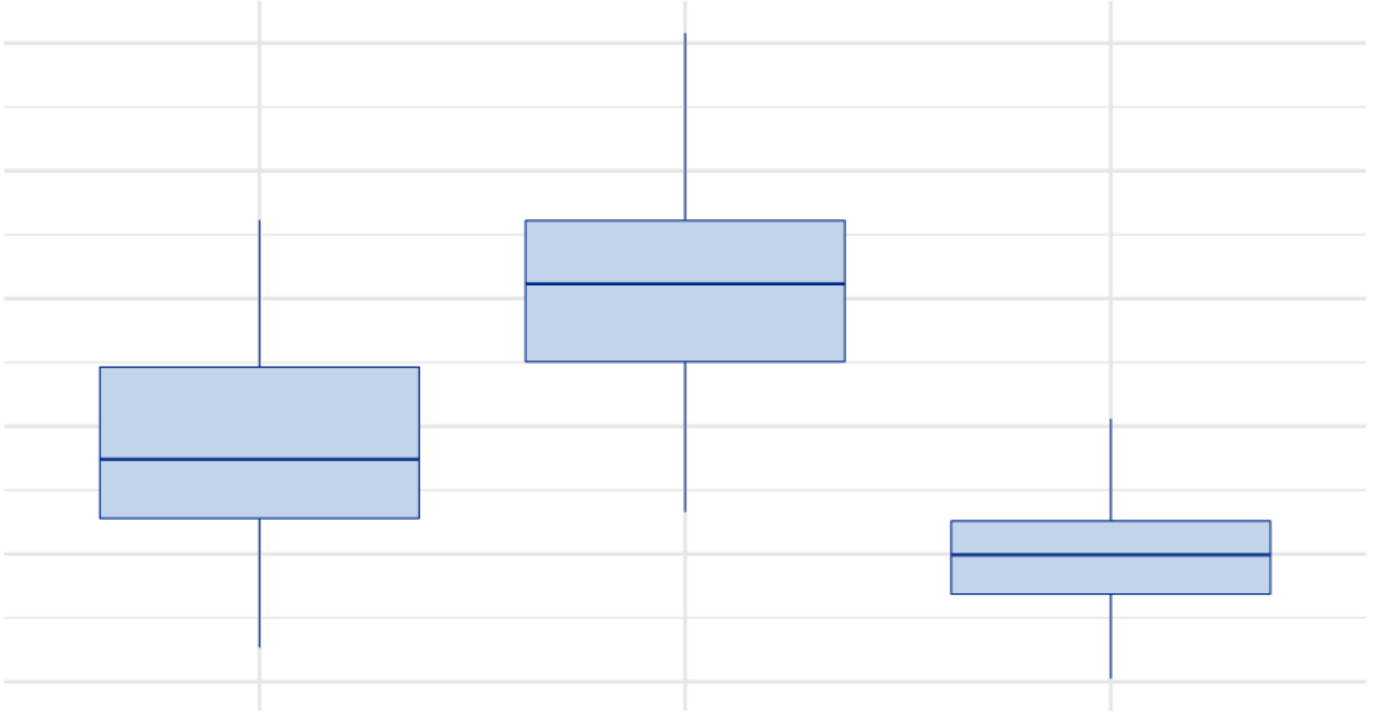


Grouped data

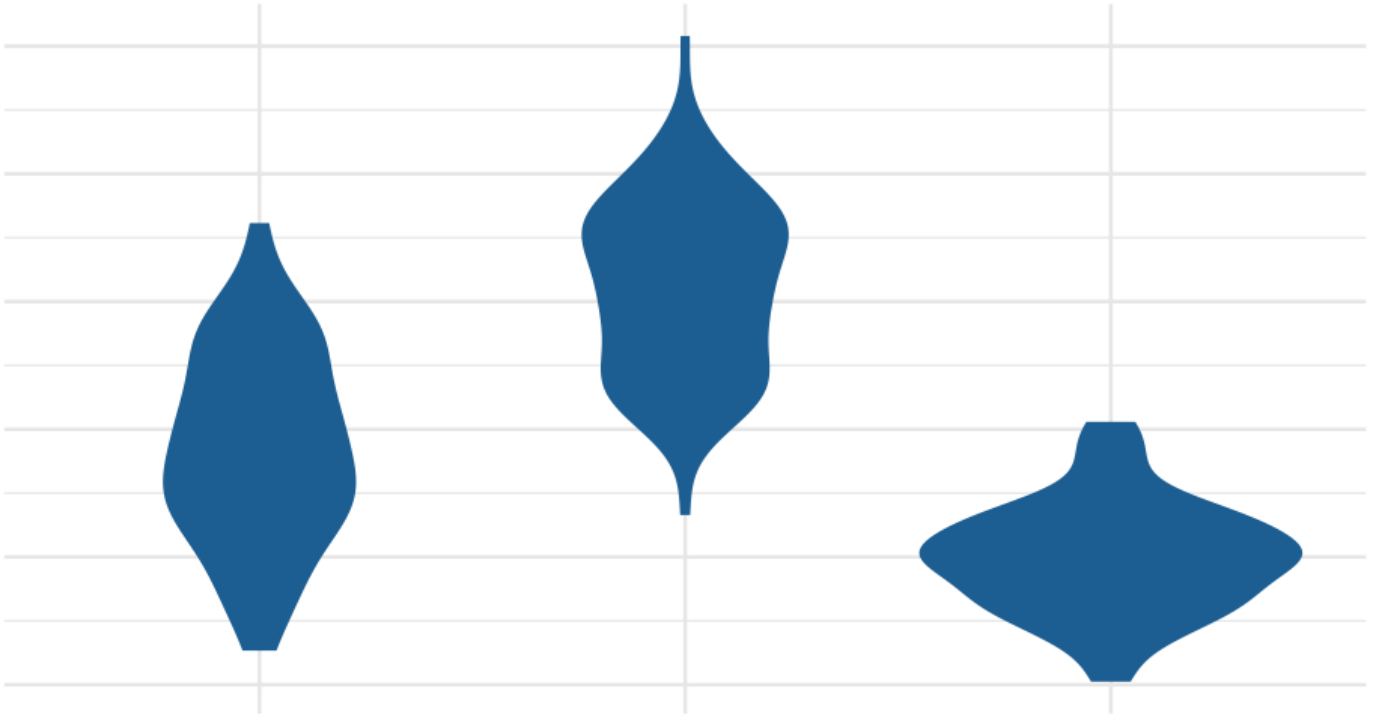
Distributions

How do we display more than one distribution at a time?

