Welcome!

Intro to visualizations, simple visualizations for continuous variables and string data, and downloading data from API,

Maithreyi Gopalan

Week 2

Agenda

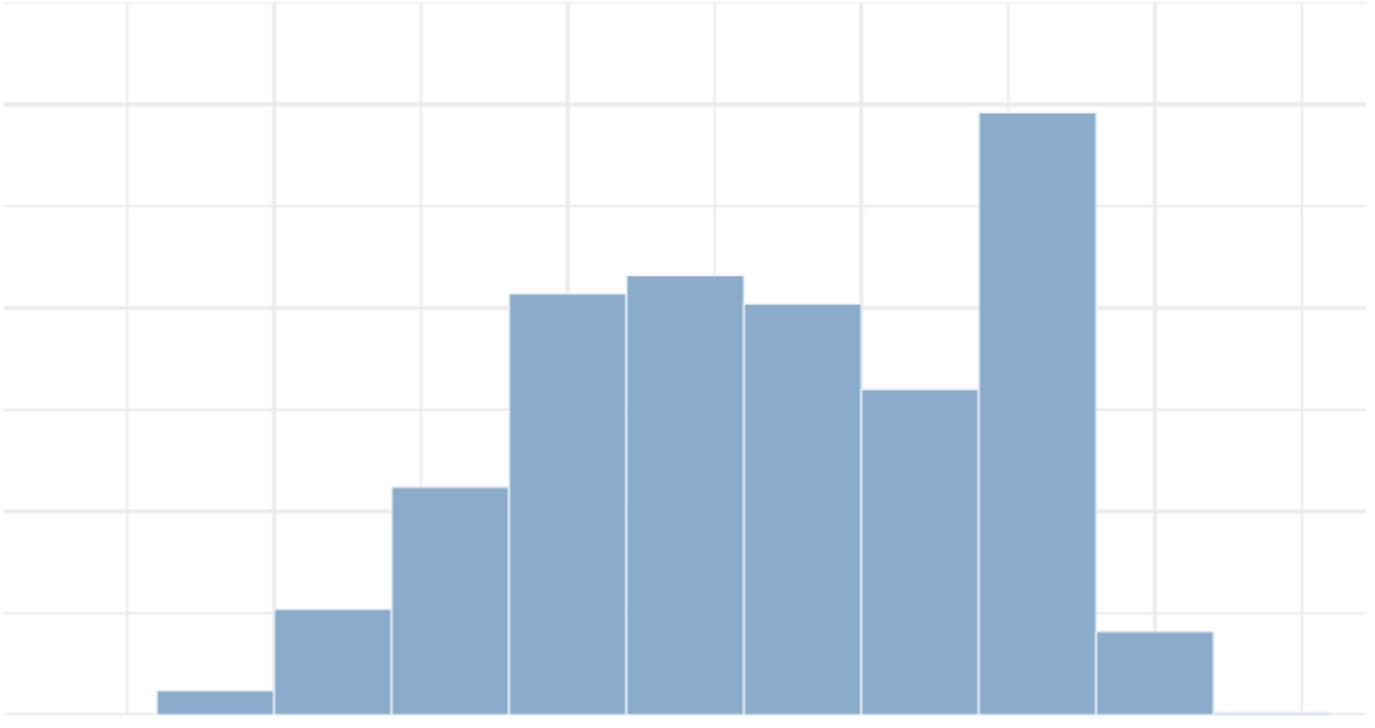
- Visualizing distributions
  - histograms
  - density plots
  - Empirical cumulative density plots
  - QQ plots
- Visualizing amounts
  - bar plots
  - dot plots
  - heatmaps
- Working textual data
  - Splitting into words, n-grams
  - Visualizing word frequencies
- Cleaning string data
  - Substrings, basic transformations
  - Substitutions and quick pattern matching
- Using API keys to download data
  - Understand packages/wrappers in R to download

Learning Objectives

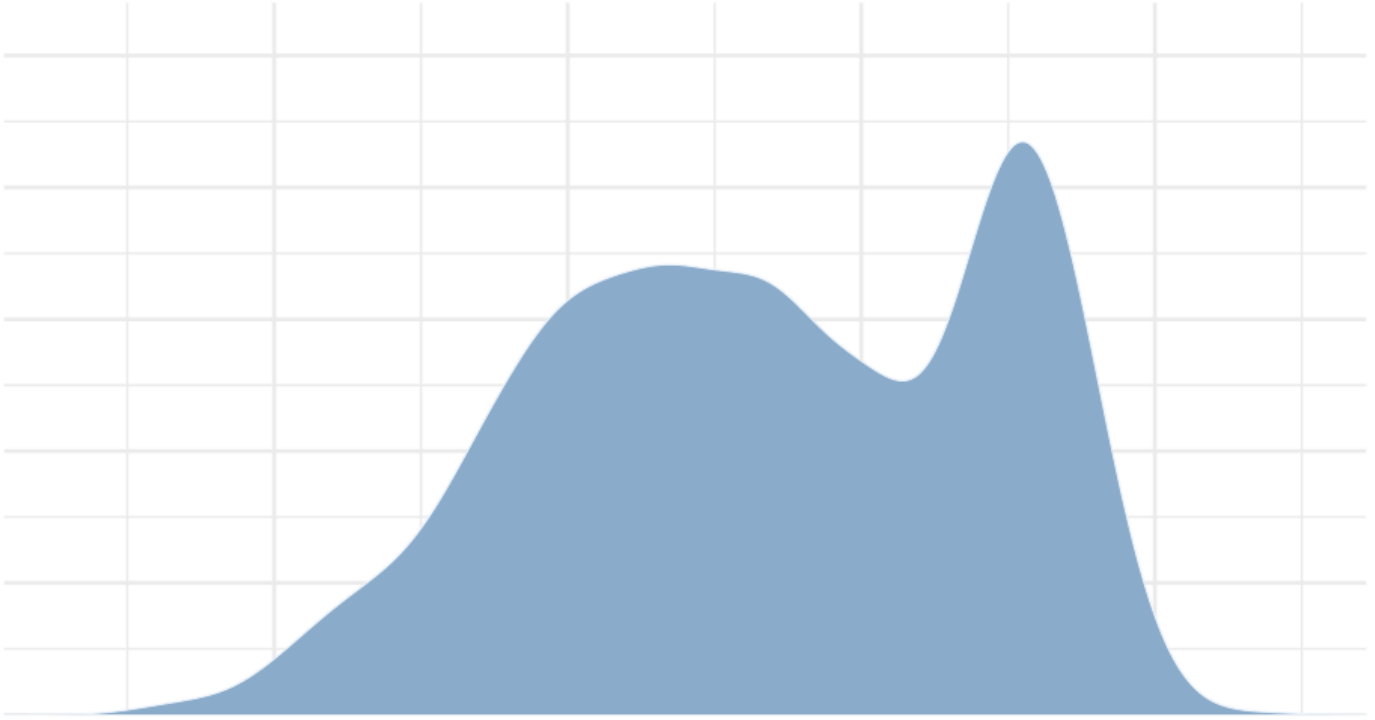
- Understand various ways the same underlying data can be displayed
- Think through pros/cons of each
- Understand the basic structure of the code to produce the various plots
- Create structured data from text and be able to visualize word frequencies
- Be able to replace patterns in strings and understand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