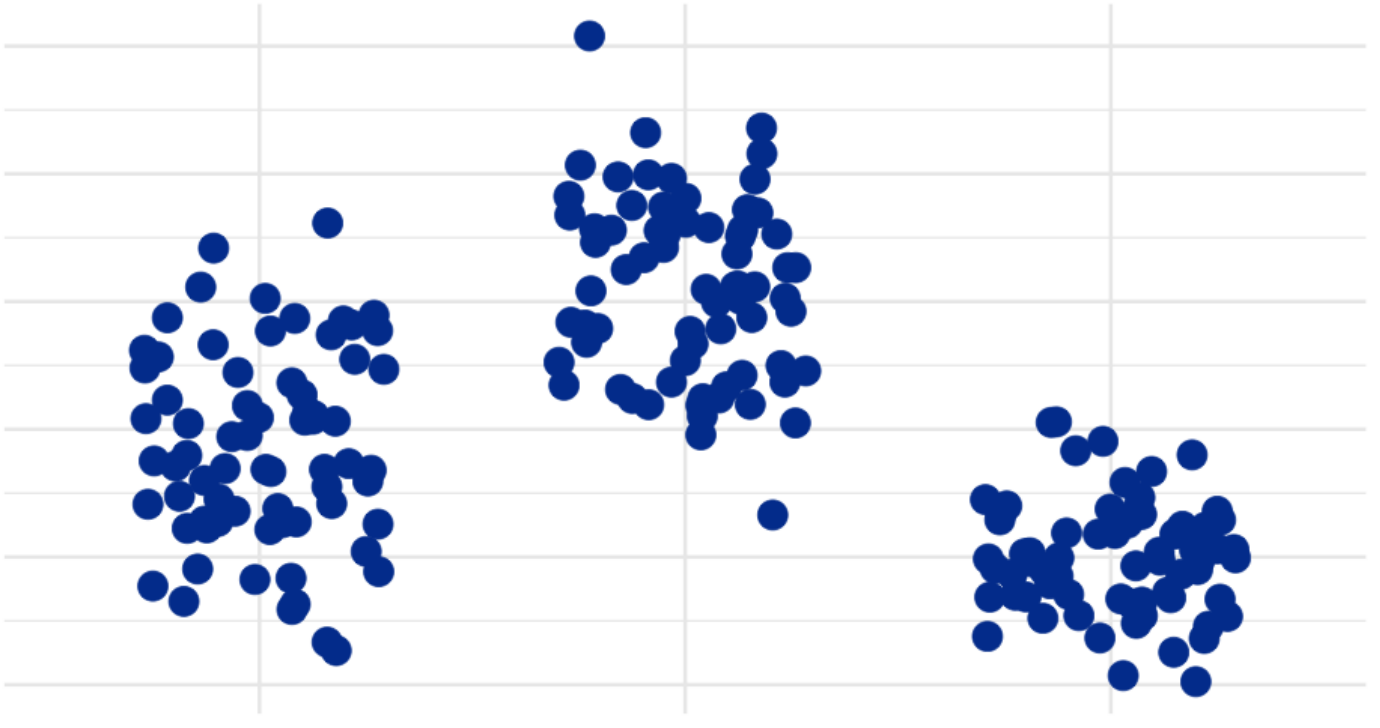
Boxplots



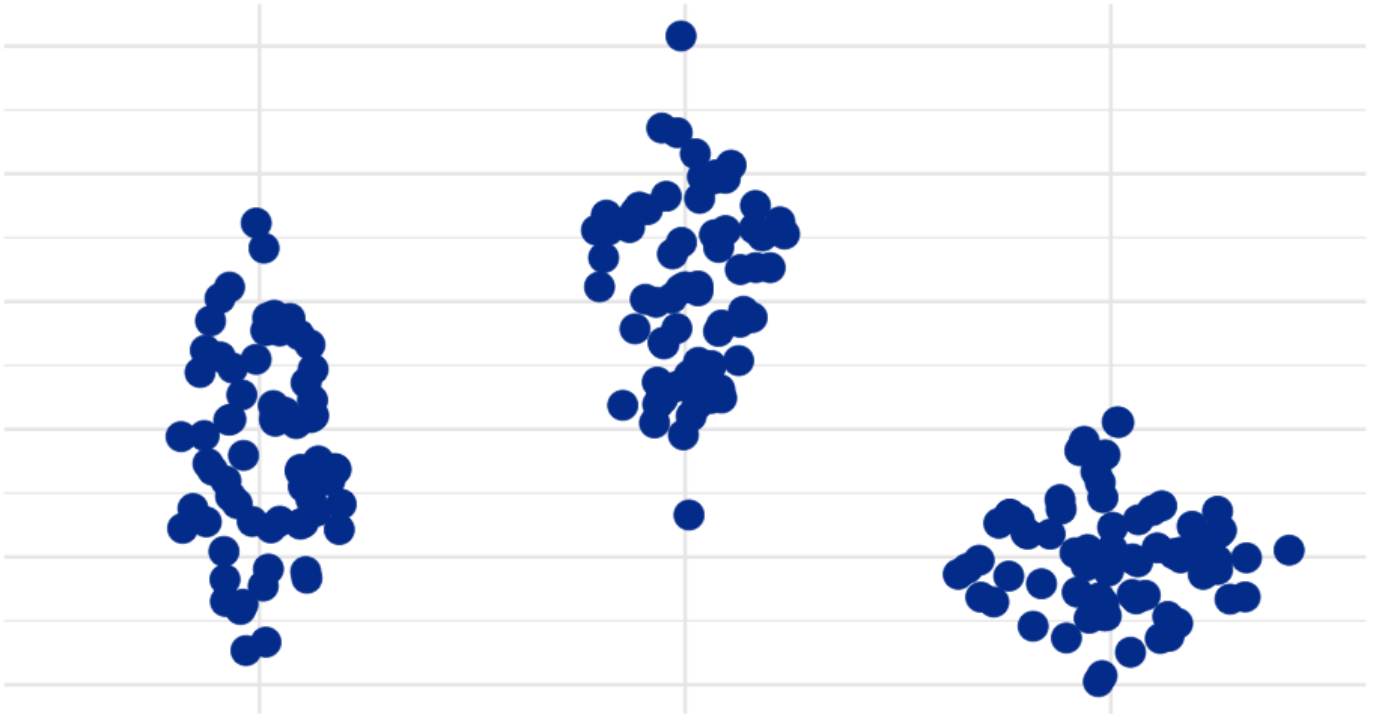
Violin plots



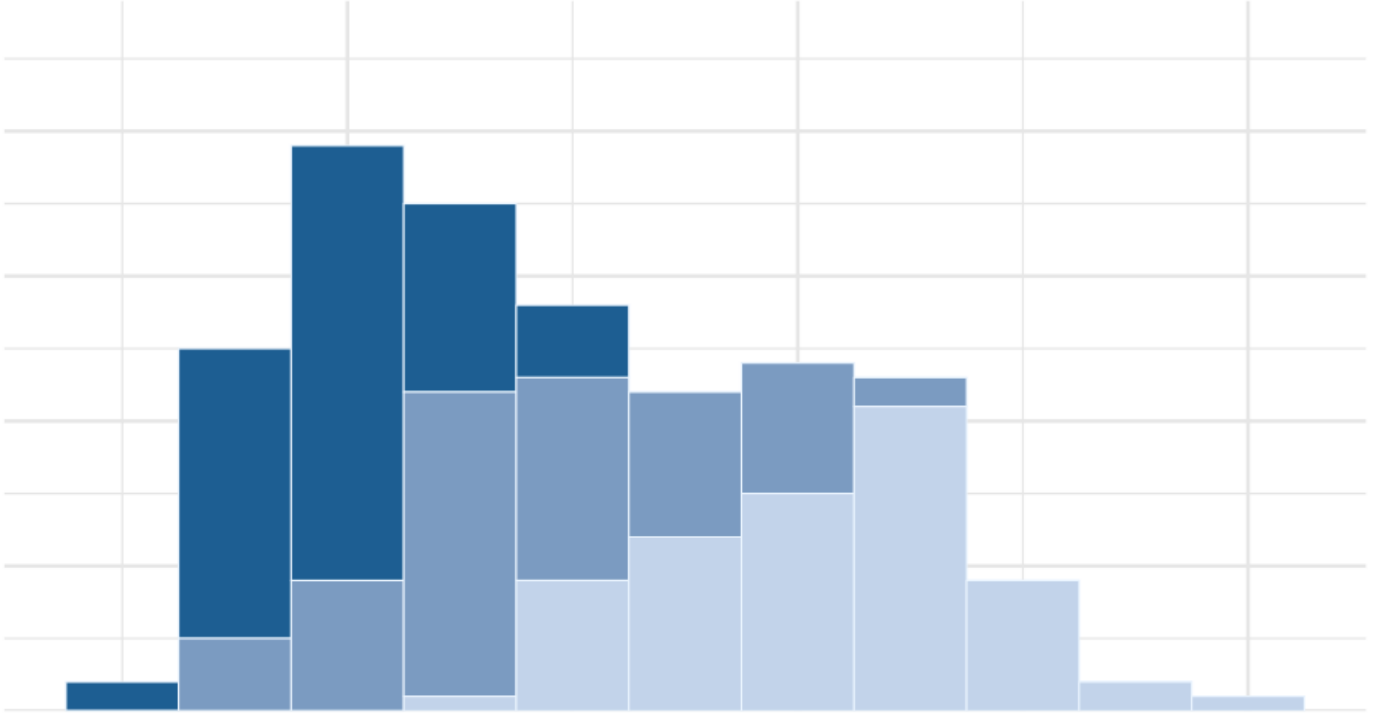
Jittered points



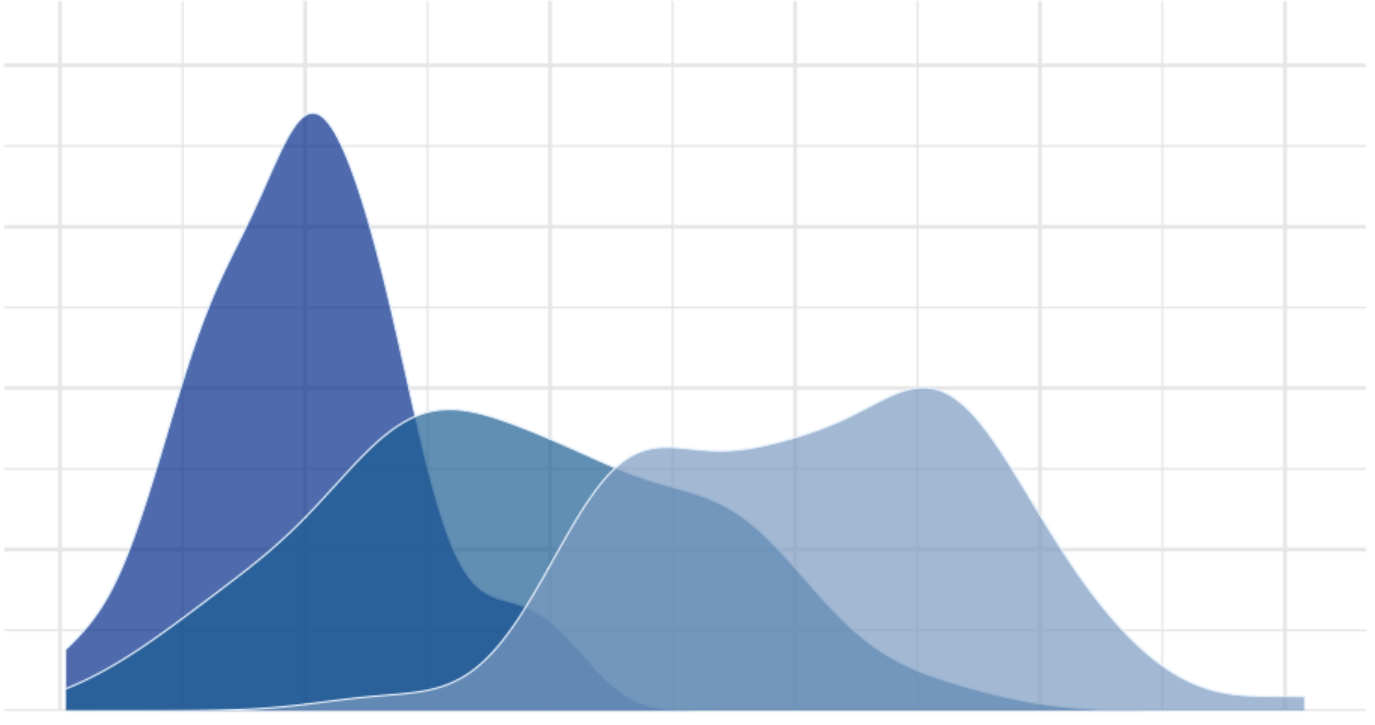
Sina plots



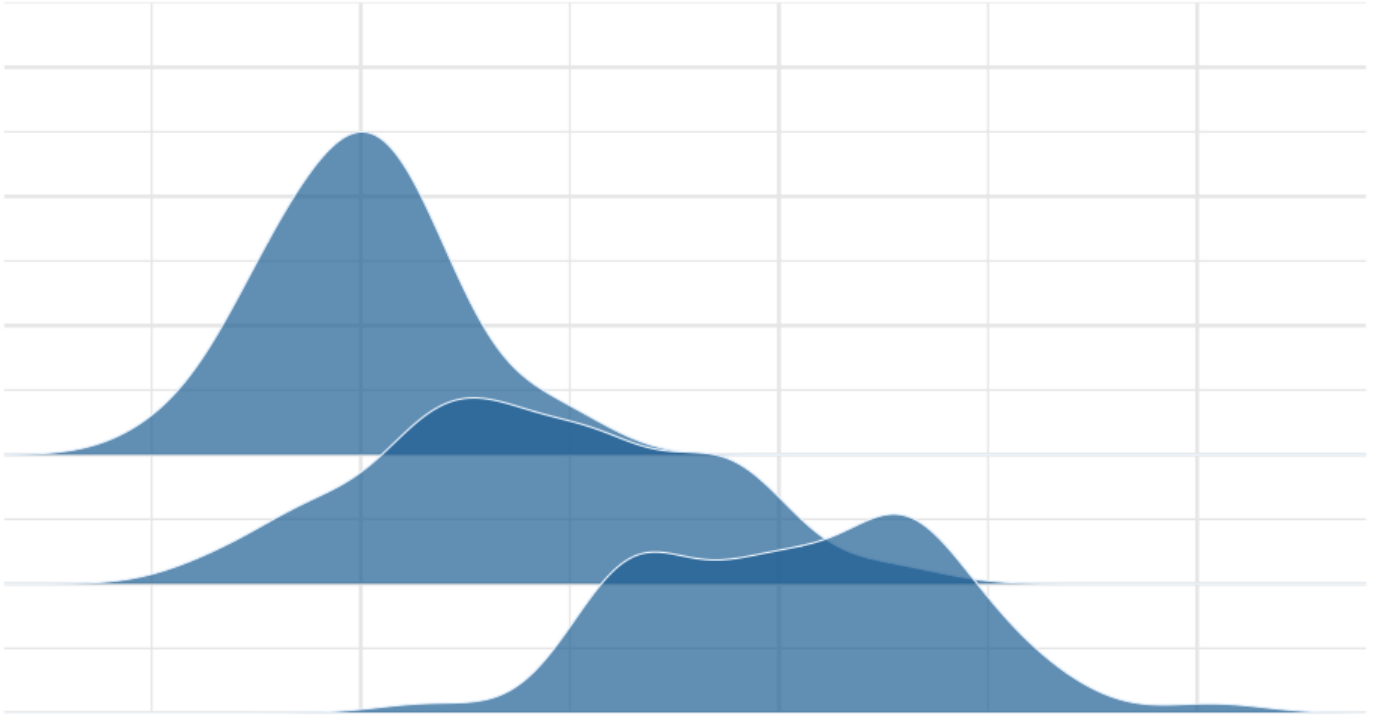
Stacked histograms



Overlapping densities



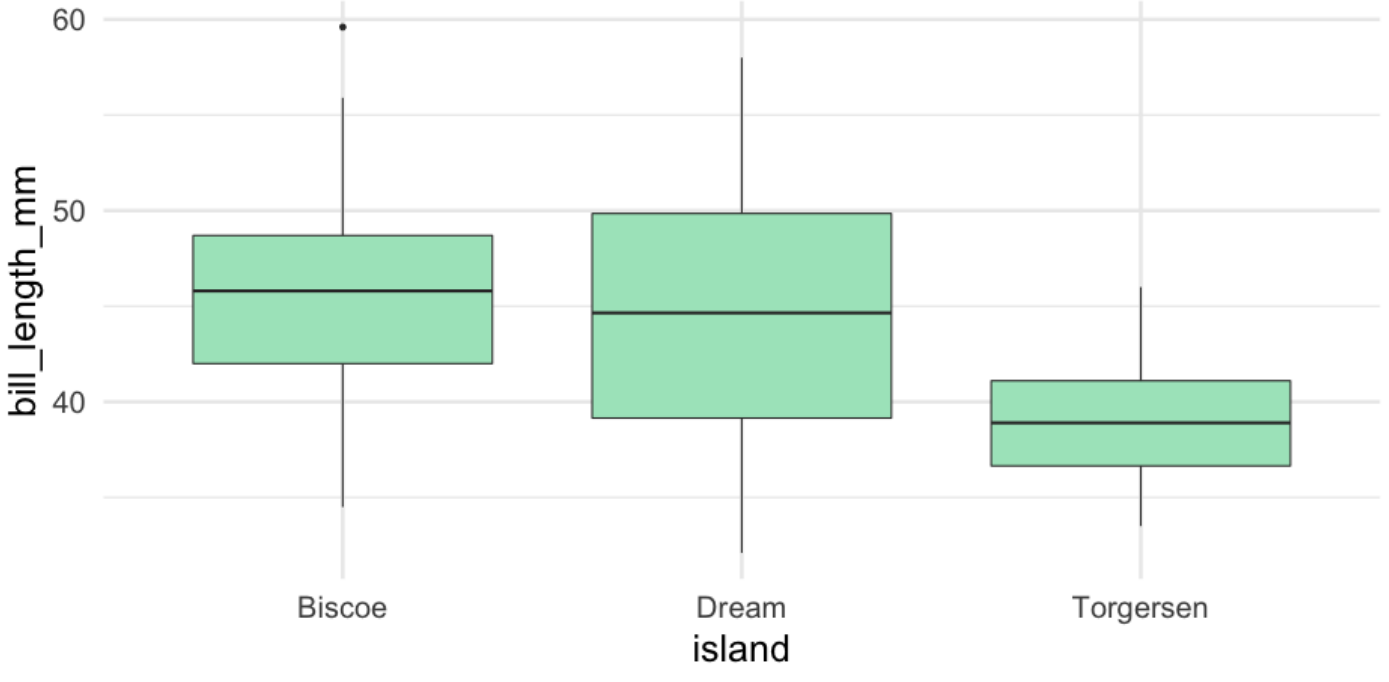
Ridgeline densities



Quick empirical examples

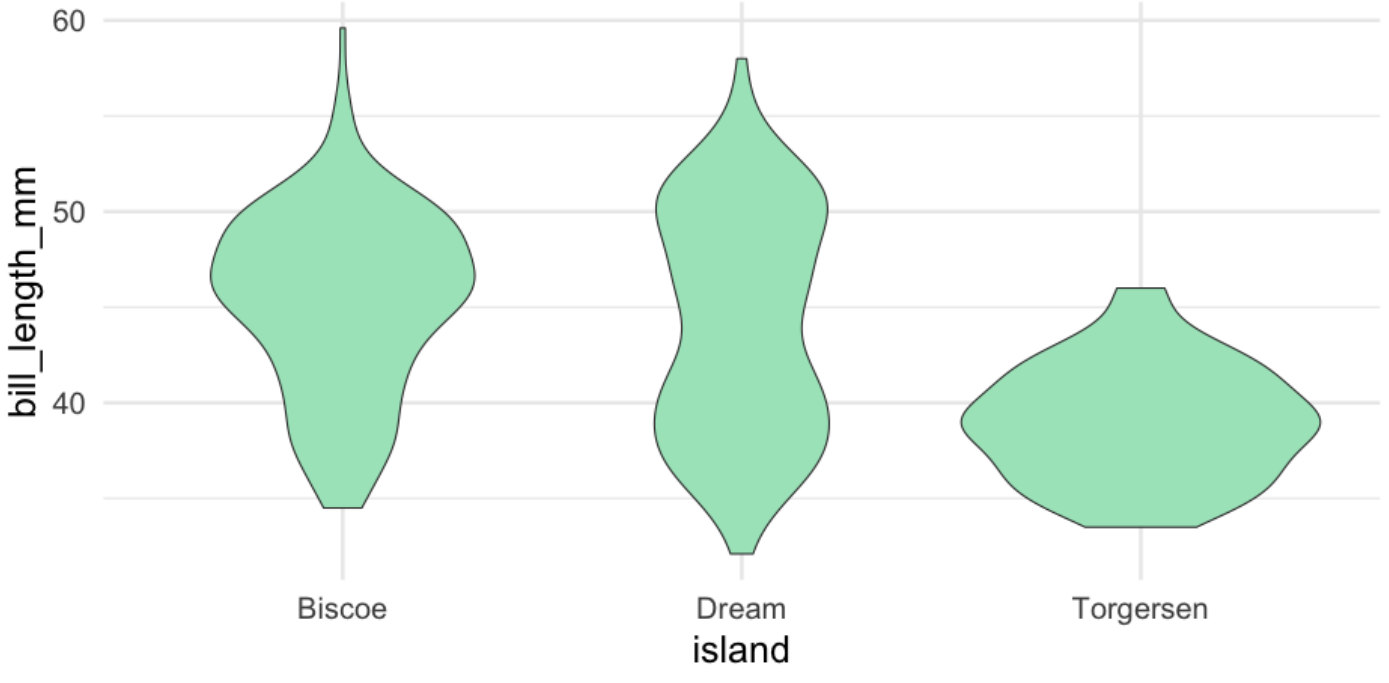
Boxplots

```
ggplot(penguins, aes(island, bill_length_mm)) +
  geom_boxplot(fill = "#A9E5C5")
```



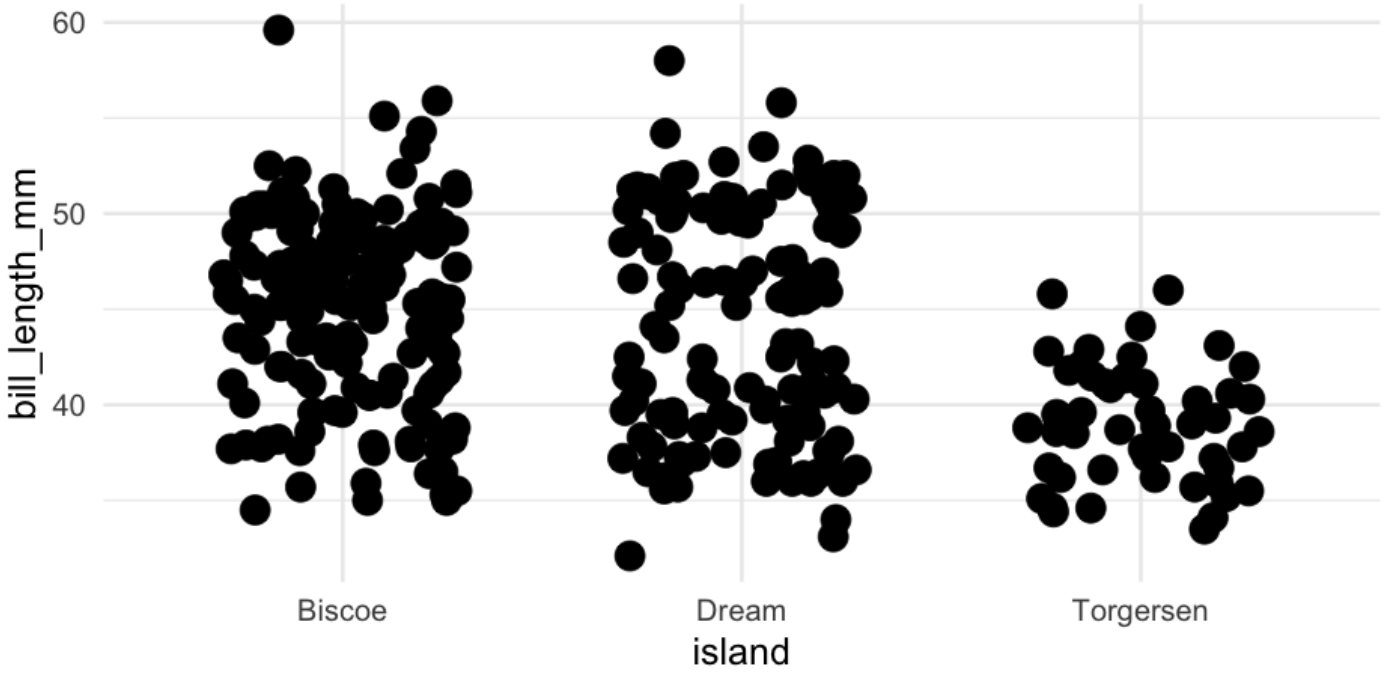
Violin plots

```
ggplot(penguins, aes(island, bill_length_mm)) +
  geom_violin(fill = "#A9E5C5")
```



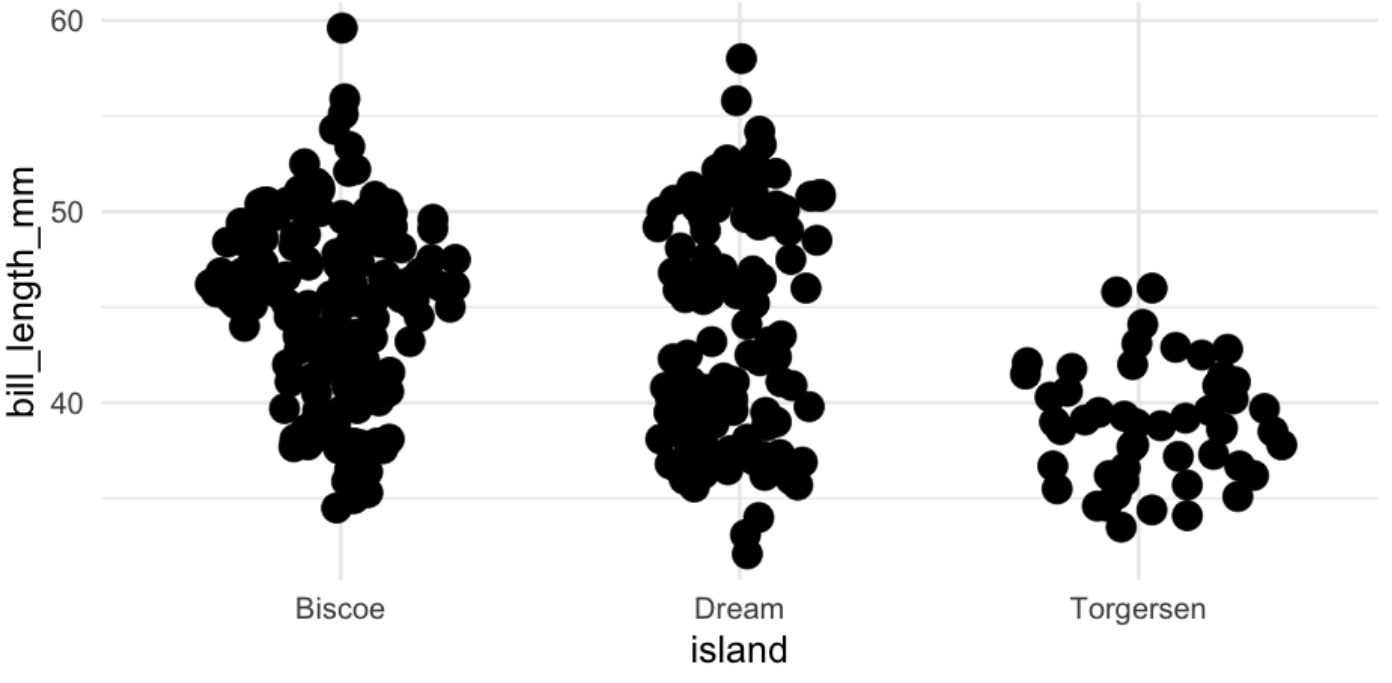
Jittered point plots

```
ggplot(penguins, aes(island, bill_length_mm)) +
  geom_jitter(width = 0.3, height = 0)
```



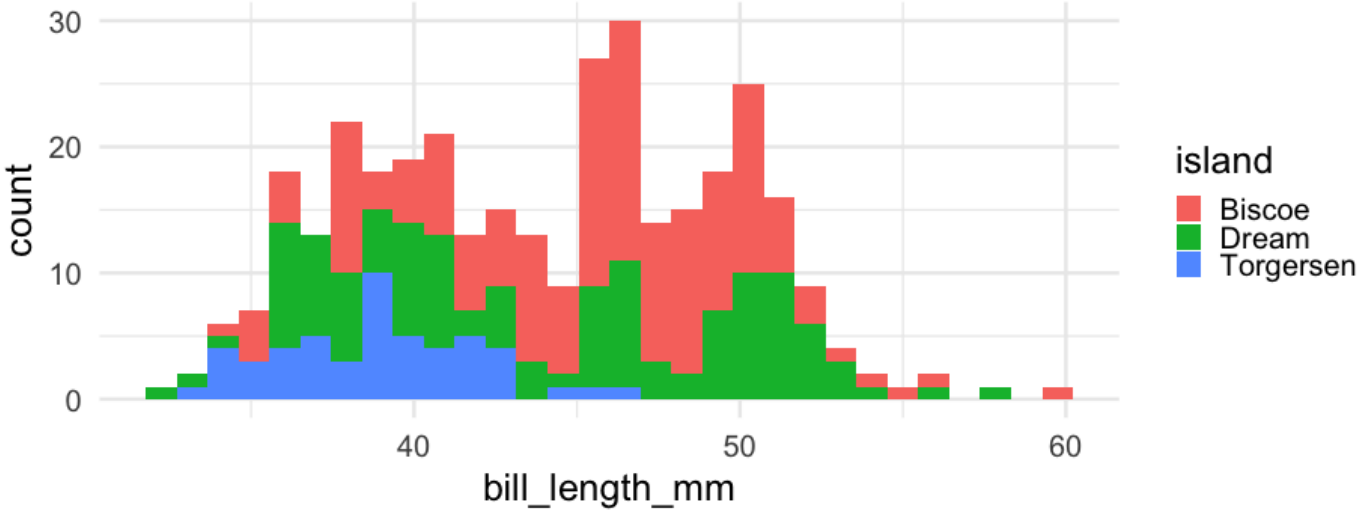
Sina plot

```
ggplot(penguins, aes(island, bill_length_mm)) +
  ggforce::geom_sina()
```



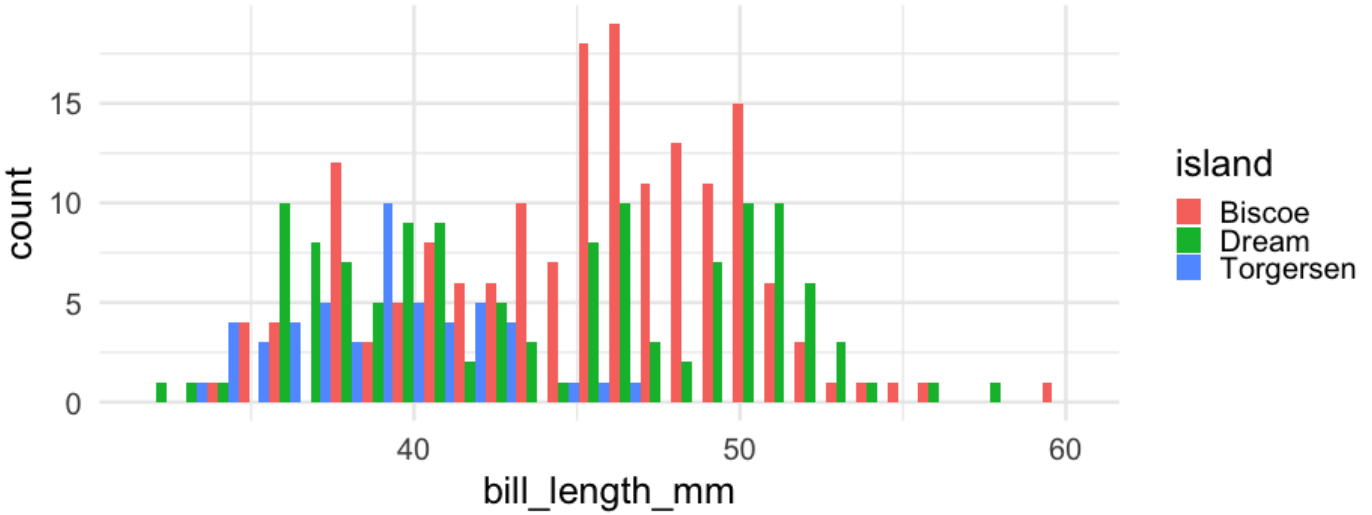
Stacked histogram

```
ggplot(penguins, aes(bill_length_mm)) +
  geom_histogram(aes(fill = island))
```



Dodged

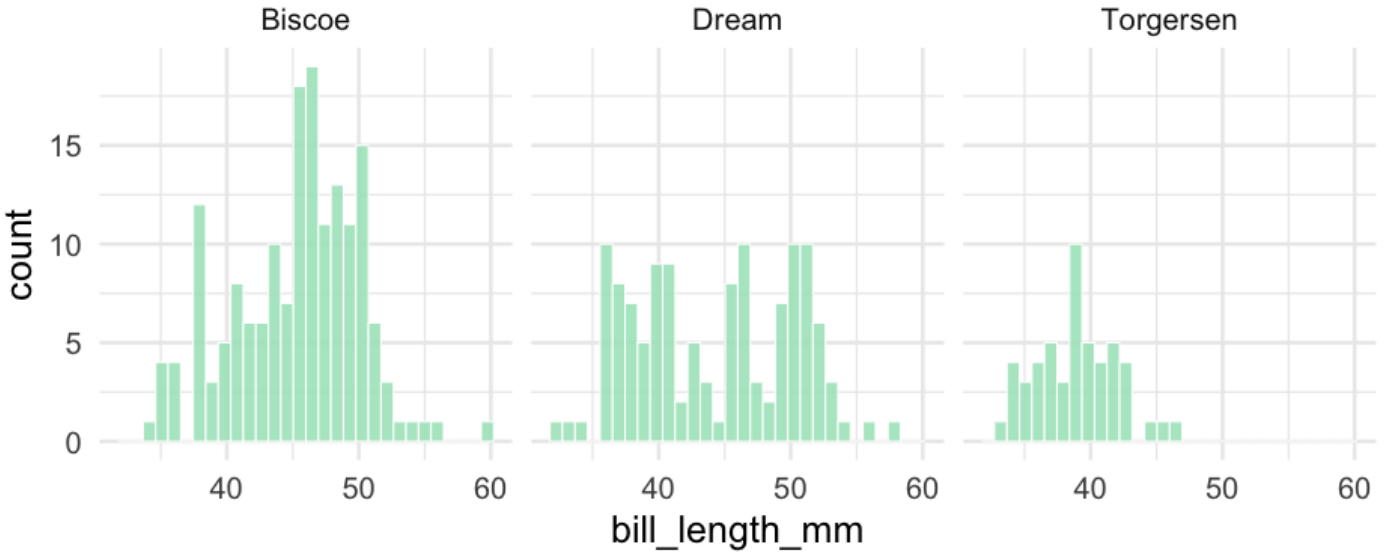
```
ggplot(penguins, aes(bill_length_mm)) +
  geom_histogram(aes(fill = island),
                 position = "dodge")
```



Note `position = "dodge"` does not go into `aes` (not accessing a variable in your dataset)

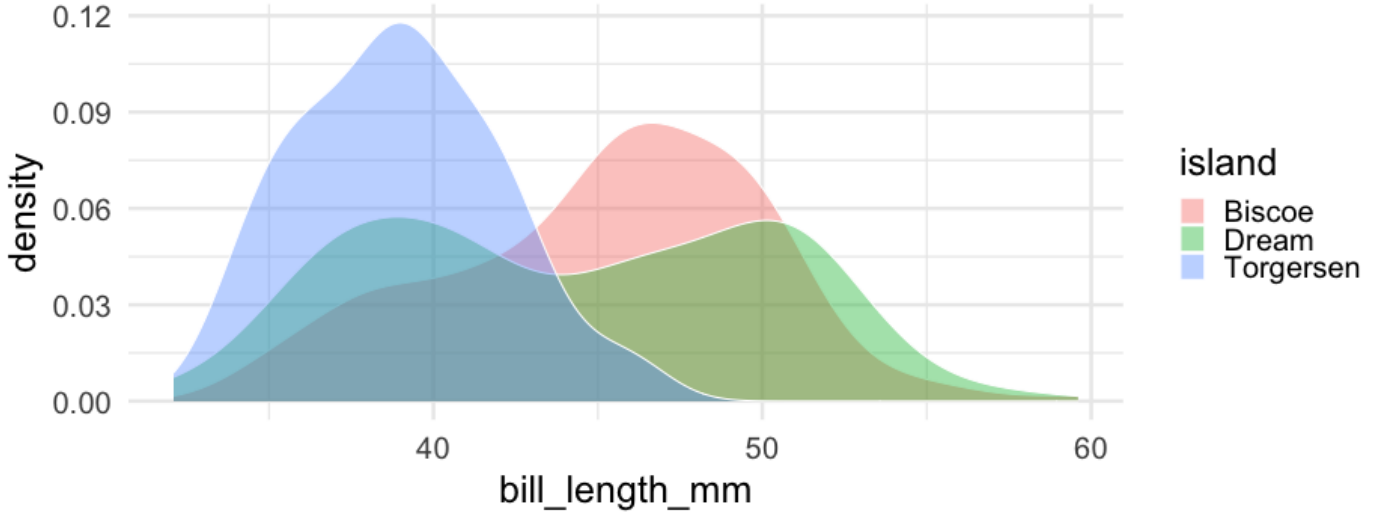
Better

```
ggplot(penguins, aes(bill_length_mm)) +
  geom_histogram(fill = "#A9E5C5",
                 color = "white",
                 alpha = 0.9,) +
  facet_wrap(~island)
```



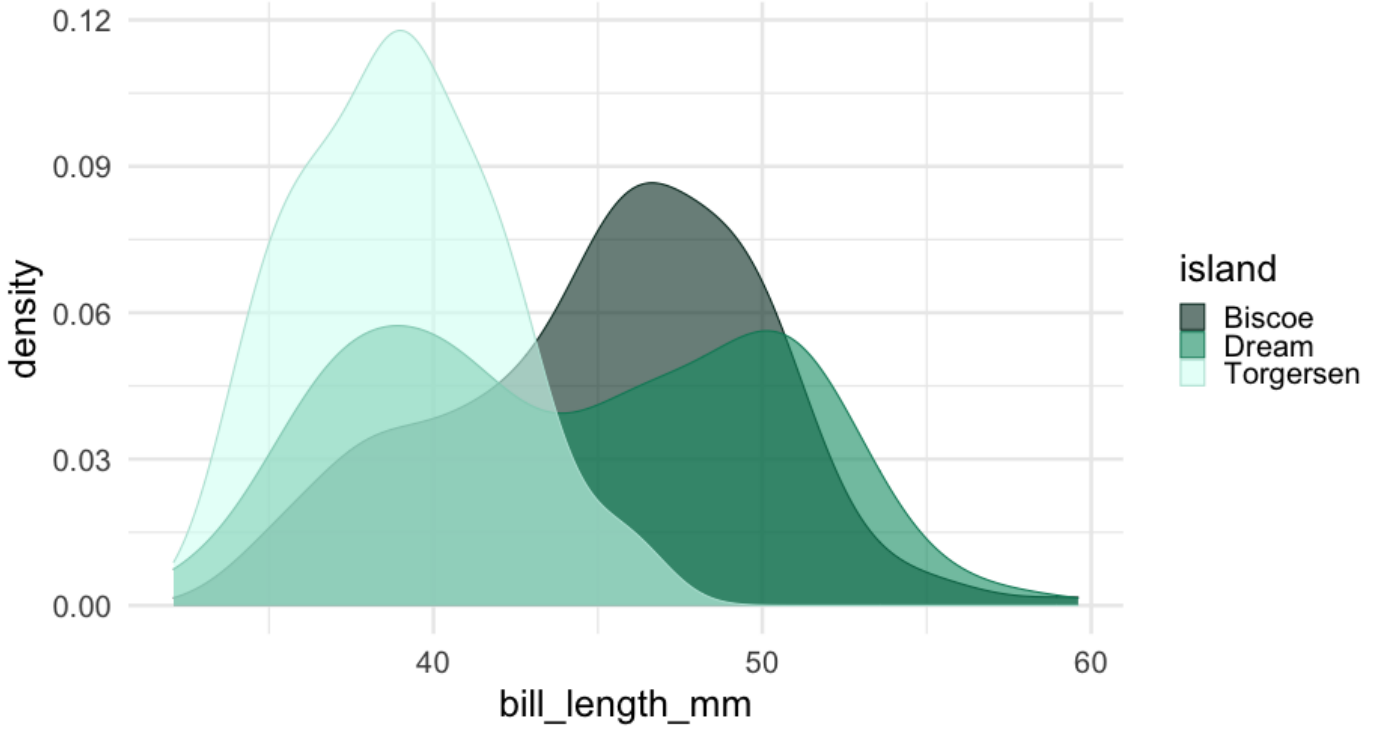
Overlapping densities

```
ggplot(penguins, aes(bill_length_mm)) +
  geom_density(aes(fill = island),
               color = "white",
               alpha = 0.4)
```



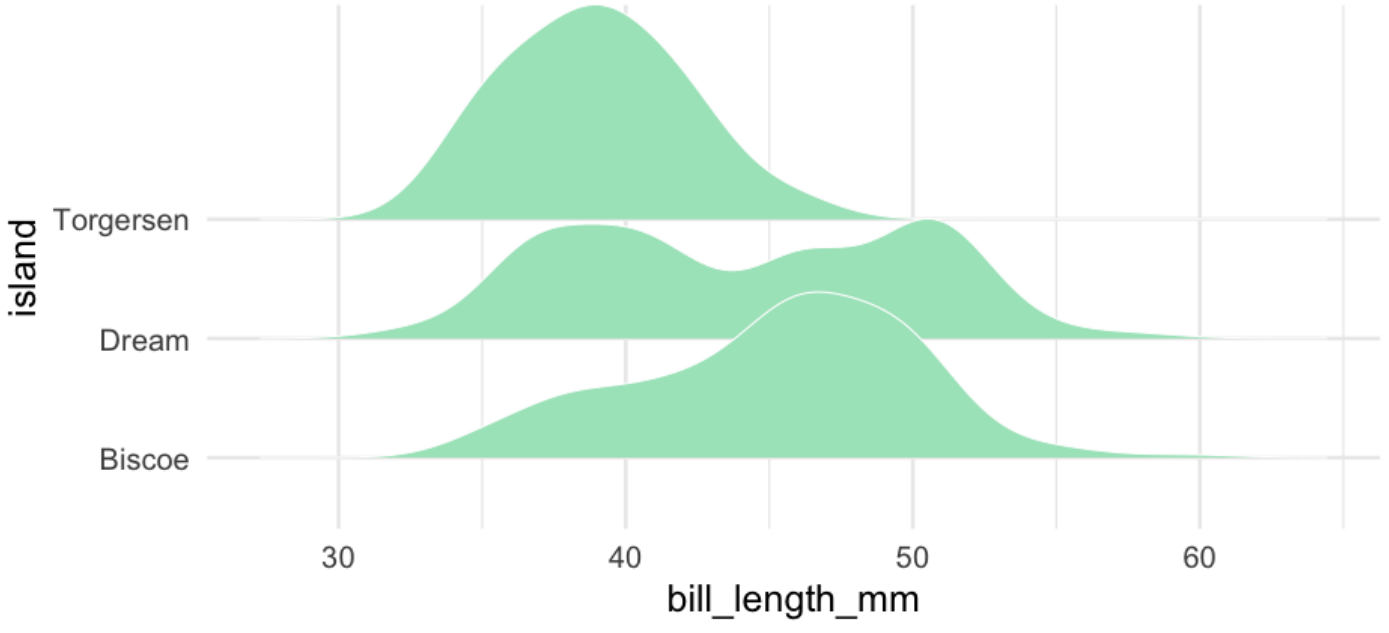
Note the default colors generally don't work great in most of these

```
ggplot(penguins, aes(bill_length_mm)) +
  geom_density(aes(color = island, fill = island),
               alpha = 0.6) +
  scale_fill_manual(values = c("#003326", "#009973", "#d6fff5"))
  scale_color_manual(
    values = darken(c("#003326", "#009973", "#d6fff5"), .1)
  )
```



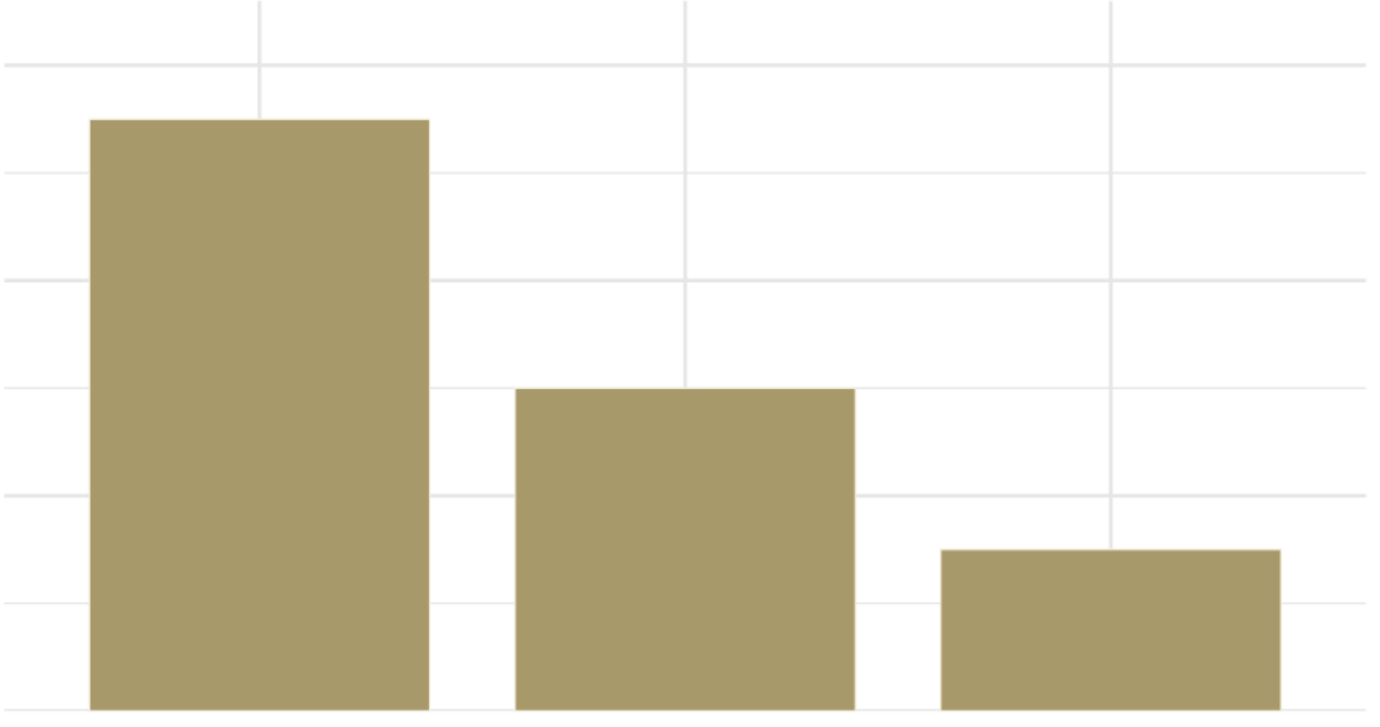
Ridgeline densities

```
ggplot(penguins, aes(bill_length_mm, island)) +
  ggridges::geom_density_ridges(color = "white",
                                fill = "#A9E5C5")
```