One continuous variable

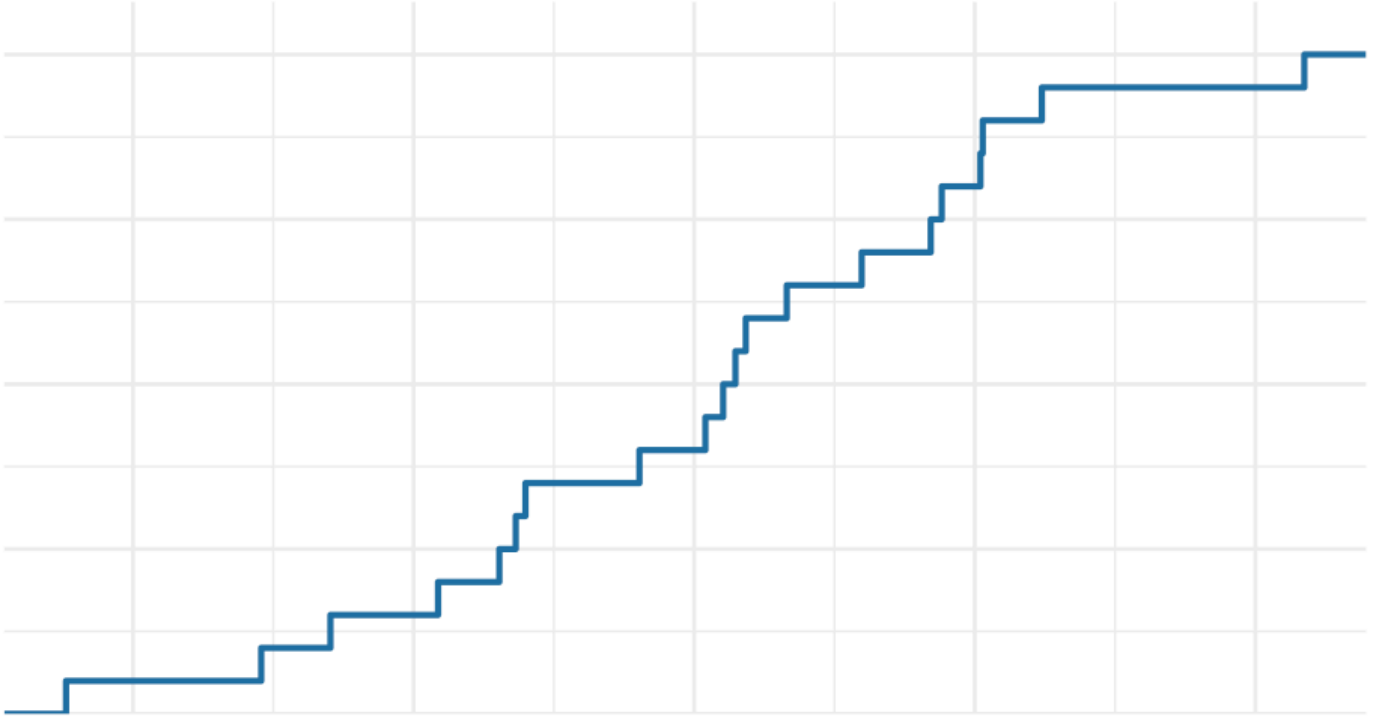
Histogram



Density plot

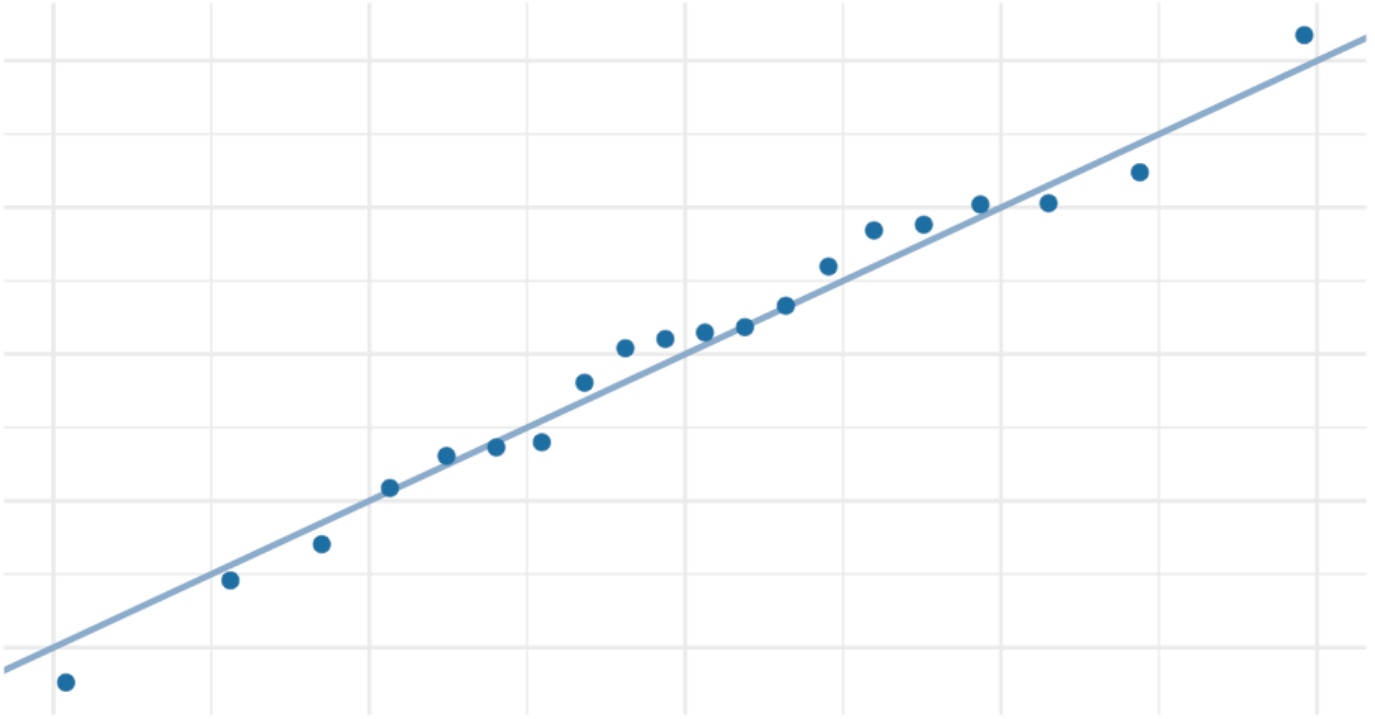


(Empirical) Cumulative Density



QQ Plot

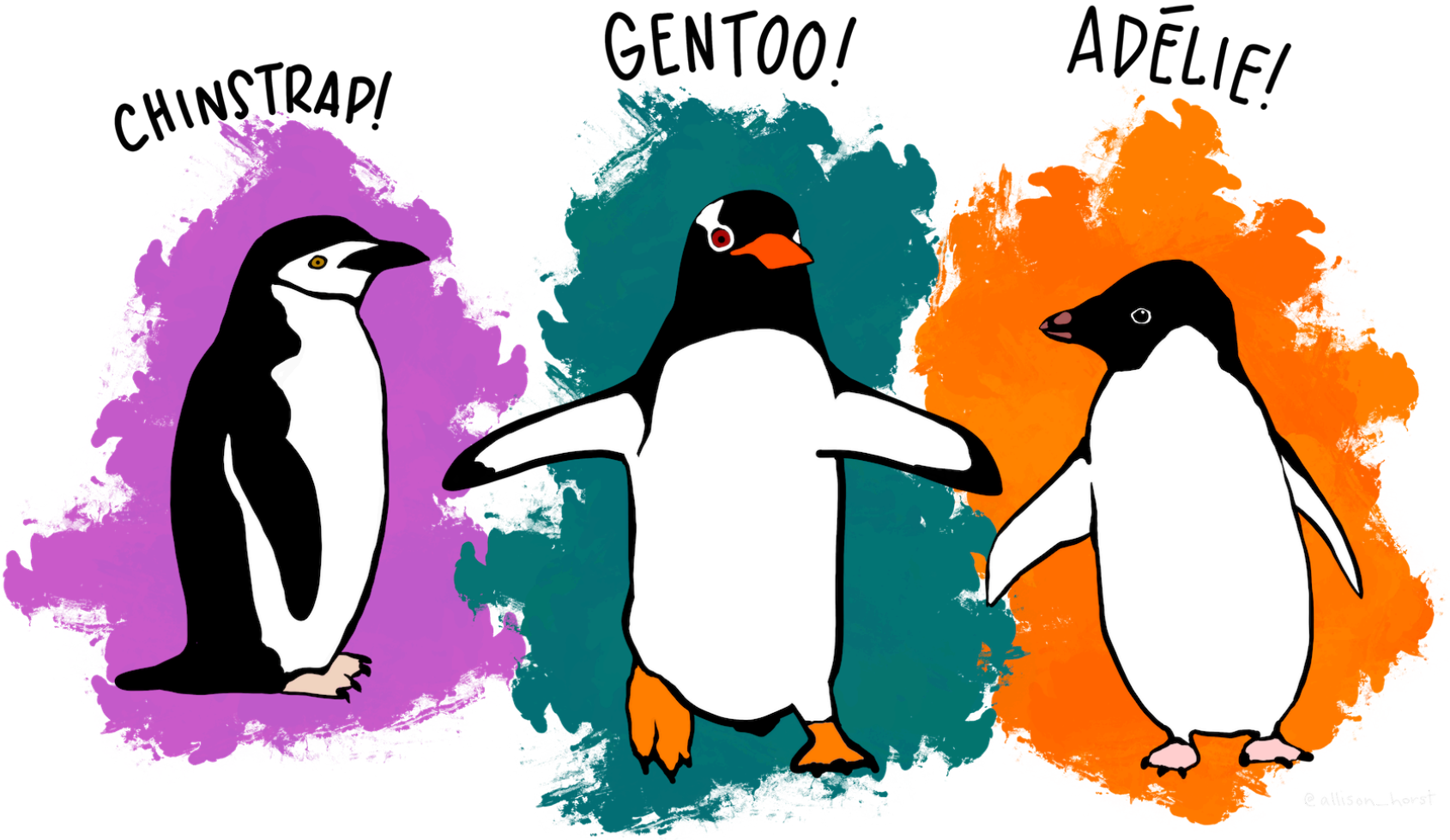
Compare to theoretical quantiles (for normality)



Empirical examples

I am going to go slow on this example section, so if you want to follow along, that will be a good idea; and can help you in the lab later today!