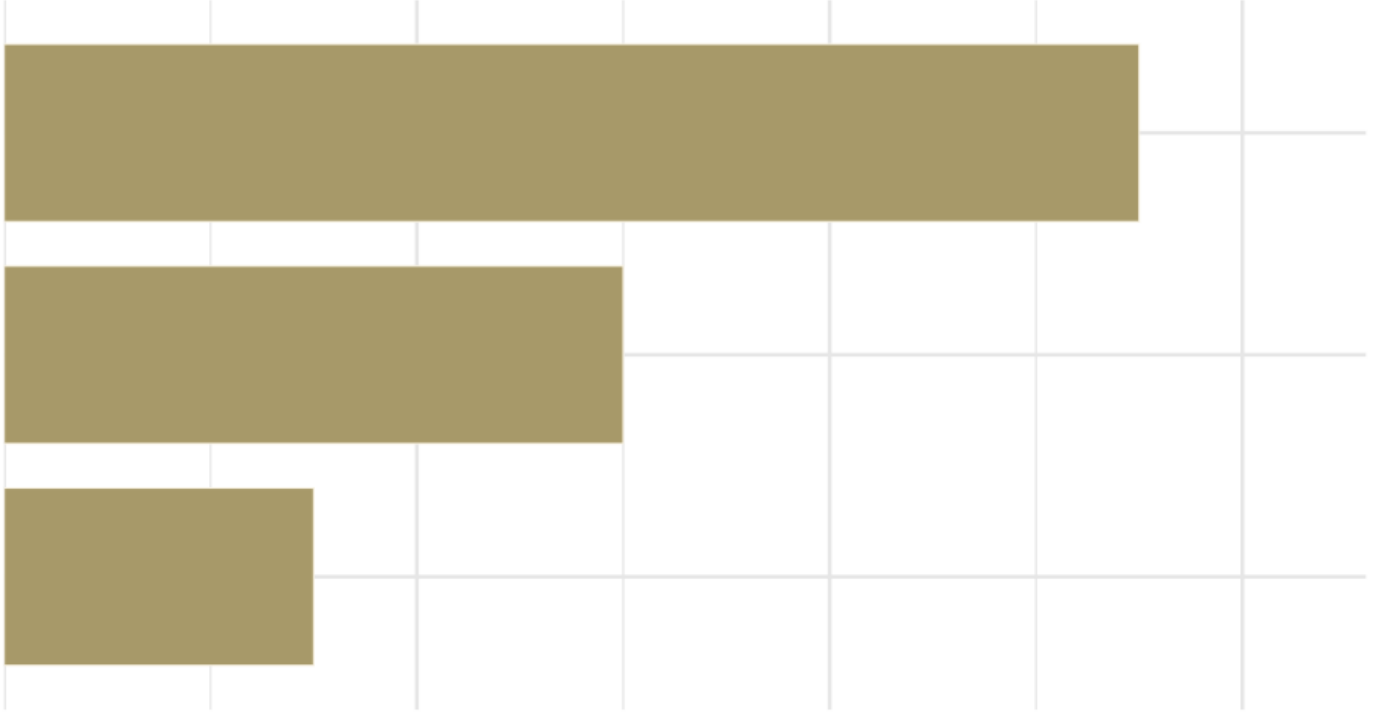


Visualizing amounts

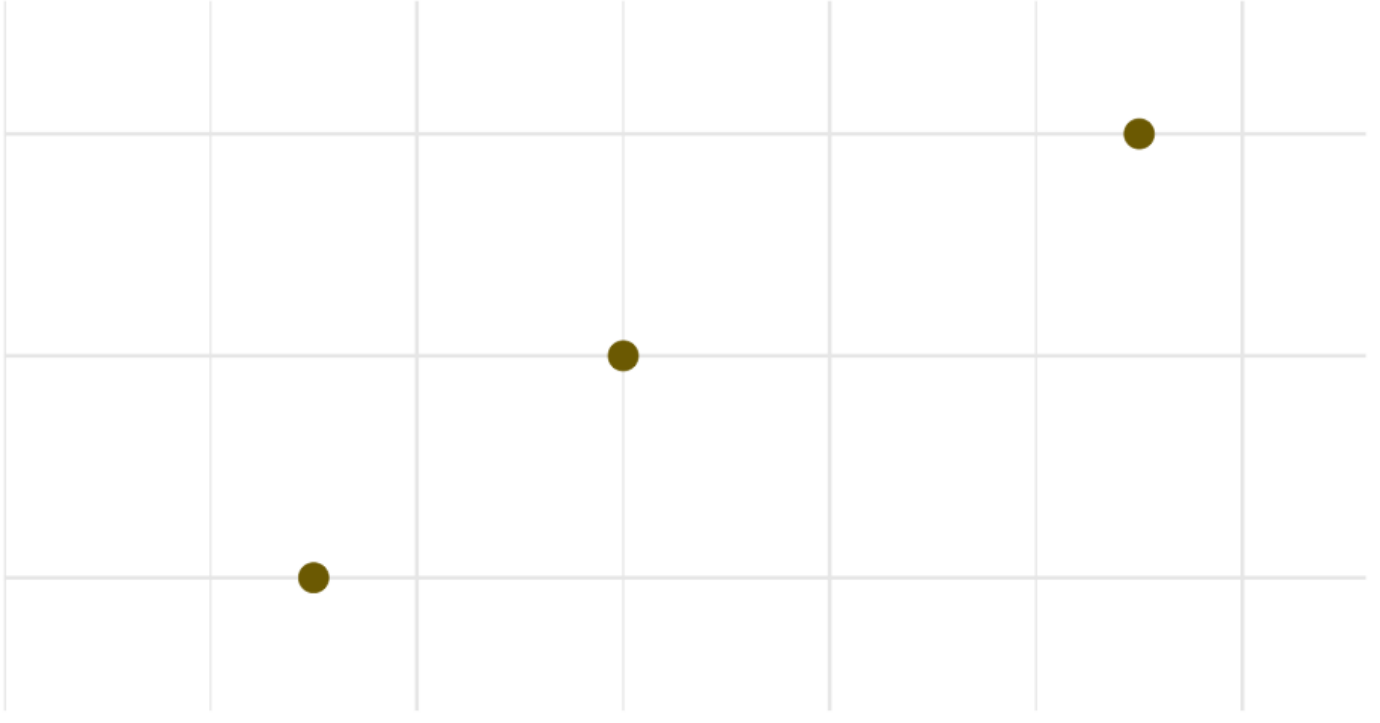
Bar plots



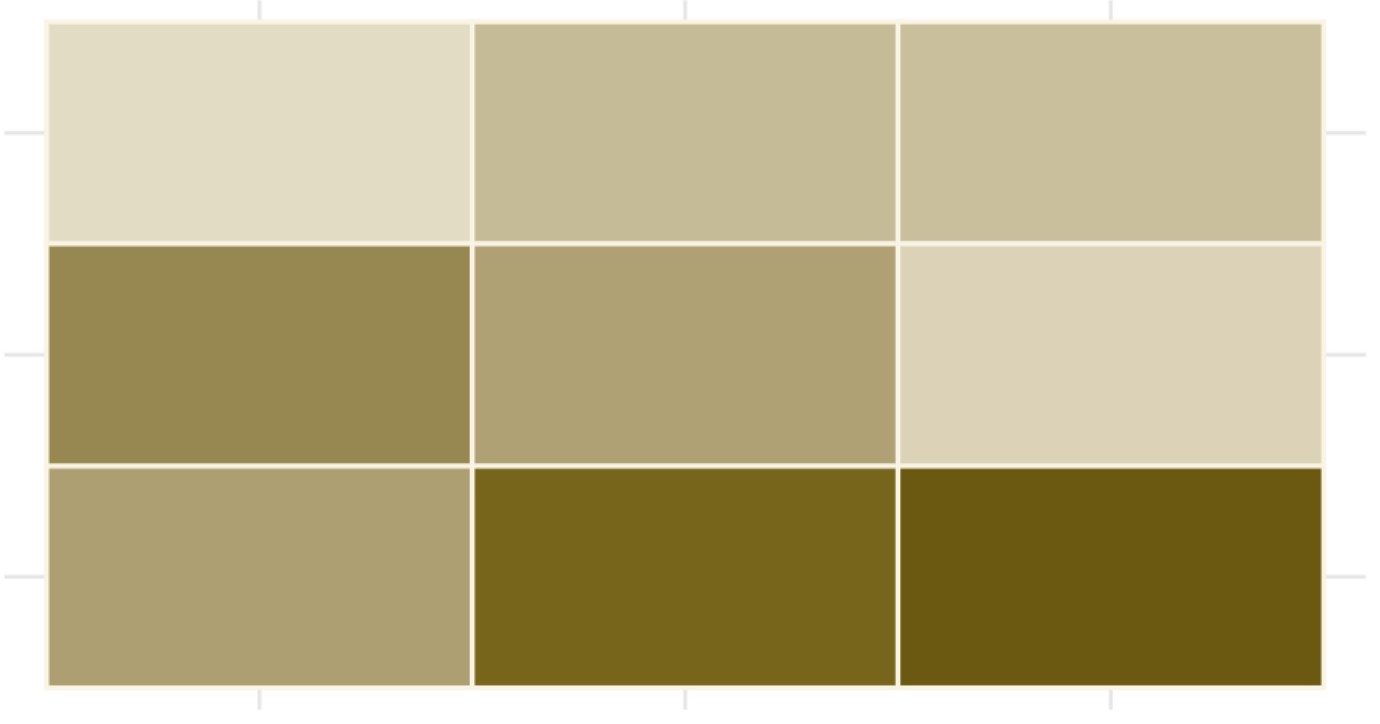
Flipped bars



Dotplot



Heatmap



Empirical examples

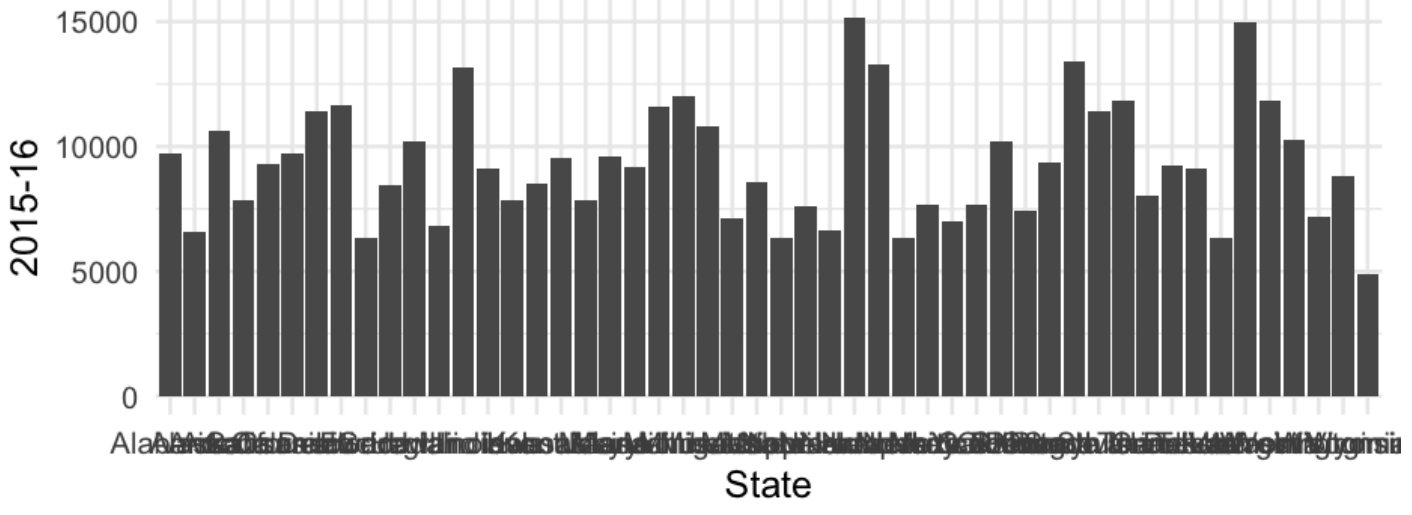
How much does college cost?

```
library(here)
library(rio)
tuition <- import(here("data", "us_avg_tuition.xlsx"),
                  setclass = "tbl_df")
head(tuition)
```

```
## # A tibble: 6 × 13
##   State      `2004-05` `2005-06` `2006-07`
##   <chr>          <dbl>     <dbl>     <dbl>
## 1 Alabama     5682.838  5840.550  5753.496
## 2 Alaska      4328.281  4632.623  4918.501
## 3 Arizona     5138.495  5415.516  5481.419
## 4 Arkansas    5772.302  6082.379  6231.977
## 5 California  5285.921  5527.881  5334.826
## 6 Colorado    4703.777  5406.967  5596.348
## # … with 9 more variables: `2007-08` <dbl>,
## #   `2008-09` <dbl>, `2009-10` <dbl>,
## #   `2010-11` <dbl>, `2011-12` <dbl>,
## #   `2012-13` <dbl>, `2013-14` <dbl>,
## #   `2014-15` <dbl>, `2015-16` <dbl>
```

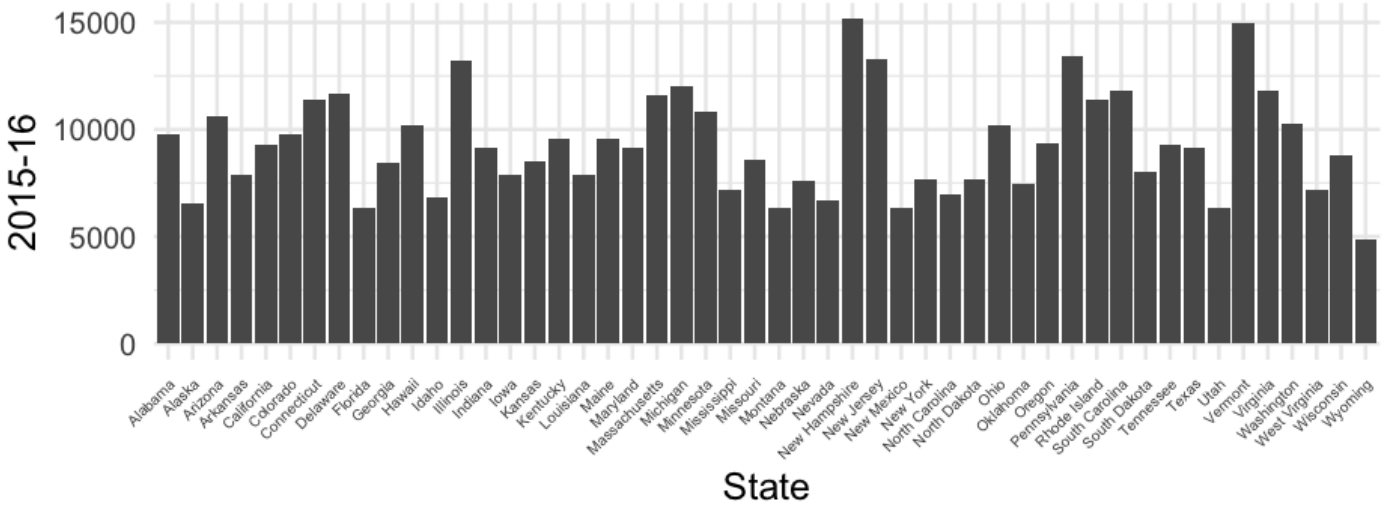
By state: 2015–16

```
ggplot(tuition, aes(State, `2015-16`)) +
  geom_col()
```



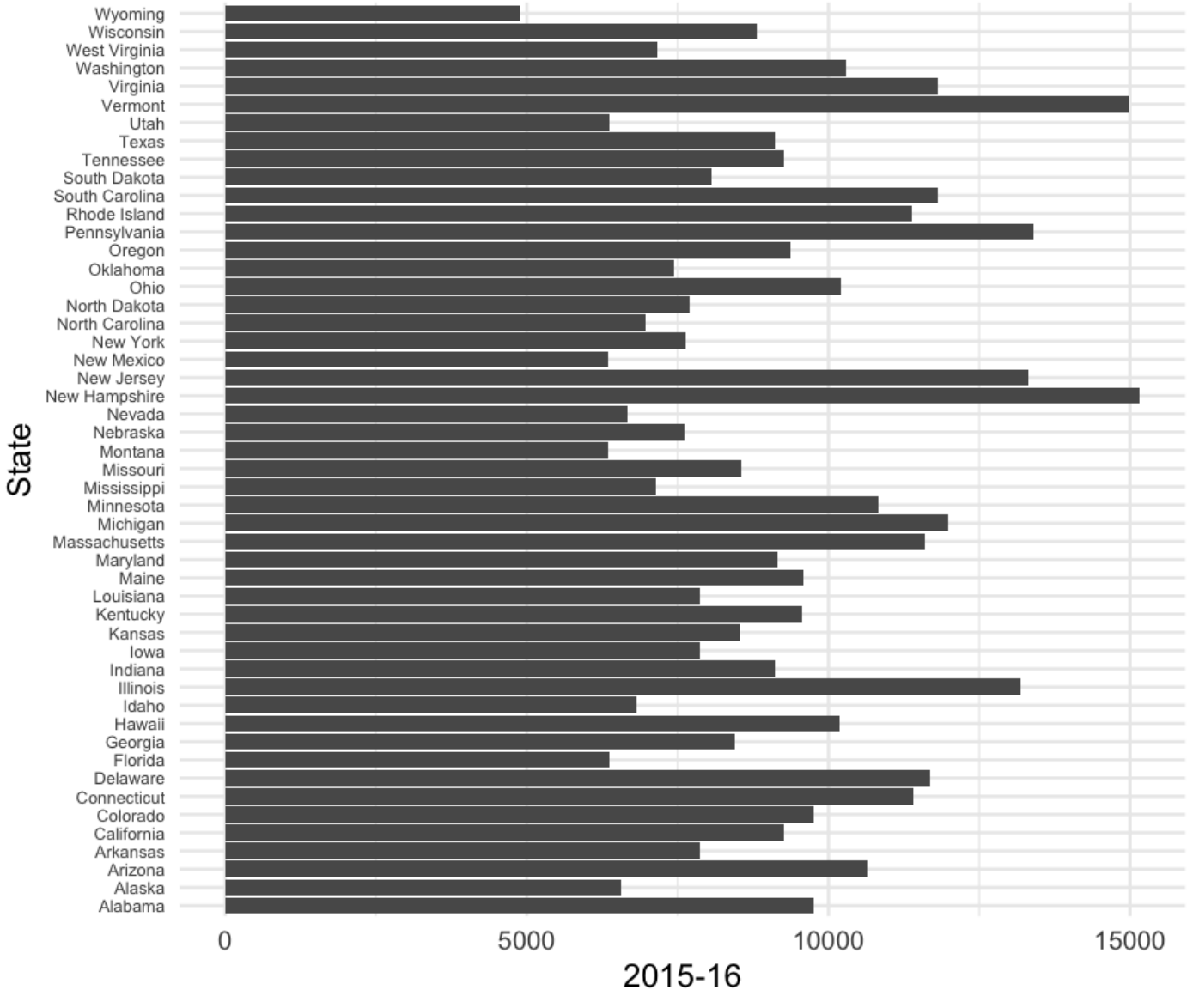
Two puke emoji version

```
ggplot(tuition, aes(State, `2015-16`)) +
  geom_col() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size =
```



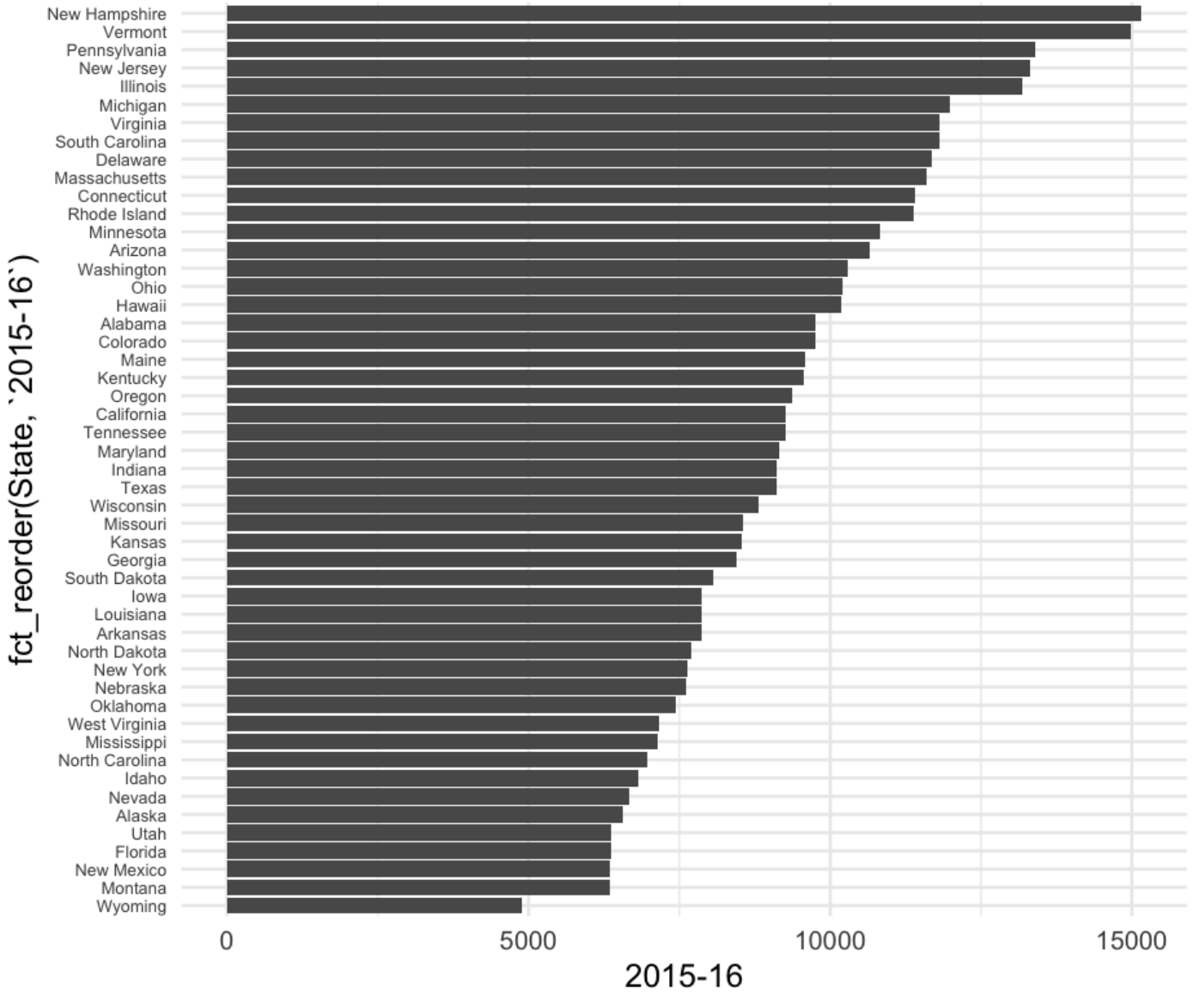
One puke emoji version

```
ggplot(tuition, aes(State, `2015-16`)) +
  geom_col() +
  coord_flip()
```


Wyoming
Wisconsin
West Virginia
Washington
Virginia
Vermont
Utah
Texas
Tennessee
South Dakota
South Carolina
Rhode Island
Pennsylvania
Oregon
Oklahoma
Ohio
North Dakota
North Carolina
New York
New Mexico
New Jersey
New Hampshire
Nevada
Nebraska
Montana
Missouri
Mississippi
Minnesota
Michigan
Massachusetts
Maryland
Maine
Louisiana
Kentucky
Kansas
Iowa
Indiana
Illinois
Idaho
Hawaii
Georgia
Florida
Delaware
Connecticut
Colorado
California
Arkansas
Arizona
Alaska
Alabama
State
0
5000
10000
15000
2015-16

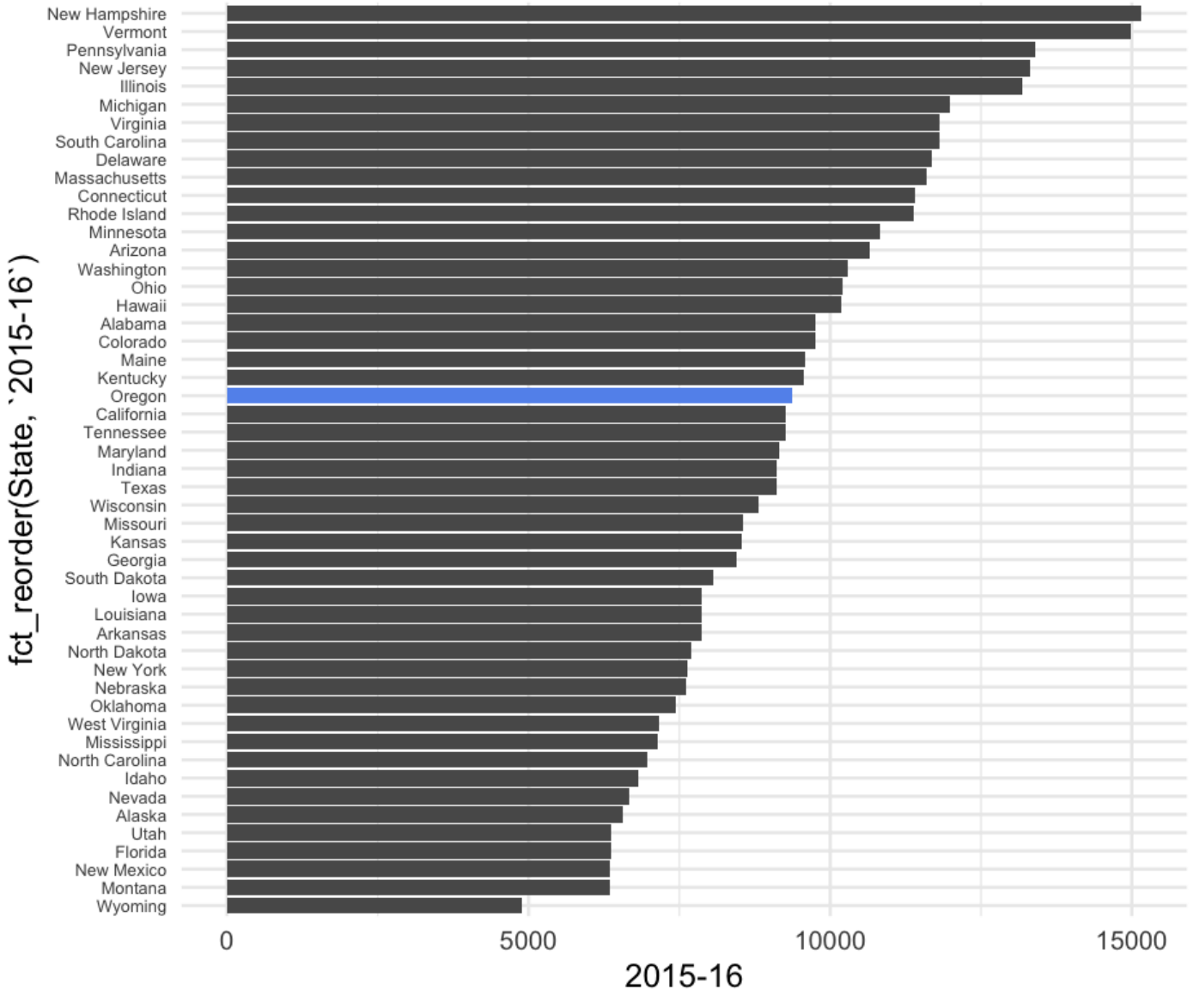
Kinda smiley version

```
ggplot(tuition, aes(fct_reorder(State, `2015-16`), `2015-16`)) +
  geom_col() +
  coord_flip()
```

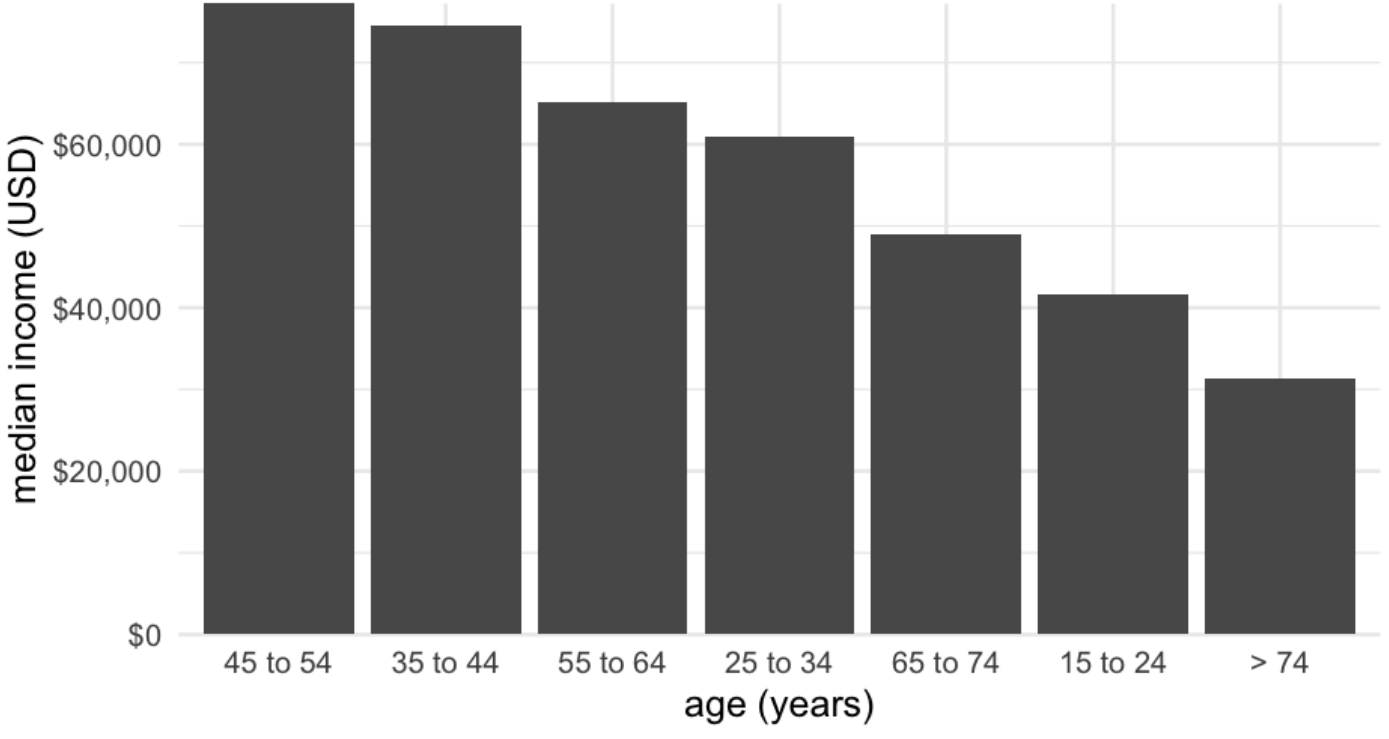

New Hampshire
Vermont
Pennsylvania
New Jersey
Illinois
Michigan
Virginia
South Carolina
Delaware
Massachusetts
Connecticut
Rhode Island
Minnesota
Arizona
Washington
Ohio
Hawaii
Alabama
Colorado
Maine
Kentucky
Oregon
California
Tennessee
Maryland
Indiana
Texas
Wisconsin
Missouri
Kansas
Georgia
South Dakota
Iowa
Louisiana
Arkansas
North Dakota
New York
Nebraska
Oklahoma
West Virginia
Mississippi
North Carolina
Idaho
Nevada
Alaska
Utah
Florida
New Mexico
Montana
Wyoming
fct_reorder(State, `2015-16`)
0
5000
10000
15000
2015-16