Penguin data



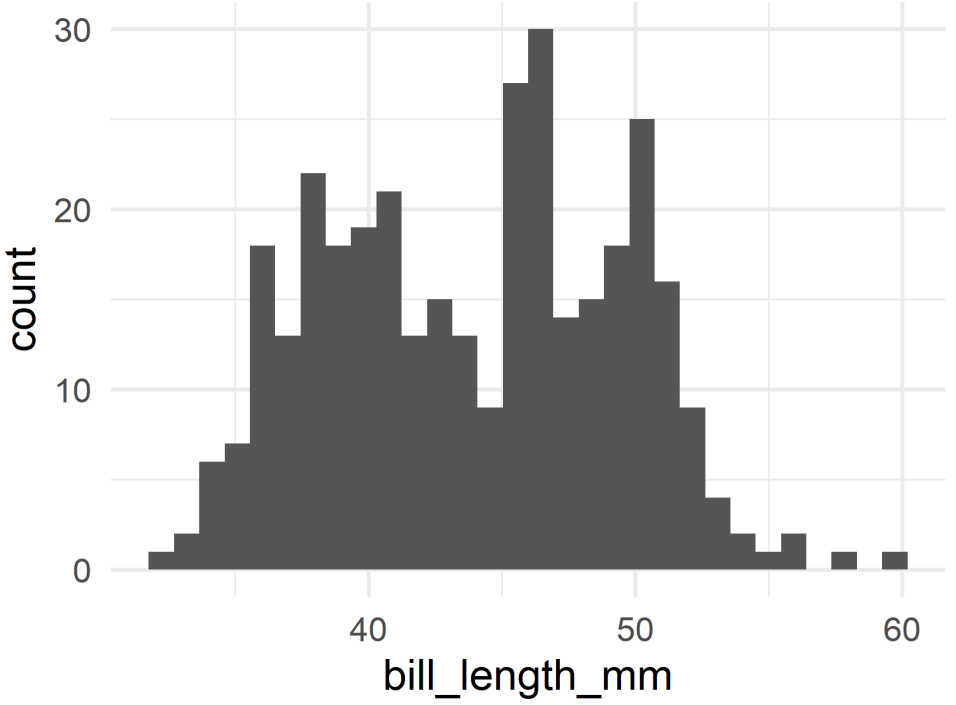
```
library(palmerpenguins)
penguins
```

```
## # A tibble: 344 × 8
##    species island    bill_length_mm bill_depth_mm flipper_length_mm body_mass_g
##    <fct>   <fct>              <dbl>         <dbl>             <int>       <int>
##  1 Adelie  Torgersen           39.1          18.7               181        3750
##  2 Adelie  Torgersen           39.5          17.4               186        3800
##  3 Adelie  Torgersen           40.3          18                 195        3250
##  4 Adelie  Torgersen           NA            NA                  NA          NA
##  5 Adelie  Torgersen           36.7          19.3               193        3450
##  6 Adelie  Torgersen           39.3          20.6               190        3650
##  7 Adelie  Torgersen           38.9          17.8               181        3625
##  8 Adelie  Torgersen           39.2          19.6               195        4675
##  9 Adelie  Torgersen           34.1          18.1               193        3475
## 10 Adelie  Torgersen           42            20.2               190        4250
## # ℹ 334 more rows
```

Basic histogram

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

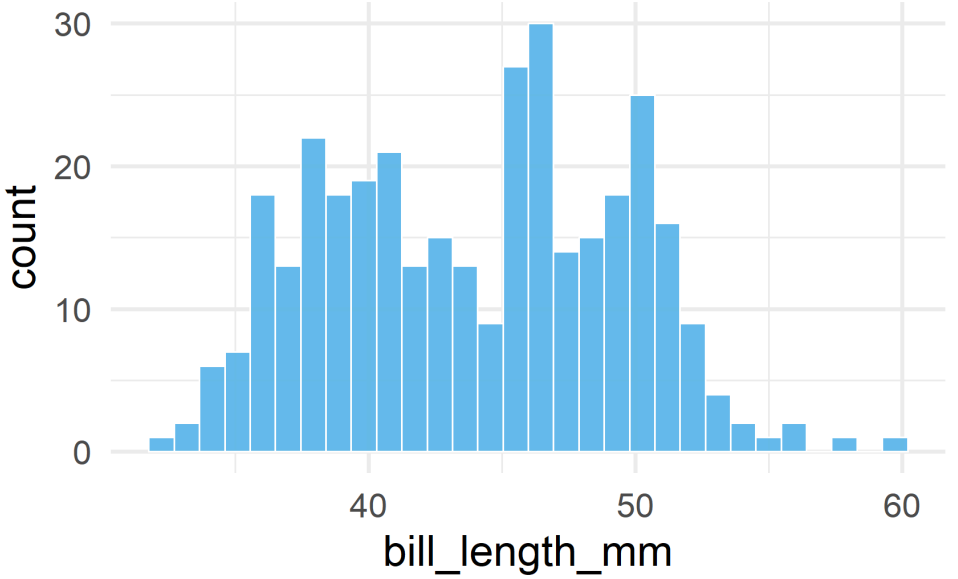
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Make it a little prettier

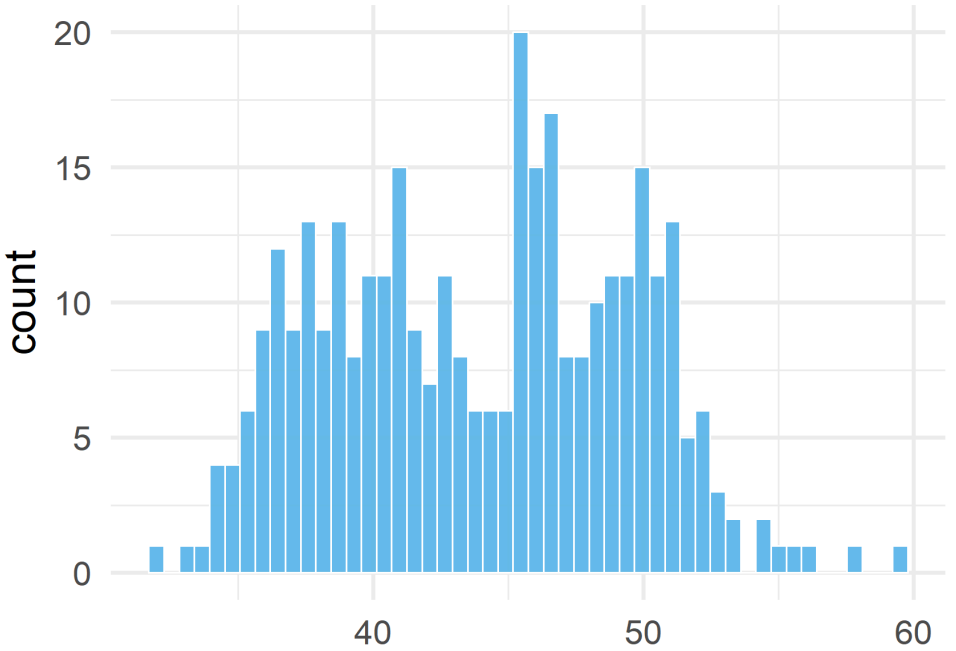
```
ggplot(penguins, aes(x = bill_length_mm)) +
  geom_histogram(fill = "#56B4E9",
                 color = "white",
                 alpha = 0.9)
```

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

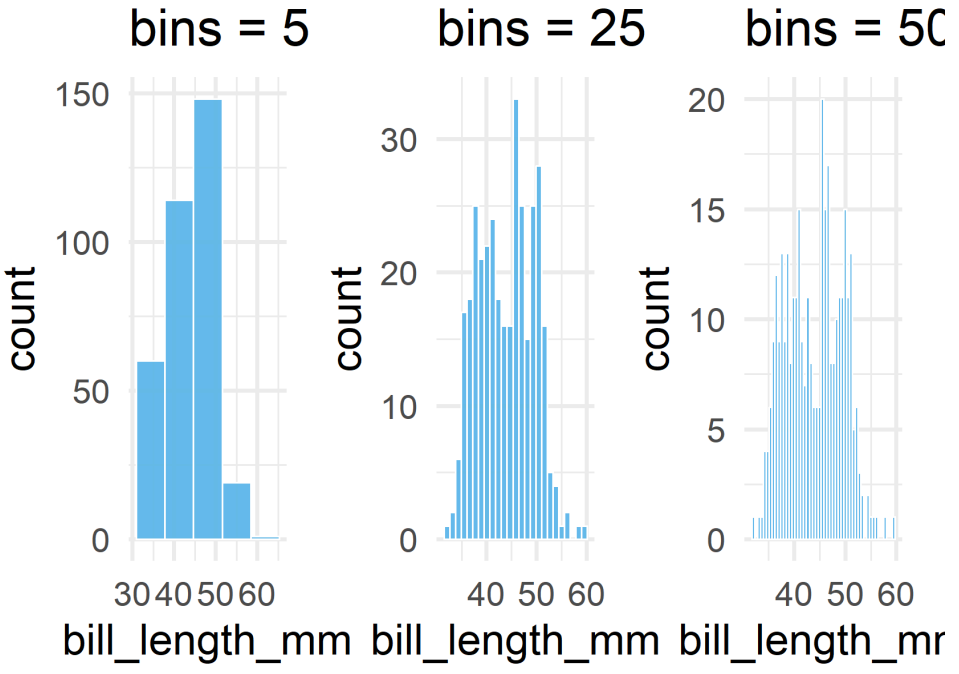


Change the number of bins

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



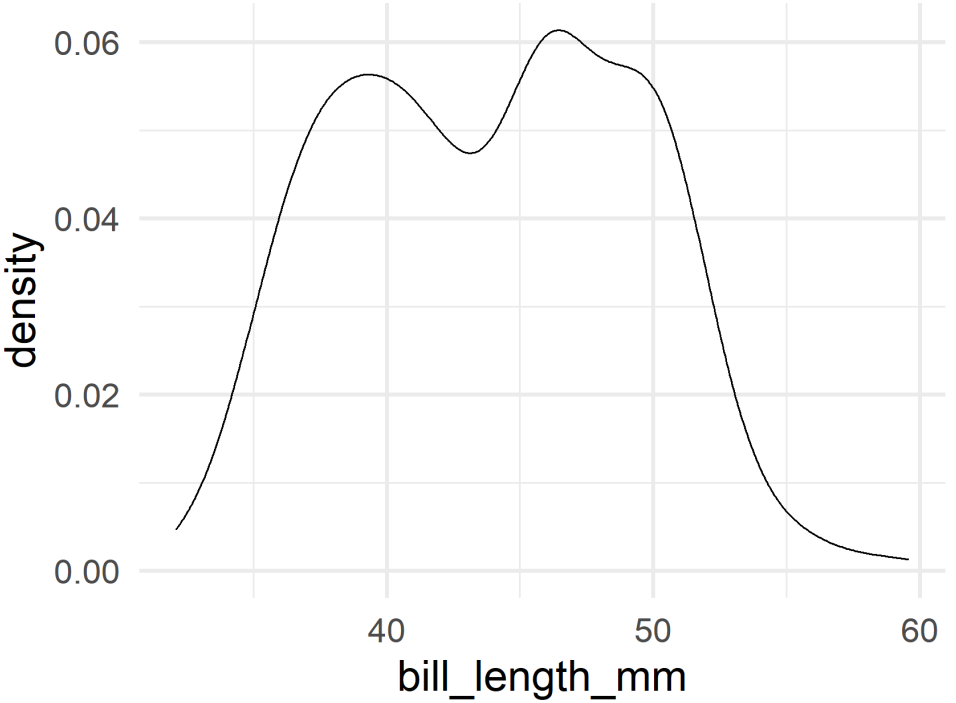
Vary the number of bins



Denisty plot

ugly 😫

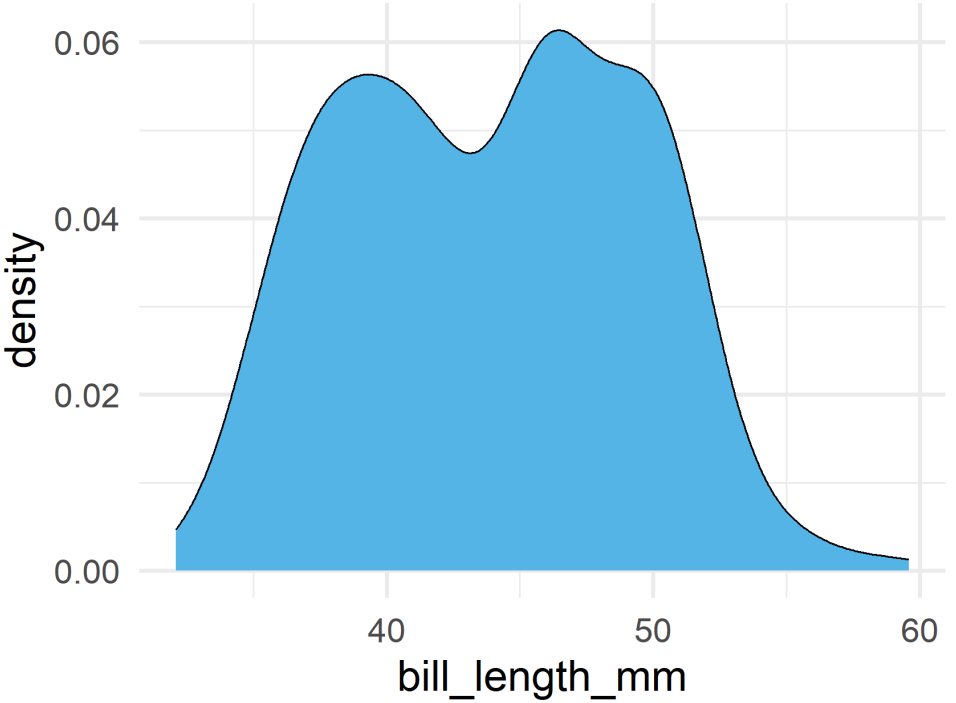
```
ggplot(penguins, aes(bill_length_mm)) +
  geom_density()
```



Denisty plot

Change the fill 😌

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



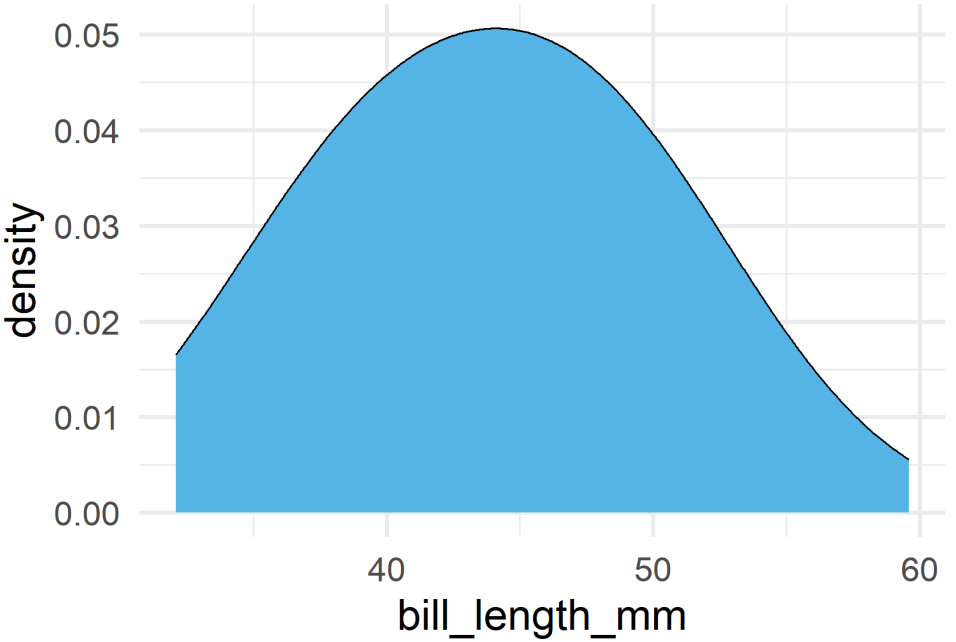
Density plot estimation

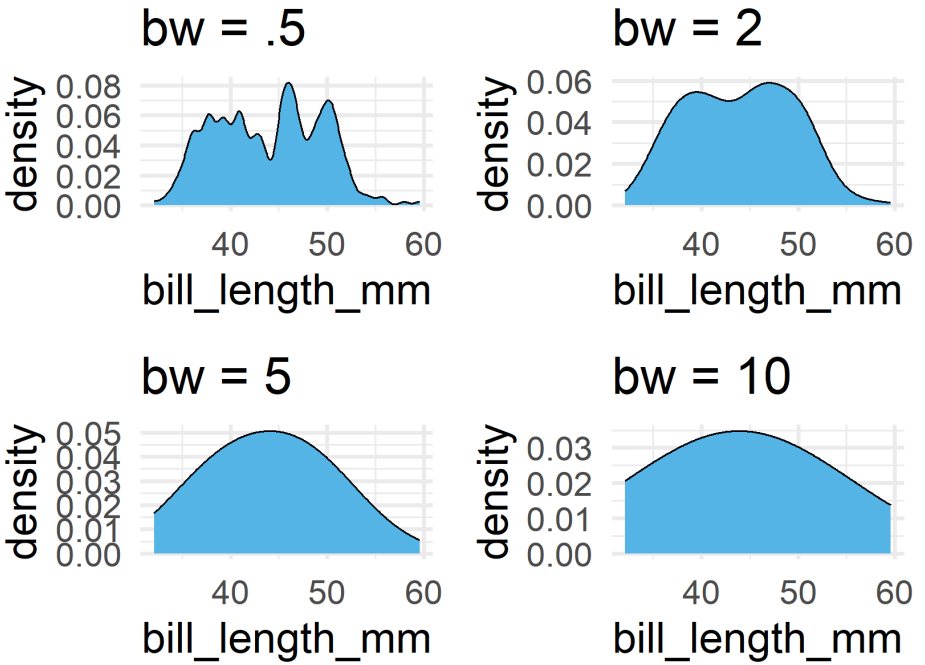
- Kernal density estimation
    - Different kernal shapes can be selected
    - Bandwidth matters most
    - Smaller bands = bend more to the data
- Approximation of the underlying continuous probability function
    - Integrates to 1.0 (y-axis is somewhat difficult to interpret)

Denisty plot

change the bandwidth

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

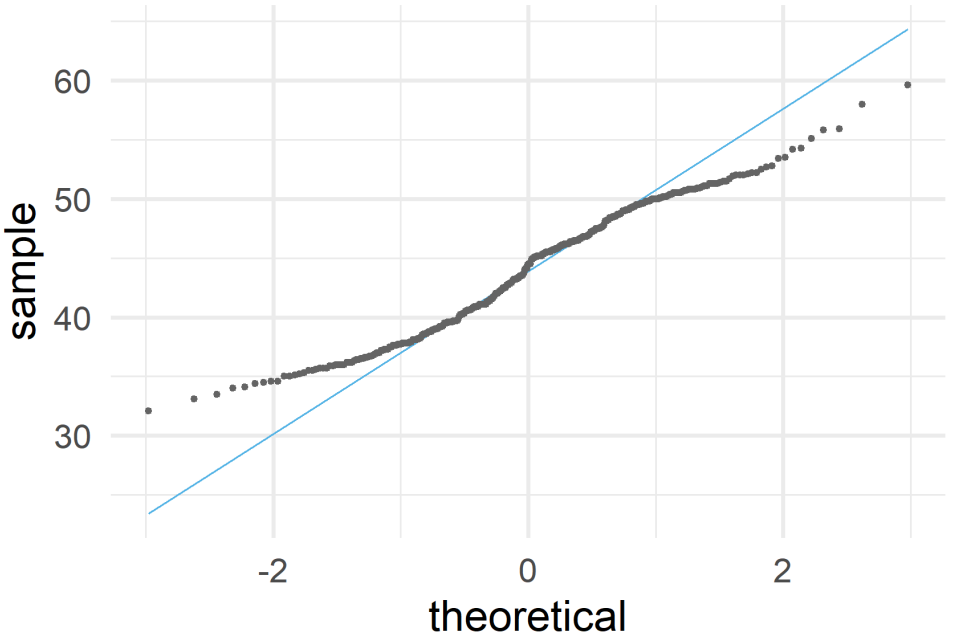



bw = .5
density
0.08
0.06
0.04
0.02
0.00
40
50
60
bill_length_mm
bw = 2
density
0.06
0.04
0.02
0.00
40
50
60
bill_length_mm
bw = 5
density
0.05
0.04
0.03
0.02
0.01
0.00
40
50
60
bill_length_mm
bw = 10
density
0.03
0.02
0.01
0.00
40
50
60
bill_length_mm