Highlight Oregon

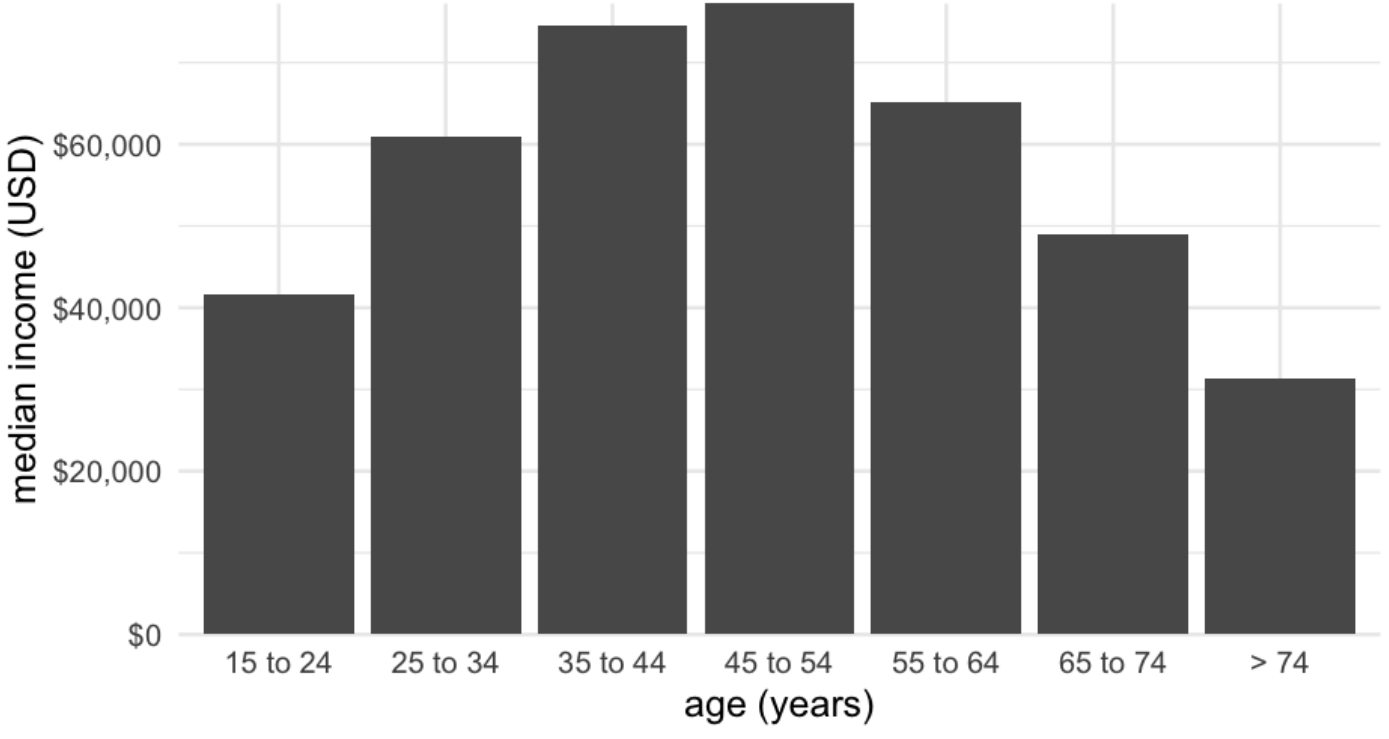
```
ggplot(tuition, aes(fct_reorder(State, `2015-16`), `2015-16`)) +
  geom_col() +
  geom_col(fill = "cornflowerblue",
           data = filter(tuition, State == "Oregon")) +
  coord_flip()
```


New Hampshire
Vermont
Pennsylvania
New Jersey
Illinois
Michigan
Virginia
South Carolina
Delaware
Massachusetts
Connecticut
Rhode Island
Minnesota
Arizona
Washington
Ohio
Hawaii
Alabama
Colorado
Maine
Kentucky
Oregon
California
Tennessee
Maryland
Indiana
Texas
Wisconsin
Missouri
Kansas
Georgia
South Dakota
Iowa
Louisiana
Arkansas
North Dakota
New York
Nebraska
Oklahoma
West Virginia
Mississippi
North Carolina
Idaho
Nevada
Alaska
Utah
Florida
New Mexico
Montana
Wyoming
fct_reorder(State, `2015-16`)
0
5000
10000
15000
2015-16

Not always good to sort



Much better


median income (USD)
$60,000
$40,000
$20,000
$0
15 to 24
25 to 34
35 to 44
45 to 54
55 to 64
65 to 74
> 74
age (years)

Average tuition by year

How?

```
head(tuition)
```

```
## # A tibble: 6 × 13
##   State      `2004-05` `2005-06` `2006-07`
##   <chr>          <dbl>     <dbl>     <dbl>
## 1 Alabama     5682.838  5840.550  5753.496
## 2 Alaska      4328.281  4632.623  4918.501
## 3 Arizona     5138.495  5415.516  5481.419
## 4 Arkansas    5772.302  6082.379  6231.977
## 5 California  5285.921  5527.881  5334.826
## 6 Colorado    4703.777  5406.967  5596.348
## # … with 9 more variables: `2007-08` <dbl>,
## #   `2008-09` <dbl>, `2009-10` <dbl>,
## #   `2010-11` <dbl>, `2011-12` <dbl>,
## #   `2012-13` <dbl>, `2013-14` <dbl>,
## #   `2014-15` <dbl>, `2015-16` <dbl>
```

Rearrange

```
tuition %>%
  pivot_longer(`2004-05`:`2015-16`,
               names_to = "year",
               values_to = "avg_tuition")
```

```
## # A tibble: 600 × 3
##    State   year    avg_tuition
##    <chr>   <chr>         <dbl>
##  1 Alabama 2004-05    5682.838
##  2 Alabama 2005-06    5840.550
##  3 Alabama 2006-07    5753.496
##  4 Alabama 2007-08    6008.169
##  5 Alabama 2008-09    6475.092
##  6 Alabama 2009-10    7188.954
##  7 Alabama 2010-11    8071.134
##  8 Alabama 2011-12    8451.902
##  9 Alabama 2012-13    9098.069
## 10 Alabama 2013-14    9358.929
## # … with 590 more rows
```

Compute summaries

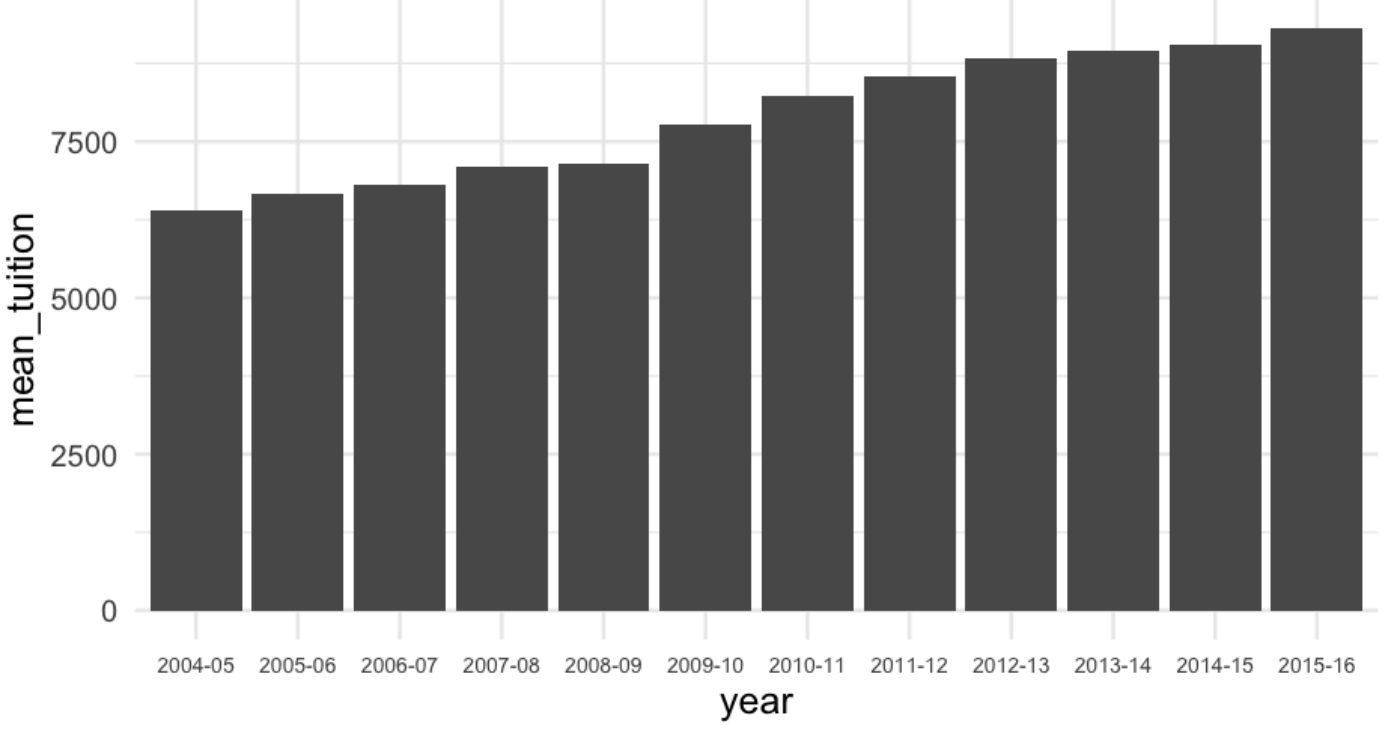
```
annual_means <- tuition %>%
  pivot_longer(`2004-05`:`2015-16`,
               names_to = "year",
               values_to = "avg_tuition")  %>%
  group_by(year) %>%
  summarize(mean_tuition = mean(avg_tuition))

annual_means
```

```
## # A tibble: 12 × 2
##    year    mean_tuition
##    <chr>          <dbl>
##  1 2004-05     6409.564
##  2 2005-06     6654.177
##  3 2006-07     6809.914
##  4 2007-08     7085.881
##  5 2008-09     7156.560
##  6 2009-10     7761.810
##  7 2010-11     8228.834
##  8 2011-12     8539.115
##  9 2012-13     8842.357
## 10 2013-14     8947.938
## 11 2014-15     9037.357
## 12 2015-16     9317.633
```

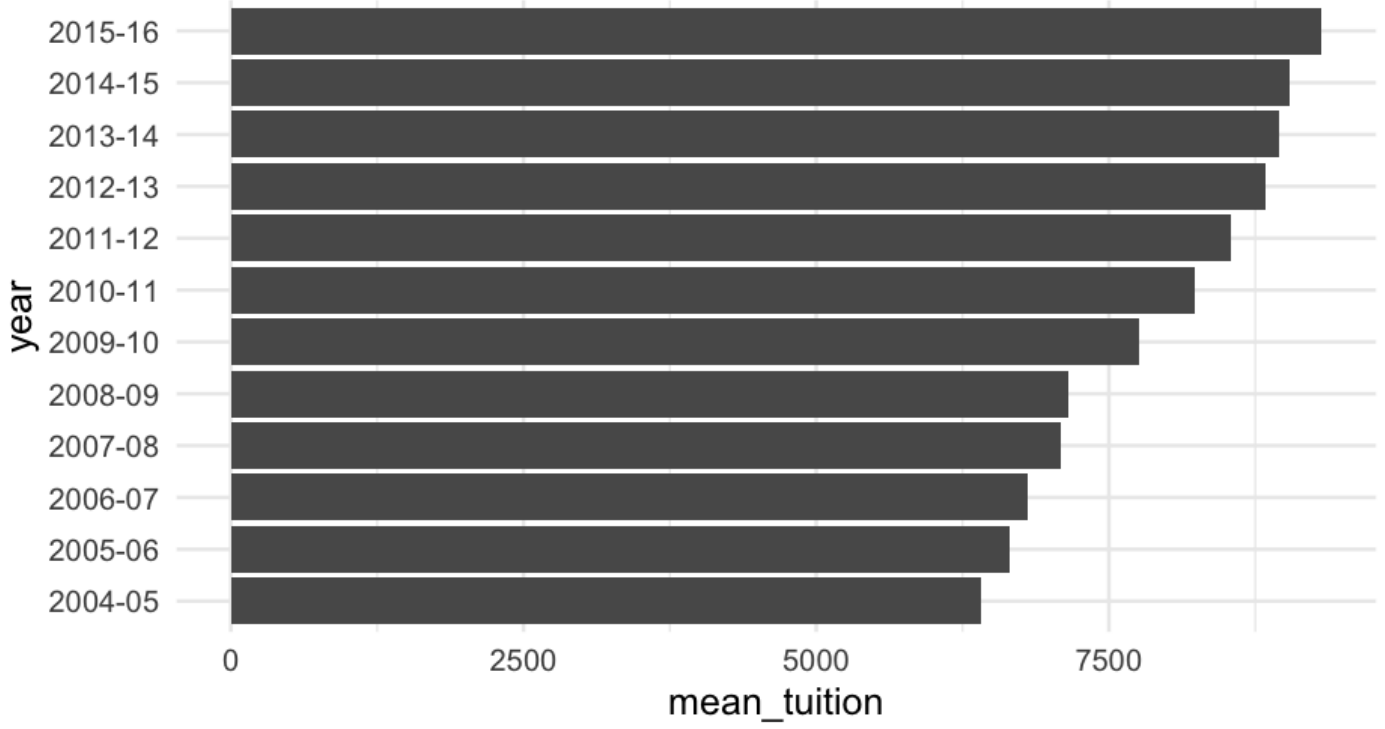
Good

```
ggplot(annual_means, aes(year, mean_tuition)) +
  geom_col()
```



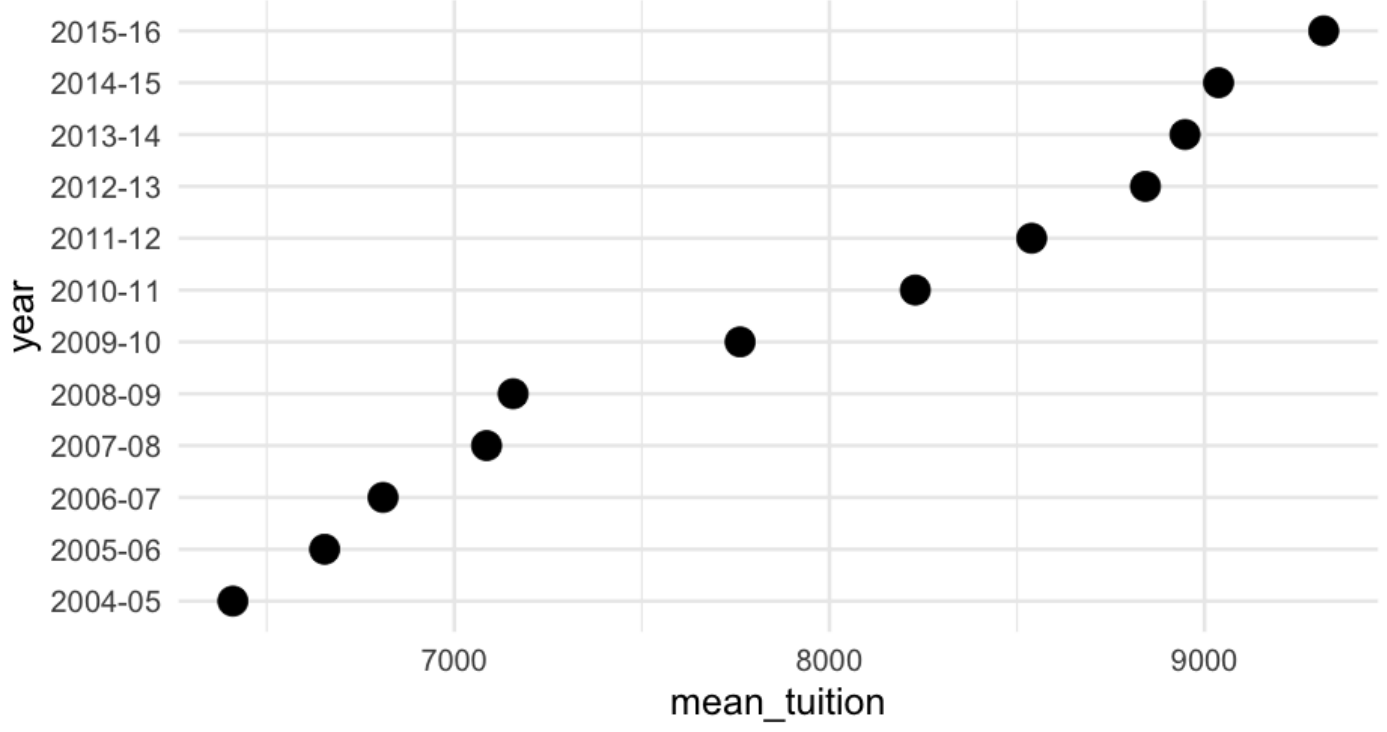
Better?

```
ggplot(annual_means, aes(year, mean_tuition)) +
  geom_col() +
  coord_flip()
```



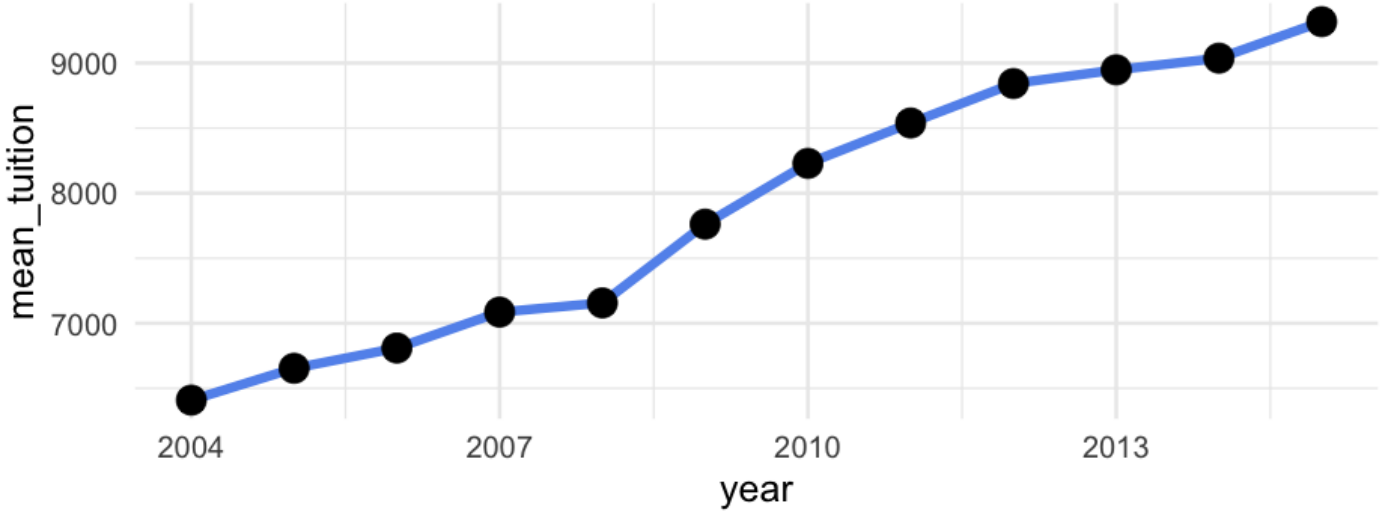
Better still?

```
ggplot(annual_means, aes(year, mean_tuition)) +
  geom_point() +
  coord_flip()
```