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")
```



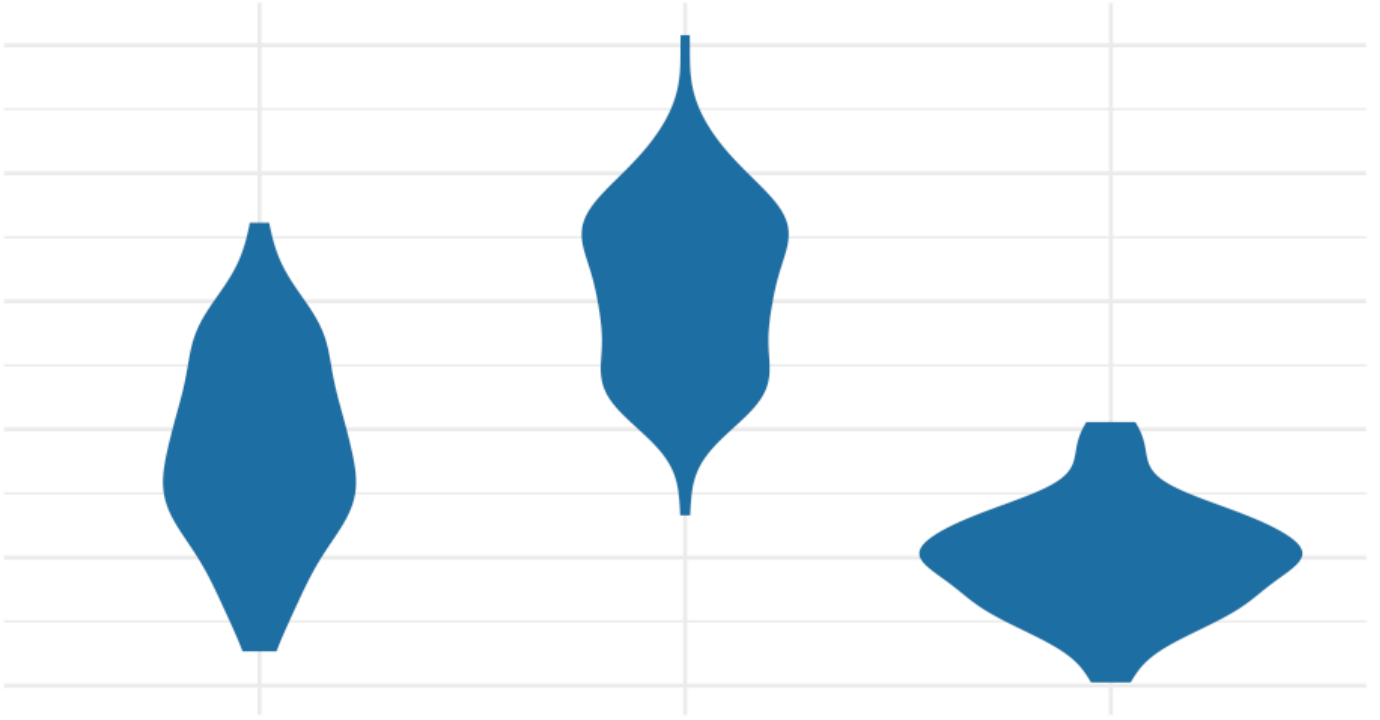
Grouped data

Distributions

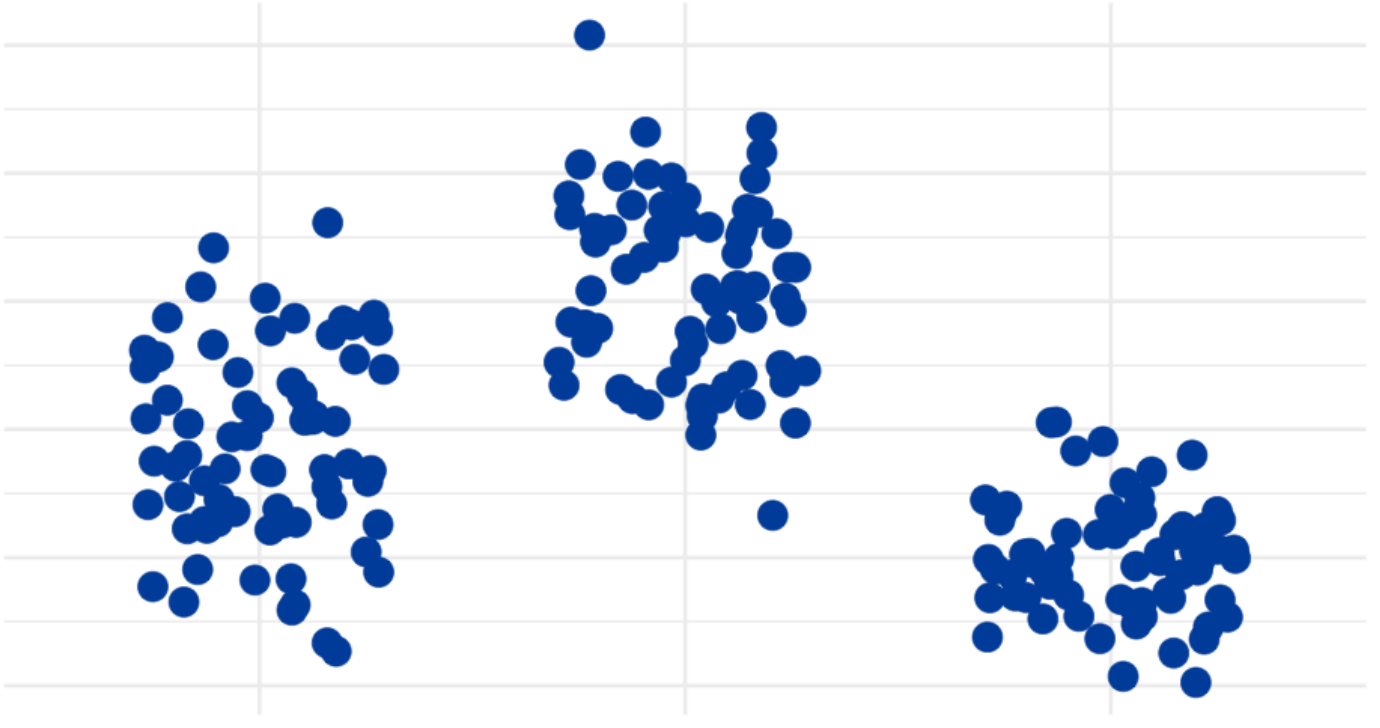
How do we display more than one distribution at a time?

Boxplots

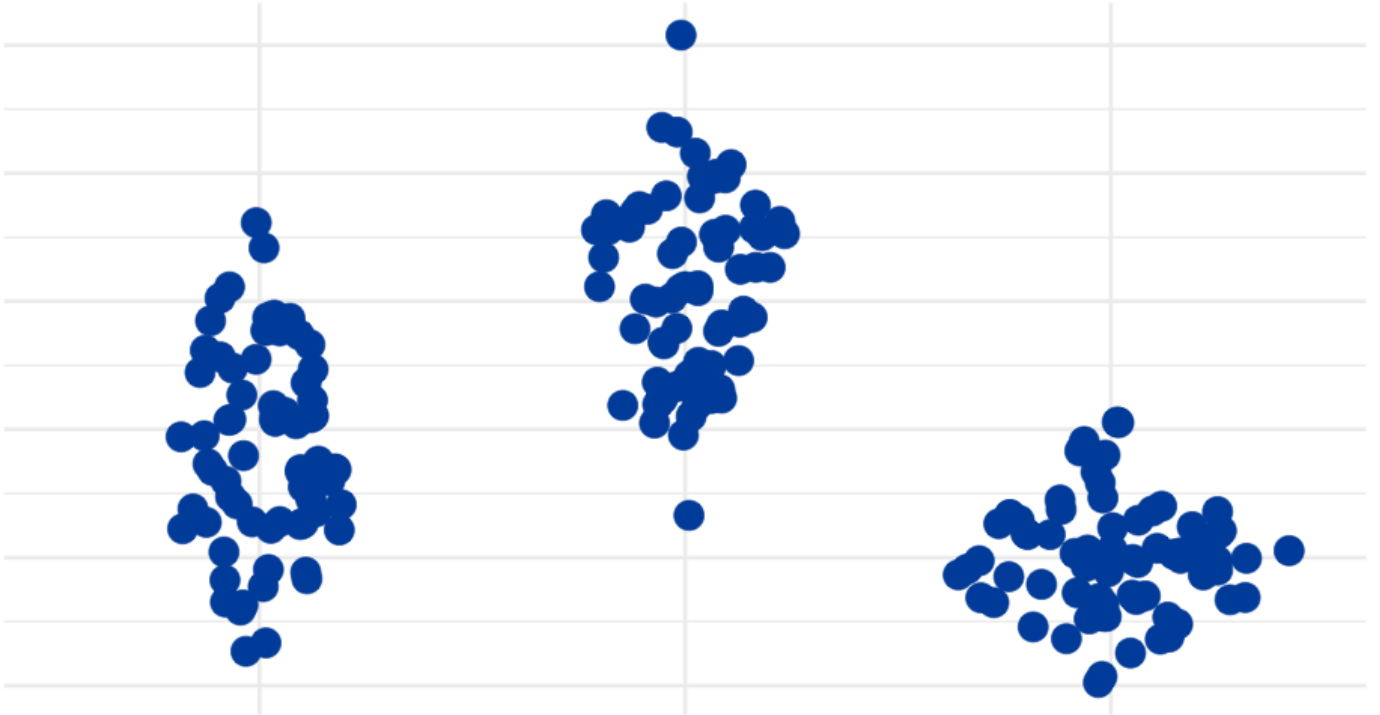
Violin plots



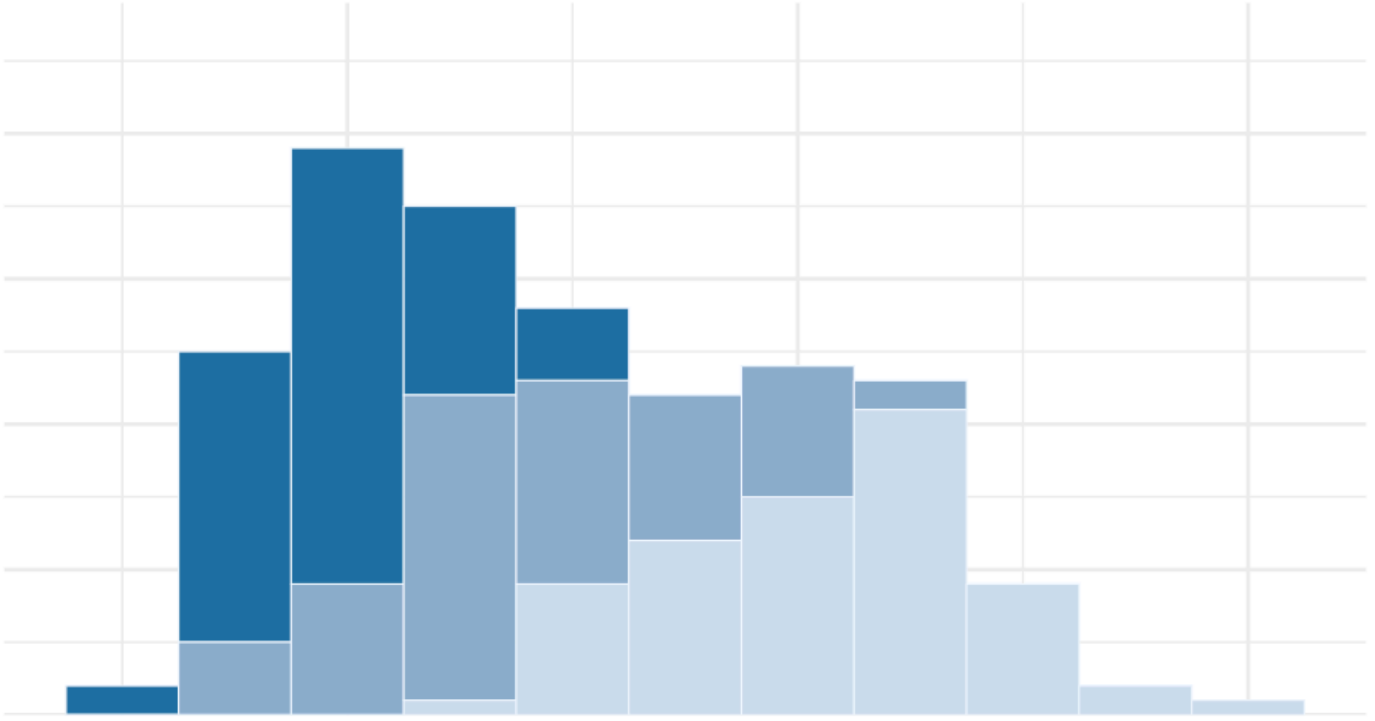
Jittered points



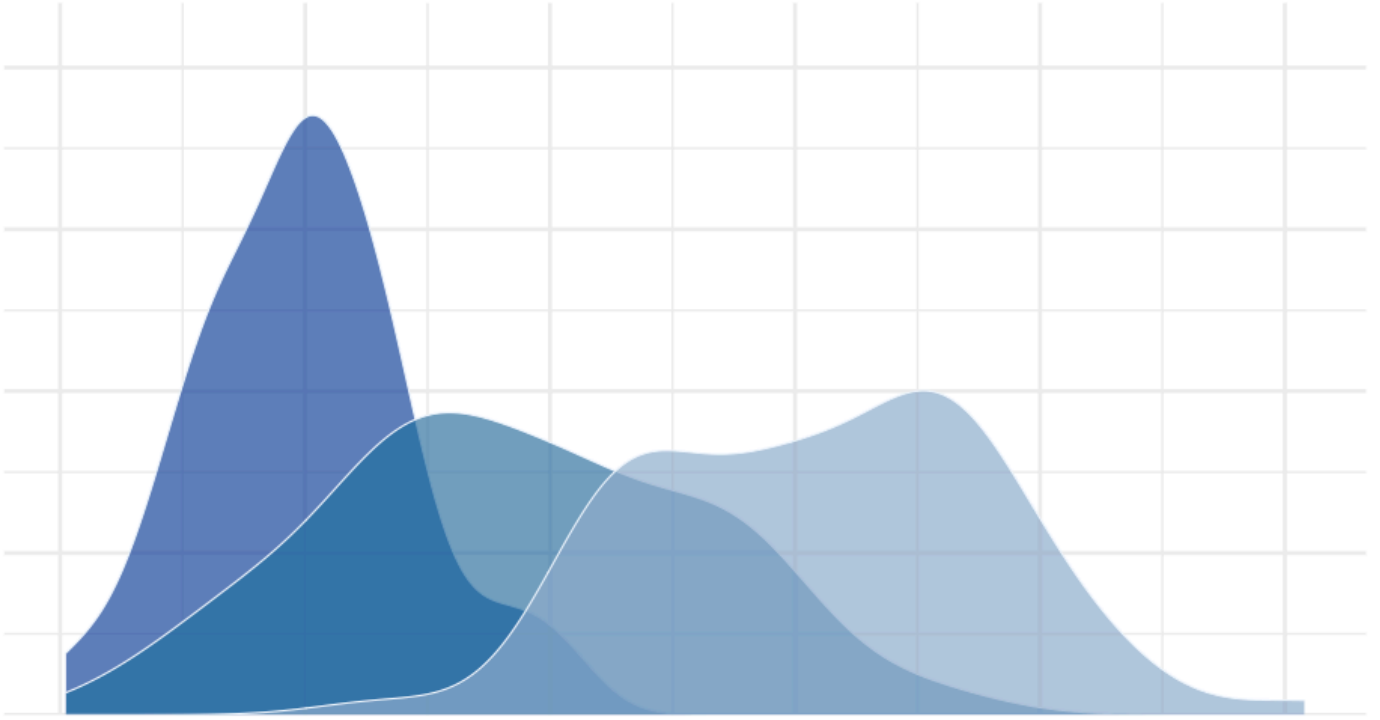
Sina plots



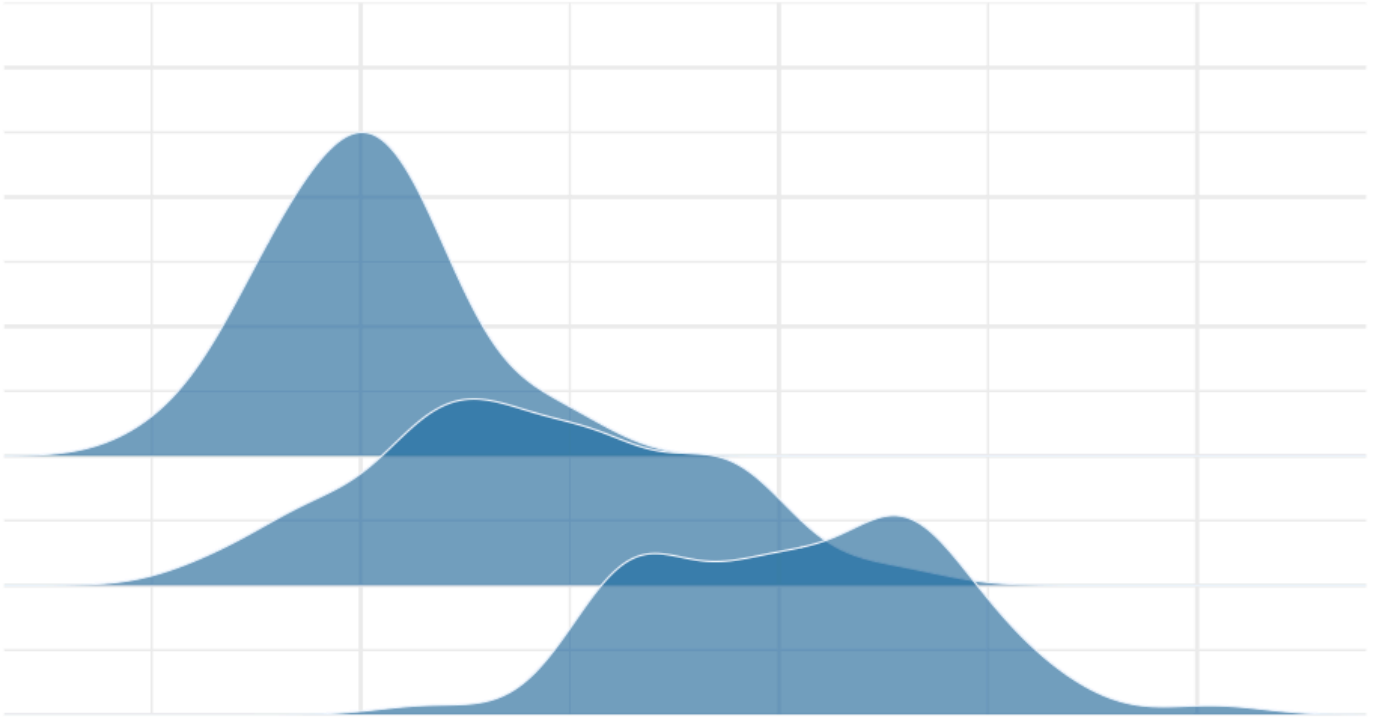
Stacked histograms



Overlapping densities



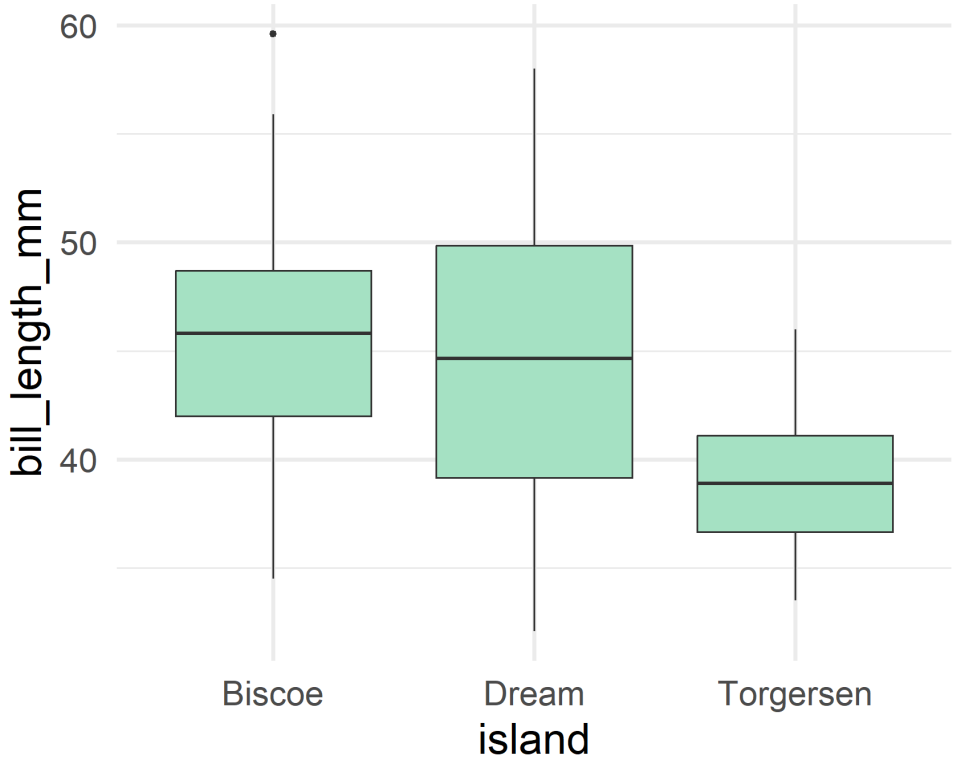
Ridgeline densities



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

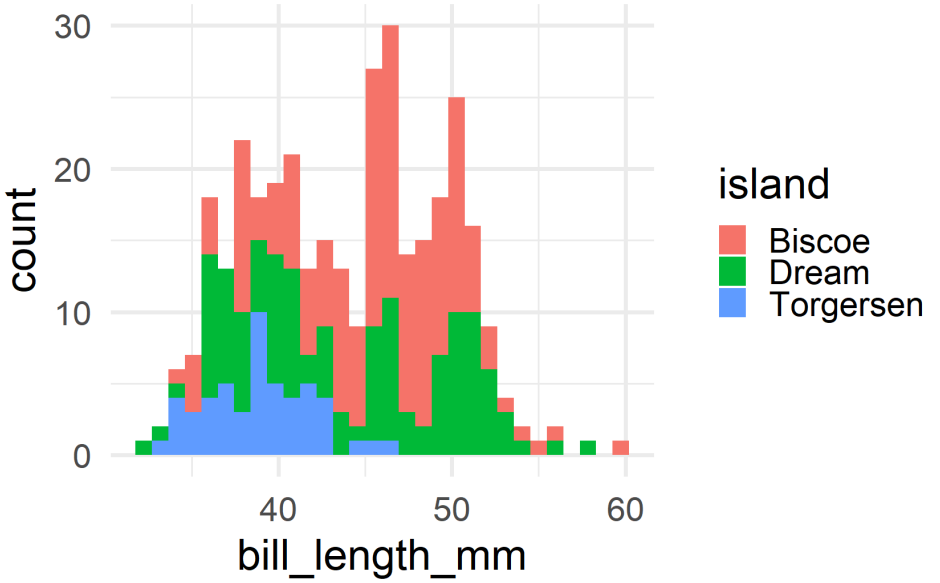
```
ggplot(penguins, aes(island, bill_length_mm)) +
  geom_jitter(width = 0.3, height = 0)
```

Sina plot

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

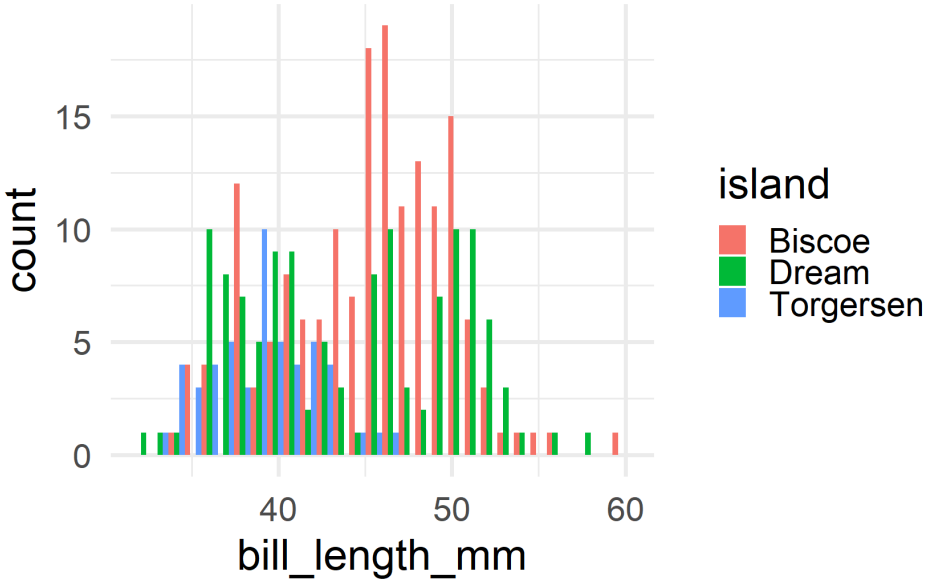
Stacked histogram

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



Dodged

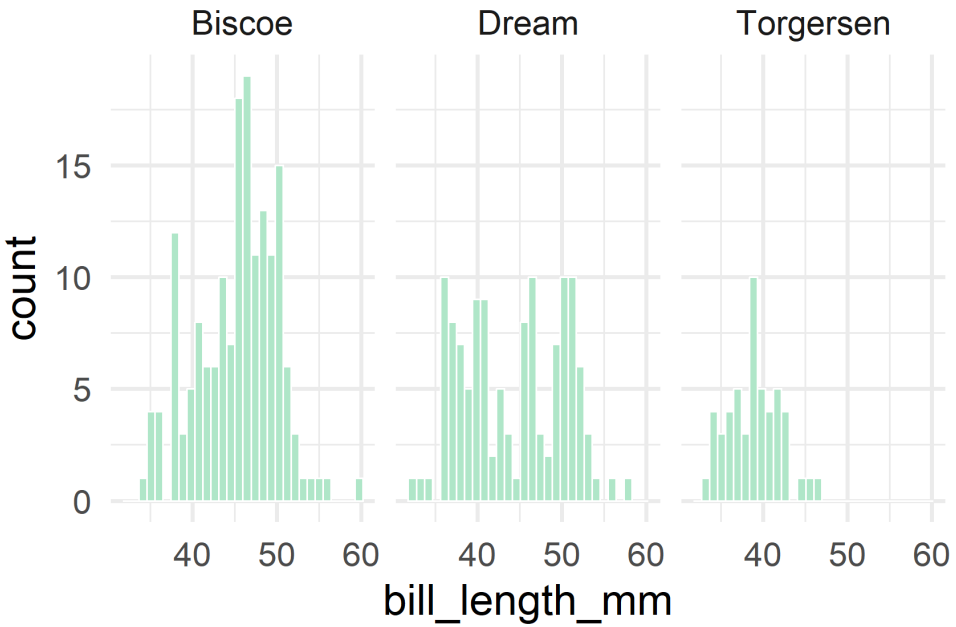
```
ggplot(penguins, aes(bill_length_mm)) +
  geom_histogram(aes(fill = island),
                 position = "dodge")
```



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