Even better

```
annual_means %>%
  mutate(year = readr::parse_number(year)) %>%
  ggplot(aes(year, mean_tuition)) +
    geom_line(color = "cornflowerblue") +
    geom_point()
```



Treat time (year) as a continuous variable

Grouped points

Show change in tuition from 05–06 to 2015–16

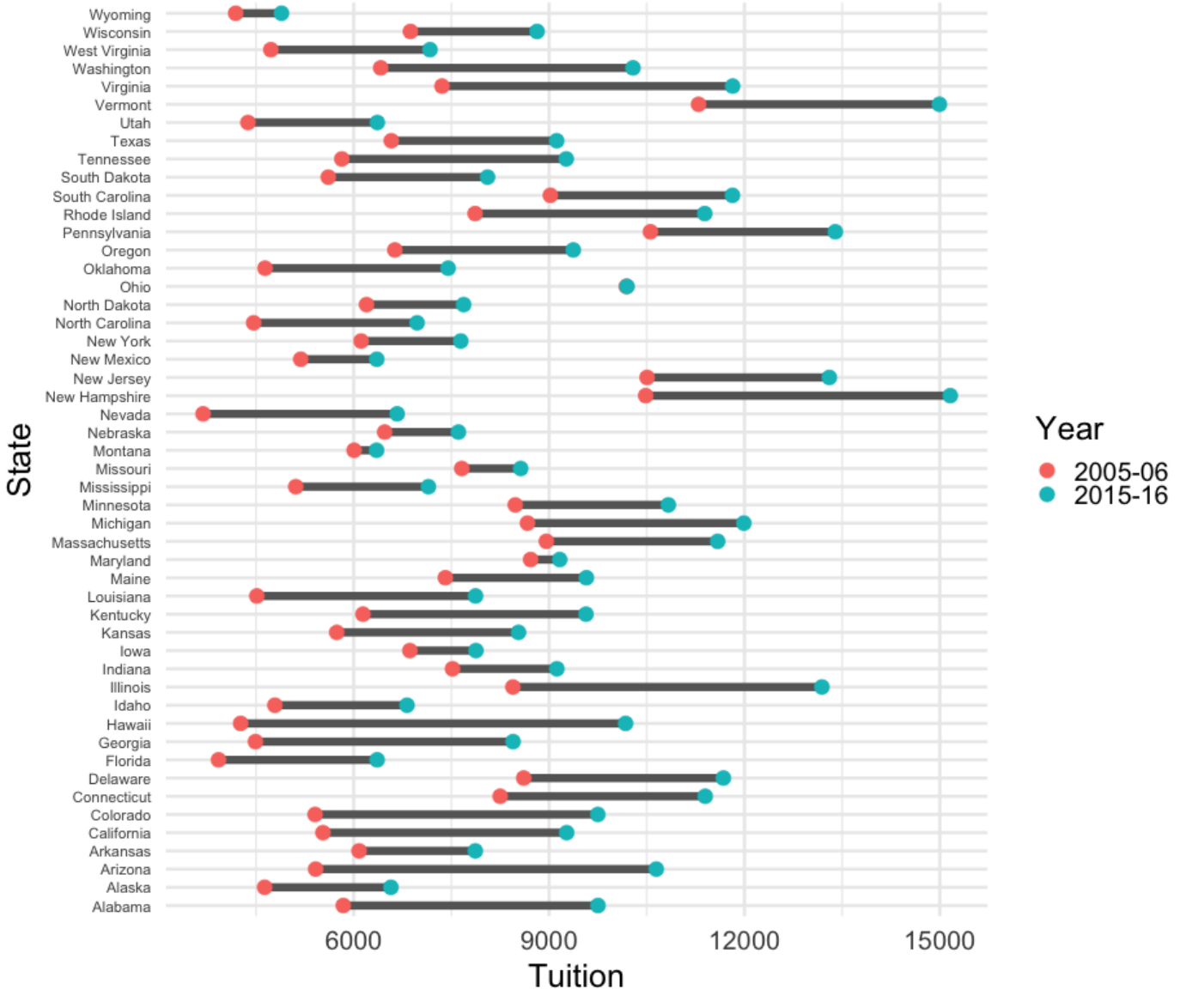
```
tuition %>%
  select(State, `2005-06`, `2015-16`)
```

```
## # A tibble: 50 × 3
##    State       `2005-06` `2015-16`
##    <chr>           <dbl>     <dbl>
##  1 Alabama      5840.550  9751.101
##  2 Alaska       4632.623  6571.340
##  3 Arizona      5415.516 10646.28
##  4 Arkansas     6082.379  7867.297
##  5 California   5527.881  9269.844
##  6 Colorado     5406.967  9748.188
##  7 Connecticut  8249.074 11397.34
##  8 Delaware     8610.597 11676.22
##  9 Florida      3924.234  6360.159
## 10 Georgia      4492.167  8446.961
## # … with 40 more rows
```

```
lt <- tuition %>%
  select(State, `2005-06`, `2015-16`) %>%
  pivot_longer(`2005-06`:`2015-16`,
               names_to = "Year",
               values_to = "Tuition")
lt
```

```
## # A tibble: 100 × 3
##    State      Year      Tuition
##    <chr>      <chr>       <dbl>
##  1 Alabama    2005-06  5840.550
##  2 Alabama    2015-16  9751.101
##  3 Alaska     2005-06  4632.623
##  4 Alaska     2015-16  6571.340
##  5 Arizona    2005-06  5415.516
##  6 Arizona    2015-16 10646.28
##  7 Arkansas   2005-06  6082.379
##  8 Arkansas   2015-16  7867.297
##  9 California 2005-06  5527.881
## 10 California 2015-16  9269.844
## # … with 90 more rows
```

```
ggplot(lt, aes(State, Tuition)) +
  geom_line(aes(group = State), color = "gray40") +
  geom_point(aes(color = Year)) +
  coord_flip()
```


Wyoming
Wisconsin
West Virginia
Washington
Virginia
Vermont
Utah
Texas
Tennessee
South Dakota
South Carolina
Rhode Island
Pennsylvania
Oregon
Oklahoma
Ohio
North Dakota
North Carolina
New York
New Mexico
New Jersey
New Hampshire
Nevada
Nebraska
Montana
Missouri
Mississippi
Minnesota
Michigan
Massachusetts
Maryland
Maine
Louisiana
Kentucky
Kansas
Iowa
Indiana
Illinois
Idaho
Hawaii
Georgia
Florida
Delaware
Connecticut
Colorado
California
Arkansas
Arizona
Alaska
Alabama
State
6000
9000
12000
15000
Tuition
Year
2005-06
2015-16

Extensions

We need to move on to other things, but we definitely would want to keep going here:

- Order states according to something more meaningful (starting tuition, ending tuition, or difference in tuition)
- Meaningful title, e.g., "Change in average tuition over a decade"
- Consider better color scheme for points
- Potentially color the difference line by magnitude

Let's back up a bit

- Lets go back to our full data, but in a format that we can have a `year` variable.

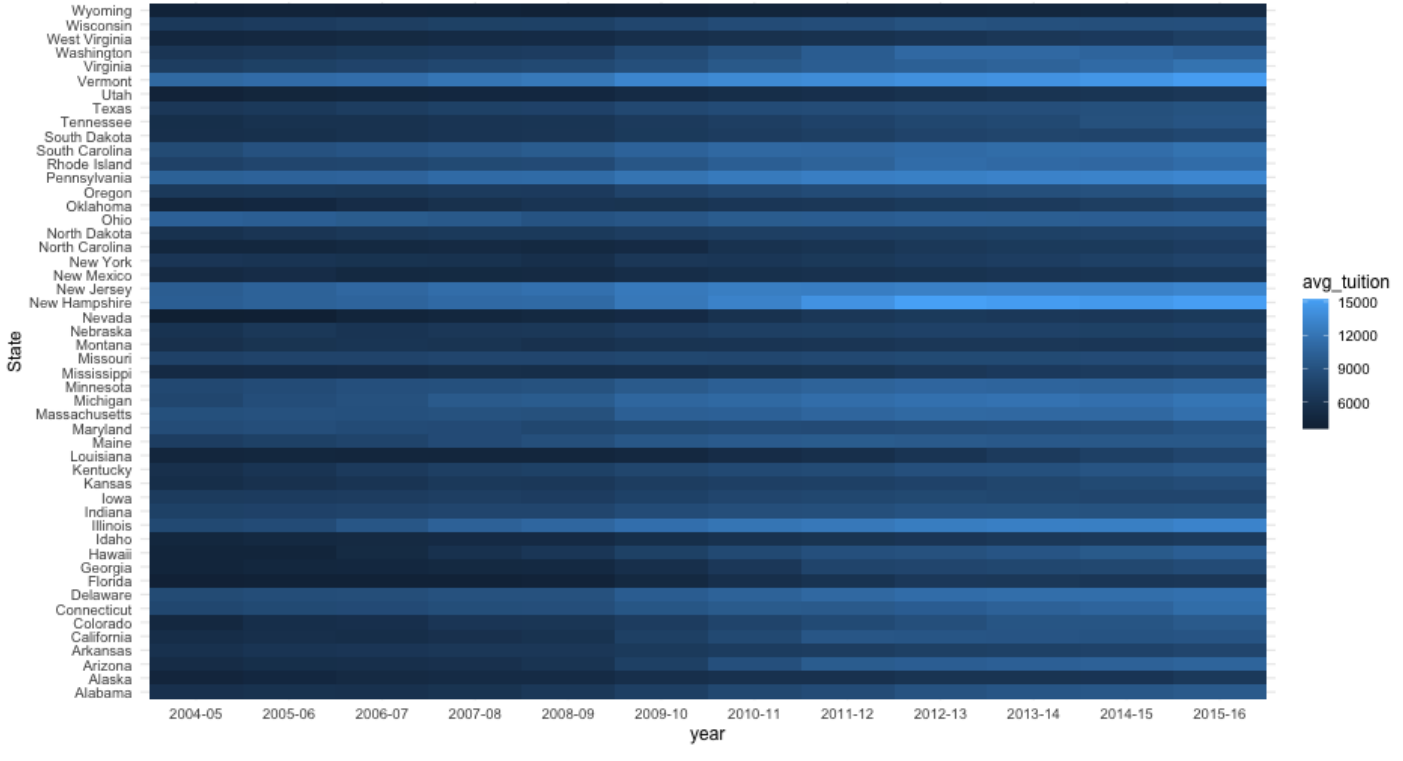
```
tuition_l <- tuition %>%
    pivot_longer(-State,
                 names_to = "year",
                 values_to = "avg_tuition")

tuition_l
```

```
## # A tibble: 600 × 3
##    State   year    avg_tuition
##    <chr>   <chr>         <dbl>
##  1 Alabama 2004-05    5682.838
##  2 Alabama 2005-06    5840.550
##  3 Alabama 2006-07    5753.496
##  4 Alabama 2007-08    6008.169
##  5 Alabama 2008-09    6475.092
##  6 Alabama 2009-10    7188.954
##  7 Alabama 2010-11    8071.134
##  8 Alabama 2011-12    8451.902
##  9 Alabama 2012-13    9098.069
## 10 Alabama 2013-14    9358.929
```

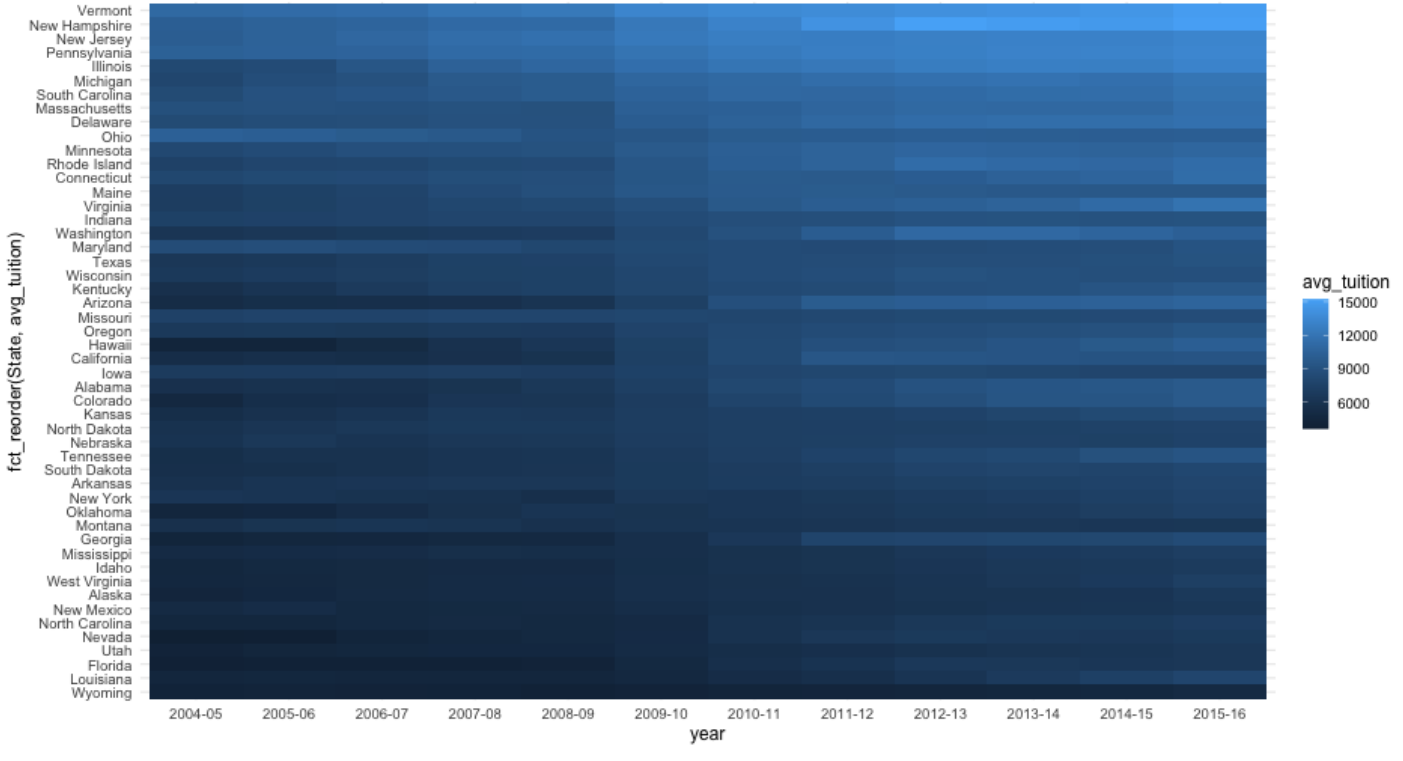
Heatmap

```
ggplot(tuition_l, aes(year, State)) +
  geom_tile(aes(fill = avg_tuition))
```



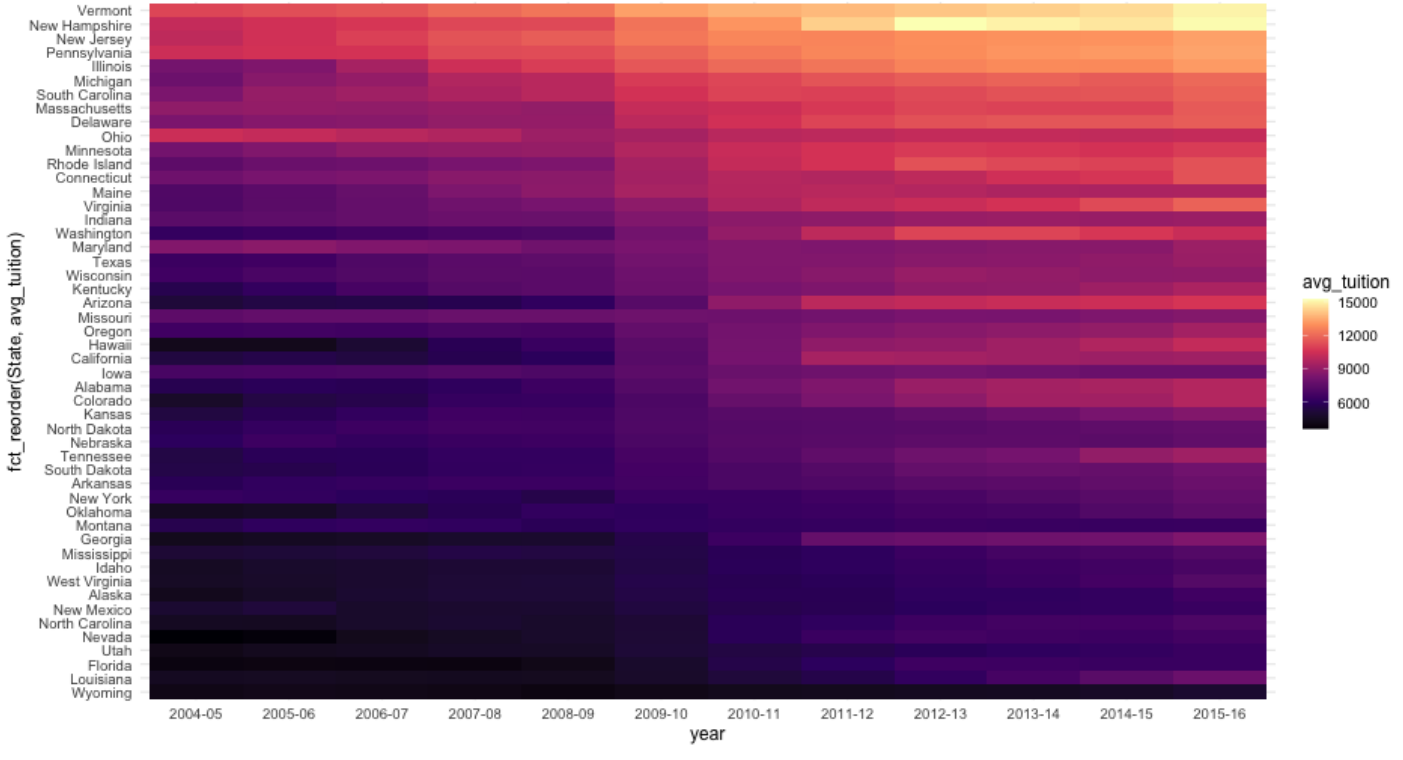
Better heatmap

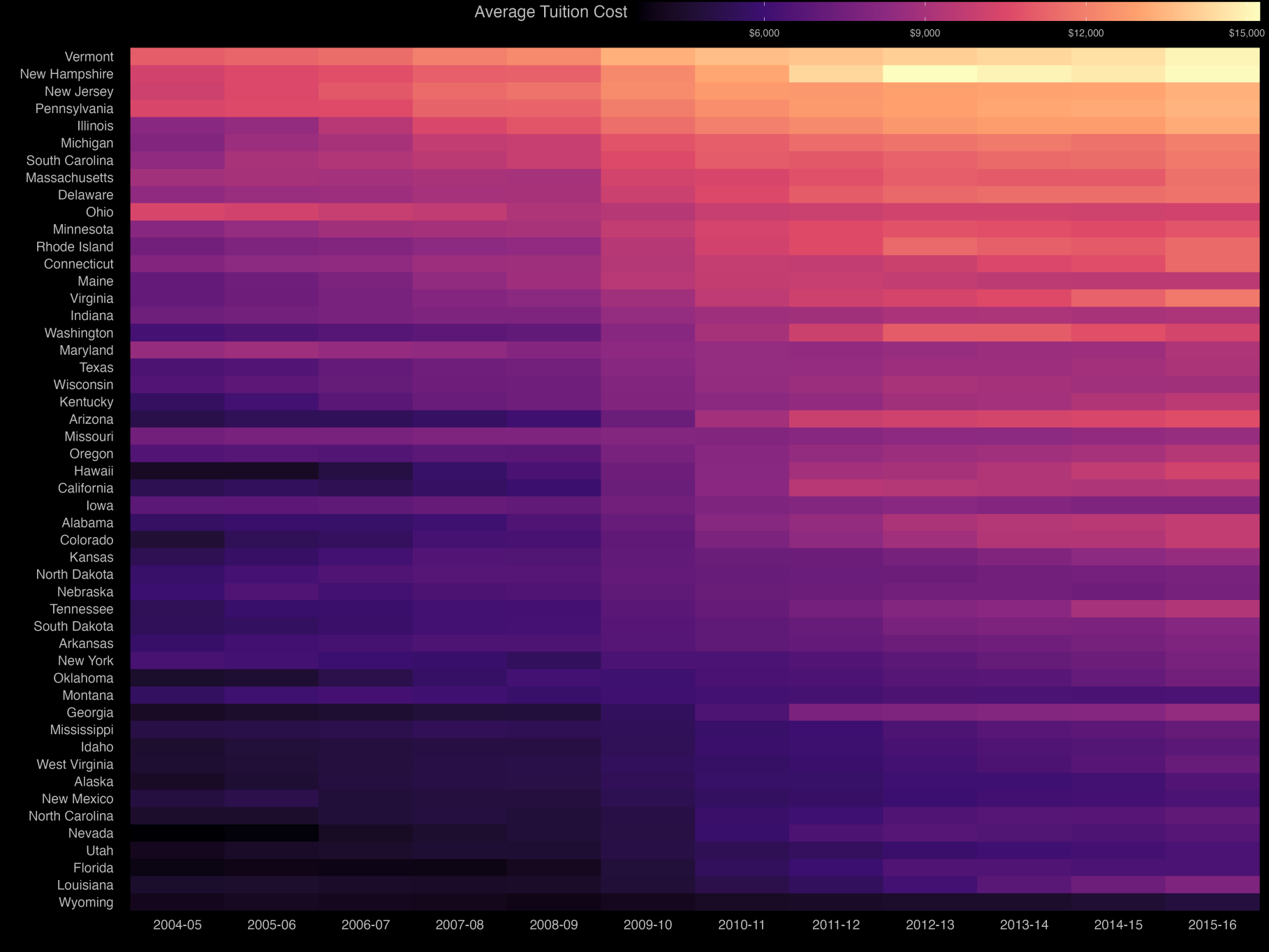
```
ggplot(tuition_l, aes(year, fct_reorder(State, avg_tuition))) +
  geom_tile(aes(fill = avg_tuition))
```