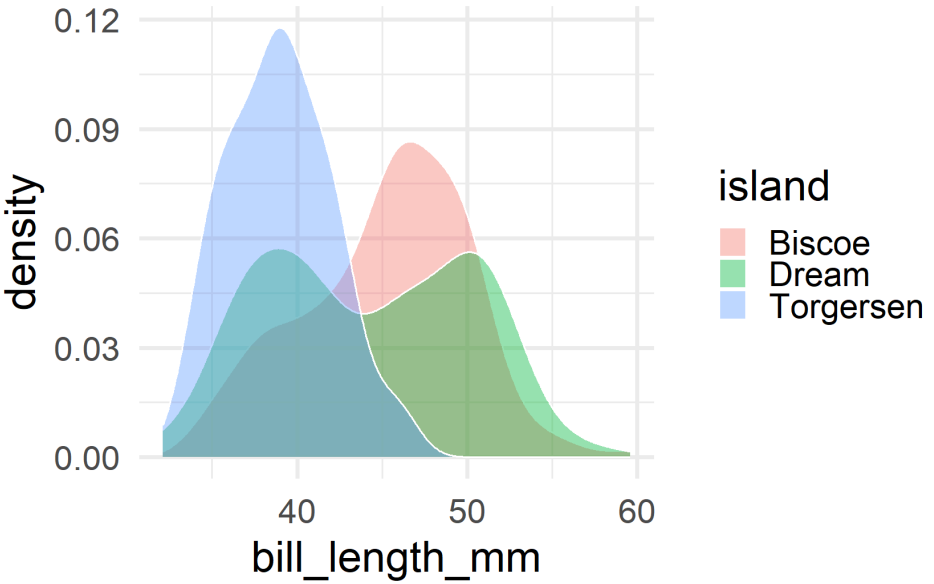
Better

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



Overlapping densities

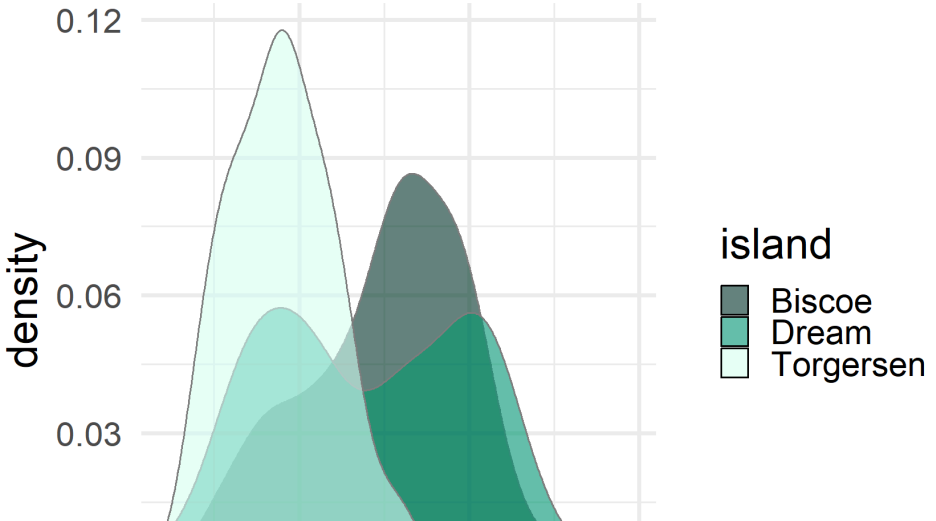
```
ggplot(penguins, aes(bill_length_mm)) +
  geom_density(aes(fill = island),
               color = "white",
               alpha = 0.4)
```



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

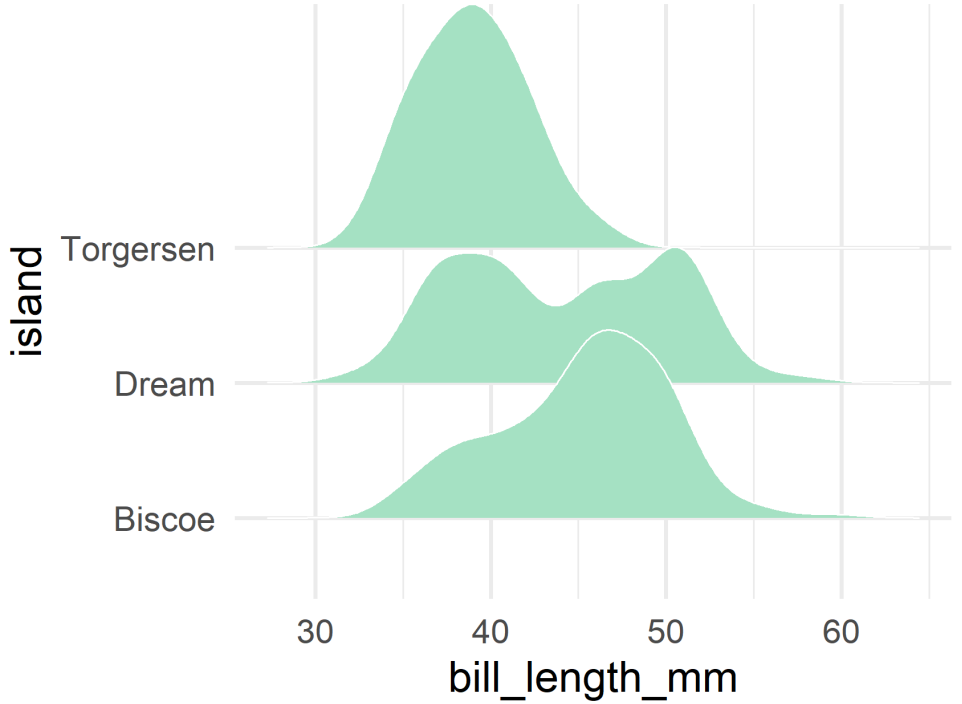
```r
darken <- function(color, factor = 1.1) {
  sapply(color, function(col) {
    rgb.val <- col2rgb(col)
    rgb(t(pmax(0, pmin(255, rgb.val * factor))), maxColorValue =
  })
}