Even better heatmap

```
ggplot(tuition_l, aes(year, fct_reorder(State, avg_tuition))) +
  geom_tile(aes(fill = avg_tuition)) +
  scale_fill_viridis_c(option = "magma")
```




Average Tuition Cost
$6,000
$9,000
$12,000
$15,000
Vermont
New Hampshire
New Jersey
Pennsylvania
Illinois
Michigan
South Carolina
Massachusetts
Delaware
Ohio
Minnesota
Rhode Island
Connecticut
Maine
Virginia
Indiana
Washington
Maryland
Texas
Wisconsin
Kentucky
Arizona
Missouri
Oregon
Hawaii
California
Iowa
Alabama
Colorado
Kansas
North Dakota
Nebraska
Tennessee
South Dakota
Arkansas
New York
Oklahoma
Montana
Georgia
Mississippi
Idaho
West Virginia
Alaska
New Mexico
North Carolina
Nevada
Utah
Florida
Louisiana
Wyoming
2004-05
2005-06
2006-07
2007-08
2008-09
2009-10
2010-11
2011-12
2012-13
2013-14
2014-15
2015-16

Quick aside

- Think about the data you have
- Given that these are state–level data, they have a geographic component

```
#install.packages("maps")
state_data <- map_data("state") %>% # ggplot2::map_data
  rename(State = region)
```

Join it

Obviously we'll talk more about joins later

```
tuition <- tuition %>%
  mutate(State = tolower(State))
states <- left_join(state_data, tuition)
head(states)
```

```
##        long      lat group order   State
## 1 -87.46201 30.38968     1     1 alabama
## 2 -87.48493 30.37249     1     2 alabama
## 3 -87.52503 30.37249     1     3 alabama
## 4 -87.53076 30.33239     1     4 alabama
## 5 -87.57087 30.32665     1     5 alabama
## 6 -87.58806 30.32665     1     6 alabama
##   subregion  2004-05 2005-06  2006-07  2007-08
## 1      <NA> 5682.838 5840.55 5753.496 6008.169
## 2      <NA> 5682.838 5840.55 5753.496 6008.169
## 3      <NA> 5682.838 5840.55 5753.496 6008.169
## 4      <NA> 5682.838 5840.55 5753.496 6008.169
## 5      <NA> 5682.838 5840.55 5753.496 6008.169
## 6      <NA> 5682.838 5840.55 5753.496 6008.169
##    2008-09  2009-10  2010-11  2011-12  2012-13
## 1 6475.092 7188.954 8071.134 8451.902 9098.069
## 2 6475.092 7188.954 8071.134 8451.902 9098.069
```

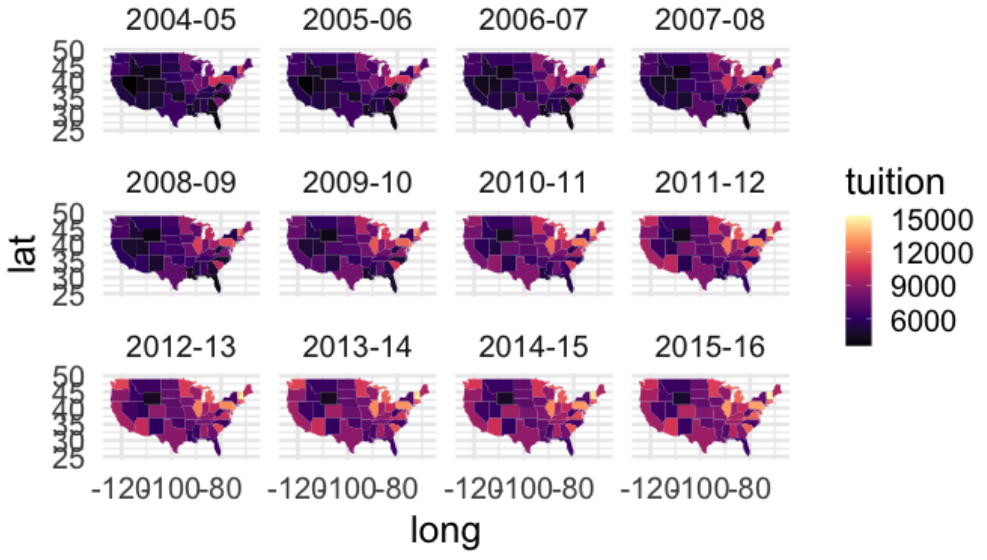
Rearrange

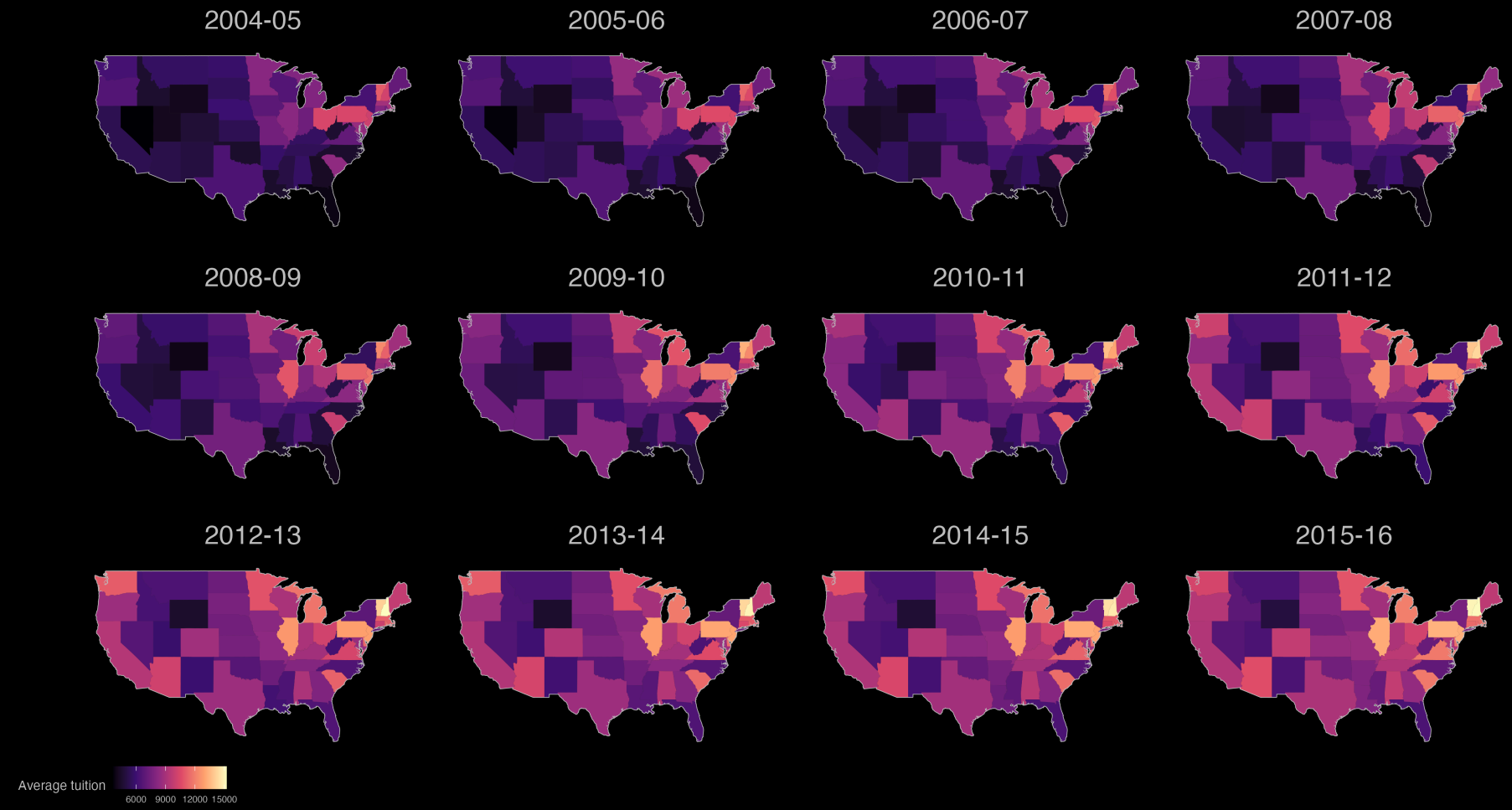
```
states <- states %>%
  gather(year, tuition, `2004-05`:`2015-16`)
head(states)
```

```
##        long      lat group order   State
## 1 -87.46201 30.38968     1     1 alabama
## 2 -87.48493 30.37249     1     2 alabama
## 3 -87.52503 30.37249     1     3 alabama
## 4 -87.53076 30.33239     1     4 alabama
## 5 -87.57087 30.32665     1     5 alabama
## 6 -87.58806 30.32665     1     6 alabama
##   subregion    year  tuition
## 1      <NA> 2004-05 5682.838
## 2      <NA> 2004-05 5682.838
## 3      <NA> 2004-05 5682.838
## 4      <NA> 2004-05 5682.838
## 5      <NA> 2004-05 5682.838
## 6      <NA> 2004-05 5682.838
```

Plot

```
ggplot(states) +
  geom_polygon(aes(long, lat, group = group, fill = tuition)) +
  coord_fixed(1.3) +
  scale_fill_viridis_c(option = "magma") +
  facet_wrap(~year)
```




2004-05
2005-06
2006-07
2007-08
2008-09
2009-10
2010-11
2011-12
2012-13
2013-14
2014-15
2015-16
Average tuition
6000
9000
12000
15000

Intro to textual data

Disclaimer:

This is going to be relatively fast, with not much depth. It's an intro, and I can work with you more individually if you end up working with text data.

Structured vs unstructured

- Most every dataset you've ever worked with is what is referred to as a **structured** dataset – it has rows and columns.
- But there is an incredible amount of data out there that is **unstructured** – it just sort of exists
- Most text data is unstructured. How would you analyze the contents of a book? No rows or columns there

Getting text data

There are **many** ways to get text data. Any digital text could potentially be used as textual data.

How about Wikipedia?

Anything that lives on the web is a common use case. Social media data being perhaps primary among them.

"Screen" scraping

Short foray into web scraping. It's not expected you fully follow this. More about "exposure" and less about building competencies.

Use the rvest package to scrape the data you see "on the screen".

Let's read in the Wikipedia page on Eugene

```
library(rvest)
eugene <- read_html("https://en.wikipedia.org/wiki/Eugene%2C_Oreg
```

WIKIPEDIA
The Free Encyclopedia

Main page
Contents
Current events
Random article
About Wikipedia
Contact us
Donate

Contribute
Help
Learn to edit
Community portal
Recent changes
Upload file

Tools
What links here
Related changes
Special pages
Permanent link
Page information
Cite this page
Wikidata item

Print/export
Download as PDF
Printable version

In other projects

Eugene, Oregon

From Wikipedia, the free encyclopedia

Coordinates: 44°03′07″N 123°05′12″W

Eugene (/juːˈdʒiːn/ *yoo-JEEN*) is a city in the U.S. state of Oregon, in the Pacific Northwest. It is at the southern end of the Willamette Valley, near the confluence of the McKenzie and Willamette rivers, about 50 miles (80 km) east of the Oregon Coast.[7]

As of the 2010 census, Eugene had a population of 156,185; it is the county seat of Lane County and the state's third most populous city after Portland and Salem, though recent state estimates suggest its population may have surpassed Salem's.[8][9] The Eugene-Springfield, Oregon metropolitan statistical area (MSA) is the 146th largest metropolitan statistical area in the US and the third-largest in the state, behind the Portland Metropolitan Area and the Salem Metropolitan Area.[10] The city's population for 2019 was estimated to be 172,622 by the U.S. Census.[11]

Eugene is home to the University of Oregon, Bushnell University, and Lane Community College.[12][13][14] The city is noted for its natural environment, recreational opportunities (especially bicycling, running/jogging, rafting, and kayaking), and focus on the arts, along with its history of civil unrest, protests, and green activism. Eugene's official slogan is "A Great City for the Arts and Outdoors".[15] It is also referred to as the "Emerald City" and as "Track Town, USA".[16] The Nike corporation had its beginnings in Eugene.[17] In 2022, the city will host the 18th Track and Field World Championships.[18]

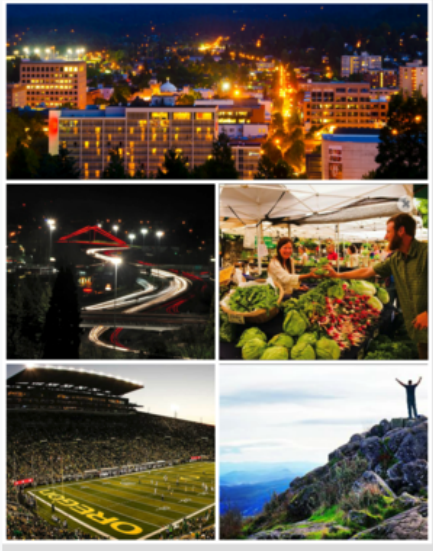
Contents [hide]

1 History
1.1 Indigenous presence
1.2 Settlement and impact
1.3 Educational institutions
1.4 Twentieth century
1.5 History of civil unrest
1.5.1 1960s: Counterculture and campus protests

Eugene, Oregon

City

City of Eugene



Clockwise: Downtown Eugene from Skinner Butte, Lane County Farmers' Market, Hiking on Spencer Butte, University of Oregon Autzen Stadium, Delta Ponds pedestrian bridge

Grab paragraphs

The `"#mw-content-text > div.mw-parser-output > p"` is the CSS selector that I pulled from the website

```
paragraphs <- eugene %>%
  html_elements("#mw-content-text > div.mw-parser-output > p") %>
  html_text2()
```

The first paragraph is just an empty line, so they are numbered p + 1

Print the first paragraph

```
cat(stringr::str_wrap(paragraphs[2], 50))
```

```
## Eugene (/juːˈdʒiːn/ yoo-JEEN) is a city in the
## U.S. state of Oregon, in the Pacific Northwest. It
## is at the southern end of the Willamette Valley,
## near the confluence of the McKenzie and Willamette
## rivers, about 50 miles (80 km) east of the Oregon
```

Print the fourth paragraph

```
cat(stringr::str_wrap(paragraphs[5], 50))
```

```
## The first people to settle in the Eugene area were
## known as the Kalapuyans, also written Calapooia
## or Calapooya. They made "seasonal rounds," moving
## around the countryside to collect and preserve
## local foods, including acorns, the bulbs of the
## wapato and camas plants, and berries. They stored
## these foods in their permanent winter village.
## When crop activities waned, they returned to their
## winter villages and took up hunting, fishing, and
## trading.[19][20] They were known as the Chifin
## Kalapuyans and called the Eugene area where they
## lived "Chifin", sometimes recorded as "Chafin" or
## "Chiffin".[21][22]
```

Analysis

How do we analyze the text? What we we even analyze?

First, let's structure it! Turn the text into a simple data frame.

```
library(tidyverse)
eugene_df <- tibble(
  paragraph = seq_along(paragraphs),
  description = paragraphs
)
eugene_df
```

```
## # A tibble: 130 × 2
##    paragraph
##        <int>
##  1         1
##  2         2
##  3         3
##  4         4
##  5         5
##  6         6
##  7         7
##  8         8
##  9         9
```

Can we analyze it now?

Not really... what would we analyze?

Words!

Let's break it into words. This is where the tidytext package comes into play.

The `unnest_tokens()` function

Just like most functions in the tidyverse, we pipe our data to `unnest_tokens()`

- First argument is the name of the new column we want in our data
- Second argument is the text data to process
- Third argument is how the text should processed. The default is `"words"`, meaning the text will be broken into words.

Example

```
library(tidytext)
eugene_tidy_words <- eugene_df %>%
  unnest_tokens(word, description)
eugene_tidy_words
```

```
## # A tibble: 7,814 × 2
##    paragraph word
##        <int> <chr>
##  1         2 eugene
##  2         2 juːˈdʒiːn
##  3         2 yoo
##  4         2 jeen
##  5         2 is
##  6         2 a
##  7         2 city
##  8         2 in
##  9         2 the
## 10         2 u.s
## # … with 7,804 more rows
```

Not perfect, but pretty good

What to do now?

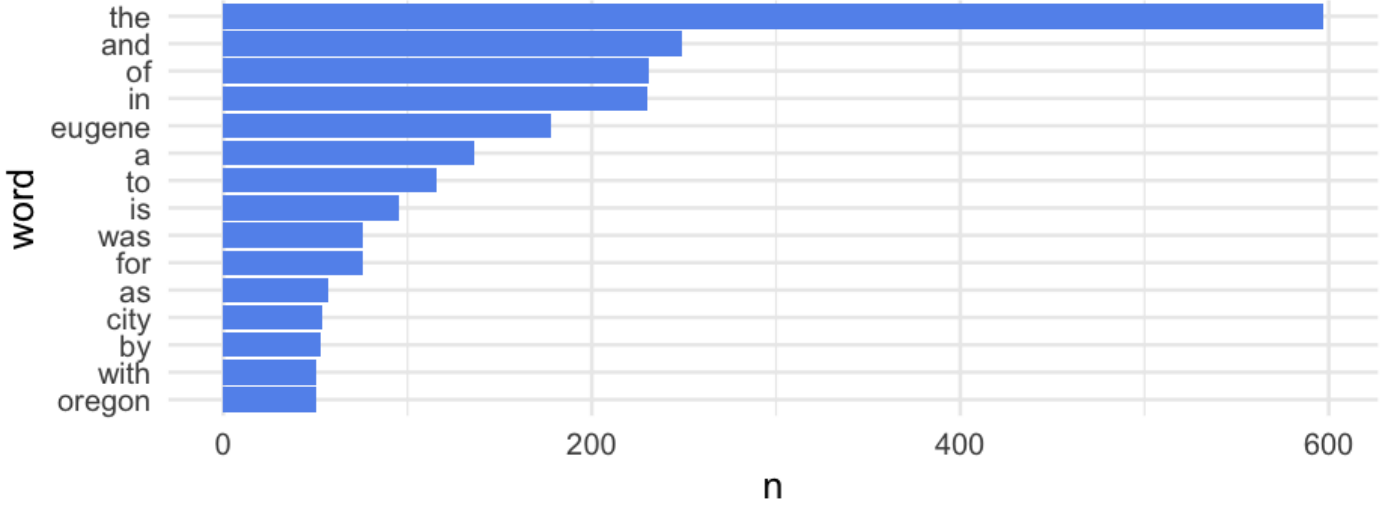
Let's count some words!

```
eugene_tidy_words %>%
  count(word, sort = TRUE)
```

```
## # A tibble: 2,478 × 2
##    word       n
##    <chr>  <int>
##  1 the      597
##  2 and      249
##  3 of       231
##  4 in       230
##  5 eugene   178
##  6 a        136
##  7 to       116
##  8 is        95
##  9 for       76
## 10 was       76
## # … with 2,468 more rows
```

Plot the top 15 words

```
eugene_tidy_words %>%
  count(word, sort = TRUE) %>%
  mutate(word = fct_reorder(word, n)) %>%
  slice(1:15) %>% # select only the first 15 rows
  ggplot(aes(n, word)) +
    geom_col(fill = "cornflowerblue")
```



Not very informative

Why?

Most of the words are common words like "the", "and", "of" (top three words)

These are referred to as "stop words".

Luckily, **tidytext** provides us with a dictionary of stop words. We can use an `anti_join()` with this dictionary to remove these words.

Quick refresher

A `semi_join()` works just like an `inner_join()`, but without adding any columns. A `semi_join()` works by **keeping** only rows that are in common with the two datasets.

An `anti_join()` does basically the opposite, by **removing** any rows that are in common between the two datasets.

Look at the stop words

This dataset is available to you as soon as you load **tidytext**.

There are three lexicons – I usually use all three.

```
stop_words
```

```
## # A tibble: 1,149 × 2
##    word        lexicon
##    <chr>       <chr>
##  1 a           SMART
##  2 a's         SMART
##  3 able        SMART
##  4 about       SMART
##  5 above       SMART
##  6 according   SMART
##  7 accordingly SMART
##  8 across      SMART
##  9 actually    SMART
## 10 after       SMART
## # … with 1,139 more rows
```

Count

Let's try counting again without the stop words included.

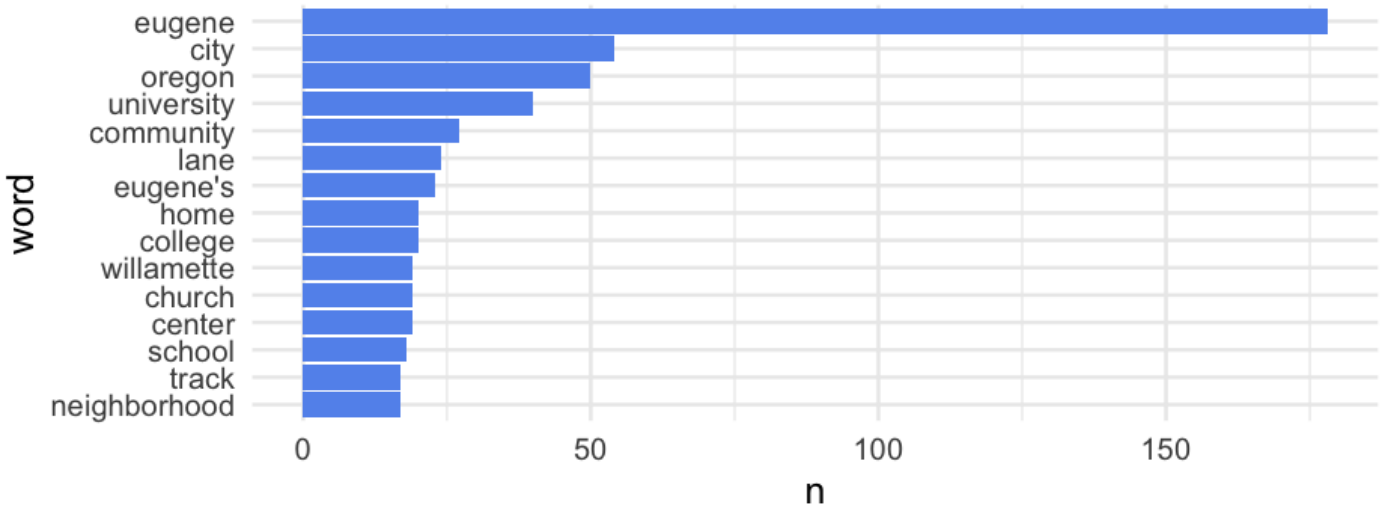
```
eugene_tidy_words %>%
  anti_join(stop_words) %>%
  count(word, sort = TRUE)
```

```
## # A tibble: 2,199 × 2
##    word            n
##    <chr>       <int>
##  1 eugene        178
##  2 city           54
##  3 oregon         50
##  4 university     40
##  5 community      27
##  6 lane           24
##  7 eugene's       23
##  8 college        20
##  9 home           20
## 10 center         19
## # … with 2,189 more rows
```

So much more informative!

Plot the top 15 words

```
eugene_tidy_words %>%
  anti_join(stop_words) %>%
  count(word, sort = TRUE) %>%
  mutate(word = reorder(word, n)) %>% # make y-axis ordered by n
  slice(1:15) %>% # select only the first 15 rows
  ggplot(aes(n, word)) +
    geom_col(fill = "cornflowerblue")
```



Add the headers in

I hid the code here because it's weird and inefficient but the HTML structure made it difficult. You can look at the source if you want. The new dataframe is called `eugene_tidy_words2`.

```
## # A tibble: 130 × 3
##    paragraph header
##        <int> <chr>
##  1         1 Intro
##  2         2 Intro
##  3         3 Intro
##  4         4 Intro
##  5         5 History
##  6         6 History
##  7         7 History
##  8         8 History
##  9         9 History
## 10        10 History
## # … with 120 more rows, and 1 more variable:
## #   description <chr>
```

Count words by header

Not surprisingly, "eugene" appears to be the most common among multiple categories.

We might want to remove "eugene" as well.

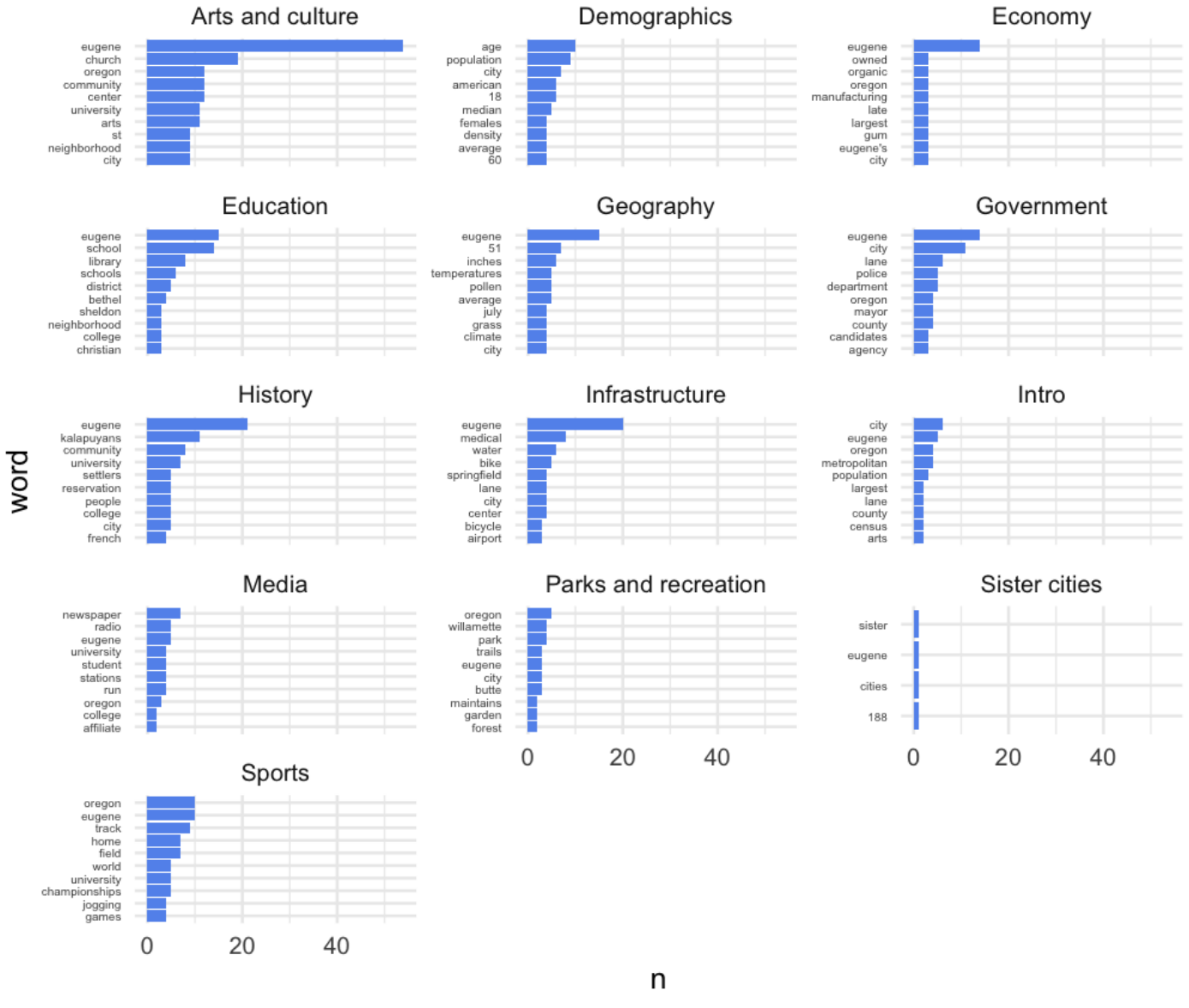
```
eugene_tidy_words2 %>%
  unnest_tokens(word, description) %>%
  count(header, word, sort = TRUE) %>%
  anti_join(stop_words)
```

```
## # A tibble: 3,029 × 3
##    header            word       n
##    <chr>             <chr>  <int>
##  1 Arts and culture  eugene    54
##  2 History           eugene    21
##  3 Infrastructure    eugene    20
##  4 Arts and culture  church    19
##  5 Education         eugene    15
##  6 Geography         eugene    15
##  7 Economy           eugene    14
##  8 Education         school    14
##  9 Government        eugene    14
```

Plot

Top 10 words by header

```
p <- eugene_tidy_words2 %>%
  unnest_tokens(word, description) %>%
  count(header, word, sort = TRUE) %>%
  anti_join(stop_words) %>%
  group_by(header) %>%
  slice(1:10) %>%
  mutate(word = reorder_within(word, n, header)) %>%
  ggplot(aes(n, word)) +
    geom_col(fill = "cornflowerblue") +
    scale_y_reordered() +
    facet_wrap(~header, scales = "free_y", ncol = 3)
```


Arts and culture
eugene
church
oregon
community
center
university
arts
st
neighborhood
city
Demographics
age
population
city
american
18
median
females
density
average
60
Economy
eugene
owned
organic
oregon
manufacturing
late
largest
gum
eugene's
city
Education
eugene
school
library
schools
district
bethel
sheldon
neighborhood
college
christian
Geography
eugene
51
inches
temperatures
pollen
average
july
grass
climate
city
Government
eugene
city
lane
police
department
oregon
mayor
county
candidates
agency
History
eugene
kalapuyans
community
university
settlers
reservation
people
college
city
french
Infrastructure
eugene
medical
water
bike
springfield
lane
city
center
bicycle
airport
Intro
city
eugene
oregon
metropolitan
population
largest
lane
county
census
arts
Media
newspaper
radio
eugene
university
student
stations
run
oregon
college
affiliate
Parks and recreation
oregon
willamette
park
trails
eugene
city
butte
maintains
garden
forest
0
20
40
Sister cities
sister
eugene
cities
188
0
20
40
Sports
oregon
eugene
track
home
field
world
university
championships
jogging
games
0
20
40
word
n

String manipulations

Base vs tidyverse

The tidyverse package is {stringr}

It is more consistent than base functions and occassionally faster

However, I tend to prefer the base functions, and they are still more commonly seen "in the wild" than **stringr**.

We'll therefore briefly cover both.

Inconsistencies

Super common example

```
set.seed(123)
ex <- tibble(
  gender = sample(
    c("f", "F", "Fem", "Female", "FEMALE",
      "m", "M", "Male", "MALE",
      "nb", "NB", "non-binary",
      "agender", "AGENDER", "Agender",
      "gender-fluid", "fluid",
      "No response"),
    500,
    replace = TRUE),
  score = rnorm(500)
)
```

Have vs want

Have

```
## # A tibble: 18 × 2
##    gender           n
##    <chr>        <int>
##  1 agender         25
##  2 Agender         26
##  3 AGENDER         29
##  4 f               24
##  5 F               24
##  6 Fem             27
##  7 Female          27
##  8 FEMALE          25
##  9 fluid           28
## 10 gender-fluid    28
## 11 m               29
## 12 M               34
## 13 Male            37
## 14 MALE            27
## 15 nb              36
## 16 NB              27
## 17 No response     21
## 18 non-binary      26
```

Want

```
## # A tibble: 6 × 2
##   gender          n
##   <chr>       <int>
## 1 agender        80
## 2 female        127
## 3 fluid          56
## 4 male          127
## 5 no response    21
## 6 non-binary     89
```

Walkthrough

Getting to what we want takes a few steps. Let's do it together!

Consistent case

- The first thing we might want to do is change everything to uppercase or lowercase. This will fix many of our inconsistencies.

- Options are `stringr::str_to_upper()`, `stringr::str_to_lower()`, `base::toupper()` or `base::tolower()`

Consistent case

Original

```
ex %>%
  count(gender)
```

```
## # A tibble: 18 × 2
##    gender            n
##    <chr>         <int>
##  1 agender          25
##  2 Agender          26
##  3 AGENDER          29
##  4 f                24
##  5 F                24
##  6 Fem              27
##  7 Female           27
##  8 FEMALE           25
##  9 fluid            28
## 10 gender-fluid     28
## 11 m                29
## 12 M                34
## 13 Male             37
## 14 MALE             27
## 15 nb               36
```

Modified

```
ex %>%
  mutate(gender = tolower(gend
  count(gender)
```

```
## # A tibble: 11 × 2
##    gender            n
##    <chr>         <int>
##  1 agender          80
##  2 f                48
##  3 fem              27
##  4 female           52
##  5 fluid            28
##  6 gender-fluid     28
##  7 m                63
##  8 male             64
##  9 nb               63
## 10 no response      21
## 11 non-binary       26
```

What next?

Collapse the genders that have "fluid"?

Use `grepl()` (global regular expression parser **l**ogical) with `ifelse()` to replace *if* a pattern is found

You could also use `stringr::str_detect()` instead. The arguments are just in reversed order

```
grepl("fluid", gender)
str_detect(gender, "fluid")
```

```r
ex %>%
  mutate(
    gender = tolower(gender),
    gender = ifelse(grepl("fluid", gender), "gender-fluid", gende
  ) %>%
  count(gender)
```

```
## # A tibble: 10 × 2
##    gender            n
##    <chr>         <int>
##  1 agender          80
##  2 f                48
##  3 fem              27
##  4 female           52
##  5 gender-fluid     56
##  6 m                63
##  7 male             64
##  8 nb               63
##  9 no response      21
## 10 non-binary       26
```

stringr

```
library(stringr)
ex %>%
  mutate(
    gender = tolower(gender),
    gender = ifelse(str_detect(gender, "fluid"), "gender-fluid",
  ) %>%
  count(gender)
```

```
## # A tibble: 10 × 2
##    gender            n
##    <chr>         <int>
##  1 agender          80
##  2 f                48
##  3 fem              27
##  4 female           52
##  5 gender-fluid     56
##  6 m                63
##  7 male             64
##  8 nb               63
##  9 no response      21
## 10 non-binary       26
```

What next?

How about – if it starts with "m", then "Male"?

Use "^" to denote "starts with"

```
ex %>%
  mutate(
    gender = tolower(gender),
    gender = ifelse(grepl("fluid", gender), "gender-fluid", gende
    gender = ifelse(grepl("^m", gender), "male", gender)
  ) %>%
  count(gender)
```

```
## # A tibble: 9 × 2
##   gender            n
##   <chr>         <int>
## 1 agender          80
## 2 f                48
## 3 fem              27
## 4 female           52
## 5 gender-fluid     56
## 6 male            127
## 7 nb               63
## 8 no response      21
## 9 non-binary       26
```

Again

Replicate the same thing, but this time with "female". Note that we couldn't do this initially, but we can now because `"fluid"` has been collapsed with `"gender-fluid"`.

You try first

```r
ex %>%
  mutate(
    gender = tolower(gender),
    gender = ifelse(grepl("fluid", gender), "gender-fluid", gende
    gender = ifelse(grepl("^m", gender), "male", gender),
    gender = ifelse(grepl("^f", gender), "female", gender)
  ) %>%
  count(gender)
```

```
## # A tibble: 7 × 2
##   gender            n
##   <chr>         <int>
## 1 agender          80
## 2 female          127
## 3 gender-fluid     56
## 4 male            127
## 5 nb               63
## 6 no response      21
## 7 non-binary       26
```

Again?

Can we do the same thing with `"^n"` for non–binary?

NO!

Little bit more complicated – use Boolean logic.

```
ex %>%
  mutate(
    gender = tolower(gender),
    gender = ifelse(grepl("fluid", gender), "gender-fluid", gende
    gender = ifelse(grepl("^m", gender), "male", gender),
    gender = ifelse(grepl("^f", gender), "female", gender),
    gender = ifelse(
      grepl("^n", gender) & gender != "no response",
      "non-binary",
      gender
    )
  ) %>%
  count(gender)
```

```
## # A tibble: 6 × 2
##   gender           n
##   <chr>        <int>
## 1 agender         80
## 2 female         127
## 3 gender-fluid    56
## 4 male           127
## 5 no response     21
## 6 non-binary      89
```

stringr version

```
ex %>%
  mutate(
    gender = tolower(gender),
    gender = ifelse(str_detect(gender, "fluid"), "gender-fluid",
    gender = ifelse(str_detect(gender, "^m"), "male", gender),
    gender = ifelse(str_detect(gender, "^f"), "female", gender),
    gender = ifelse(
      str_detect(gender, "^n") & gender != "no response",
      "non-binary",
      gender
    )
  ) %>%
  count(gender)
```

Special characters

- `^`: Anchor – matches the start of a string
- `$`: Anchor – matches the end of a string
- `*`: Matches the preceding character **zero or more** times
- `?`: Matches the preceding character **zero or one** times
- `+`: Matches the preceding character **one or more** times
- `{`: Used to specify number of matches, `a{n}`, `a{n,}`, and `a{n, m}`
- `.`: Wildcard – matches any character
- `|`: OR operator
- `[`: Alternates, also used for character matching (e.g., `[:digit:]`)
- `(`: Used for backreferencing, look aheads, or groups
- `\`: Used to escape special characters

More detail

Both of the below are good places to get more comprehensive information

- RStudio cheatsheet
- Regular expression vignette

One more quick example

```
library(edld652)
d <- get_data("EDFacts_acgr_lea_2011_2019")
```

```
##
  |
  |                                                      |   0%
  |
  |                                                      |   1%
  |
  |=                                                     |   2%
  |
  |=                                                     |   3%
  |
  |==                                                    |   4%
  |
  |==                                                    |   5%
  |
  |==                                                    |   6%
  |
  |===                                                   |   7%
  |
  |===                                                   |   8%
  |
  |====                                                  |   9%
  |
```

Do three things:

- Create a new variable that identifies if the LEA is associated with a city or a county
- Drop "City" or "County" from the LEA name (e.g., "Albertville City" would be "Albertville")
- Replace all `.` with `--DOT--` in `FILEURL` (so they are not actual links)

City or county

Ideas?

```
d <- d %>%
  mutate(county = grepl("county$", tolower(LEANM)))
```

Quick Check

```
d %>%
  select(LEANM, county) %>%
  print(n = 15)
```

```
## # A tibble: 11,326 × 2
##    LEANM             county
##    <chr>             <lgl>
##  1 Albertville City  FALSE
##  2 Marshall County   TRUE
##  3 Hoover City       FALSE
##  4 Madison City      FALSE
##  5 Leeds City        FALSE
##  6 Boaz City         FALSE
##  7 Trussville City   FALSE
##  8 Alexander City    FALSE
##  9 Andalusia City    FALSE
## 10 Anniston City     FALSE
## 11 Arab City         FALSE
## 12 Athens City       FALSE
## 13 Attalla City      FALSE
## 14 Auburn City       FALSE
## 15 Autauga County    TRUE
## # … with 11,311 more rows
```

Remove city/county

- Lots of ways to do this. Use `base::gsub()` or `stringr::str_replace_all()`
- Replace everything after the space with nothing

```
d %>%
  select(LEANM) %>%
  mutate(new_name = gsub(" .+", "", LEANM))
```

```
## # A tibble: 11,326 × 2
##    LEANM             new_name
##    <chr>             <chr>
##  1 Albertville City  Albertville
##  2 Marshall County   Marshall
##  3 Hoover City       Hoover
##  4 Madison City      Madison
##  5 Leeds City        Leeds
##  6 Boaz City         Boaz
##  7 Trussville City   Trussville
##  8 Alexander City    Alexander
##  9 Andalusia City    Andalusia
## 10 Anniston City     Anniston
```

Another way

There are other ways too, of course

```
d %>%
  select(LEANM) %>%
  mutate(new_name = gsub(" City$| County$", "", LEANM))
```

```
## # A tibble: 11,326 × 2
##    LEANM            new_name
##    <chr>            <chr>
##  1 Albertville City Albertville
##  2 Marshall County  Marshall
##  3 Hoover City      Hoover
##  4 Madison City     Madison
##  5 Leeds City       Leeds
##  6 Boaz City        Boaz
##  7 Trussville City  Trussville
##  8 Alexander City   Alexander
##  9 Andalusia City   Andalusia
## 10 Anniston City    Anniston
## # … with 11,316 more rows
```

Final step

Handling the URLs. This is a bit artificial, but it illustrates escaping, which is important.

- Remember `.` is a special character, so needs to be escaped
- `\` itself is a special character so it needs to be escaped. Functionally, then, you escape special characters with `\\`, not `\`.

```
d %>%
  select(FILEURL)
```

```
## # A tibble: 11,326 × 1
## # … with 11,316 more rows, and 1 more variable:
## #   FILEURL <chr>
```

```
d %>%
  select(FILEURL) %>%
  mutate(FILEURL = gsub("\\.", "--DOT--", FILEURL)) %>%
  as.data.frame()
```

```
##
## 1    https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 2    https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 3    https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 4    https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 5    https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 6    https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 7    https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 8    https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 9    https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 10   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 11   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 12   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 13   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 14   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 15   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 16   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 17   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 18   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 19   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 20   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 21   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 22   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
## 23   https://www2--DOT--ed--DOT--gov/about/inits/ed/edfacts/data-files/a
```

Wrapping up

This was pretty quick, still a lot we didn't get to

I'll try to embed more opportunities for you to practice these skills throughout the term

Next time

No class – MLK Jr. Day. Please do have your lab in before then.

Lab 1