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")
```



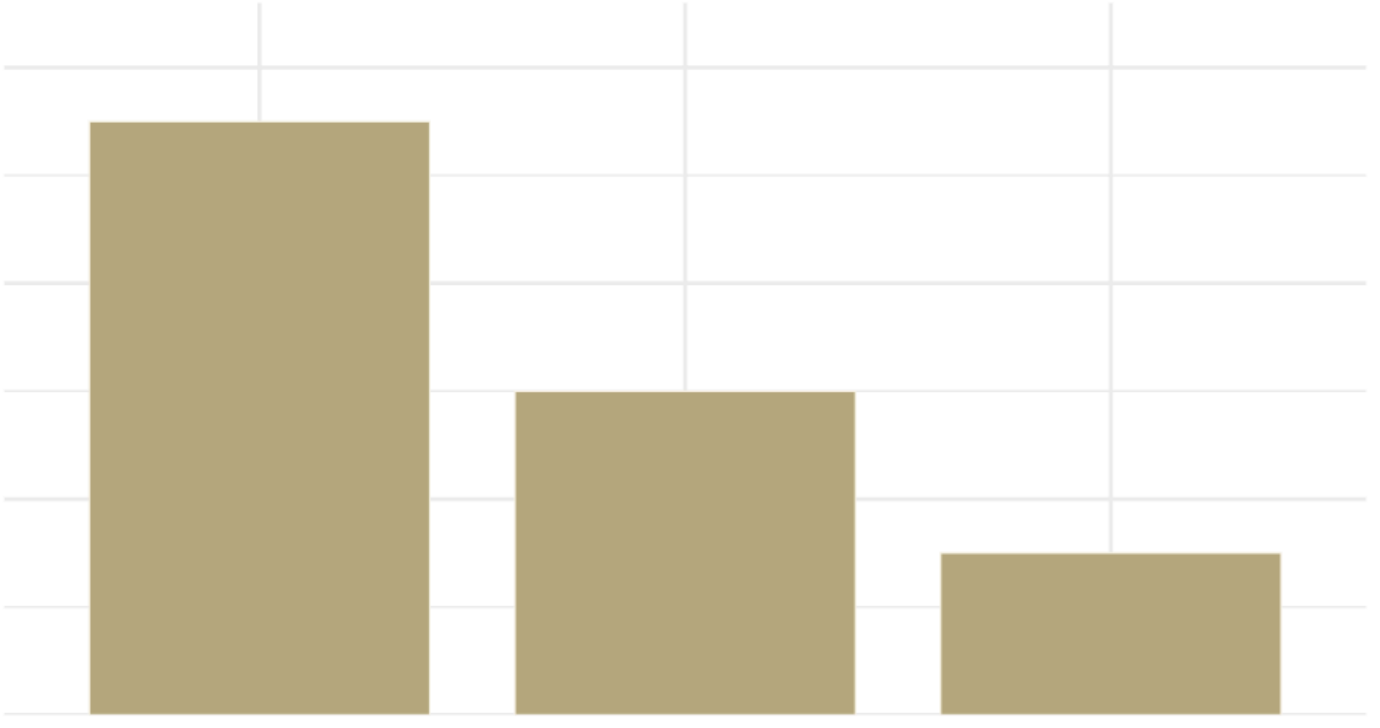
Visualizing amounts

Data viz in the wild

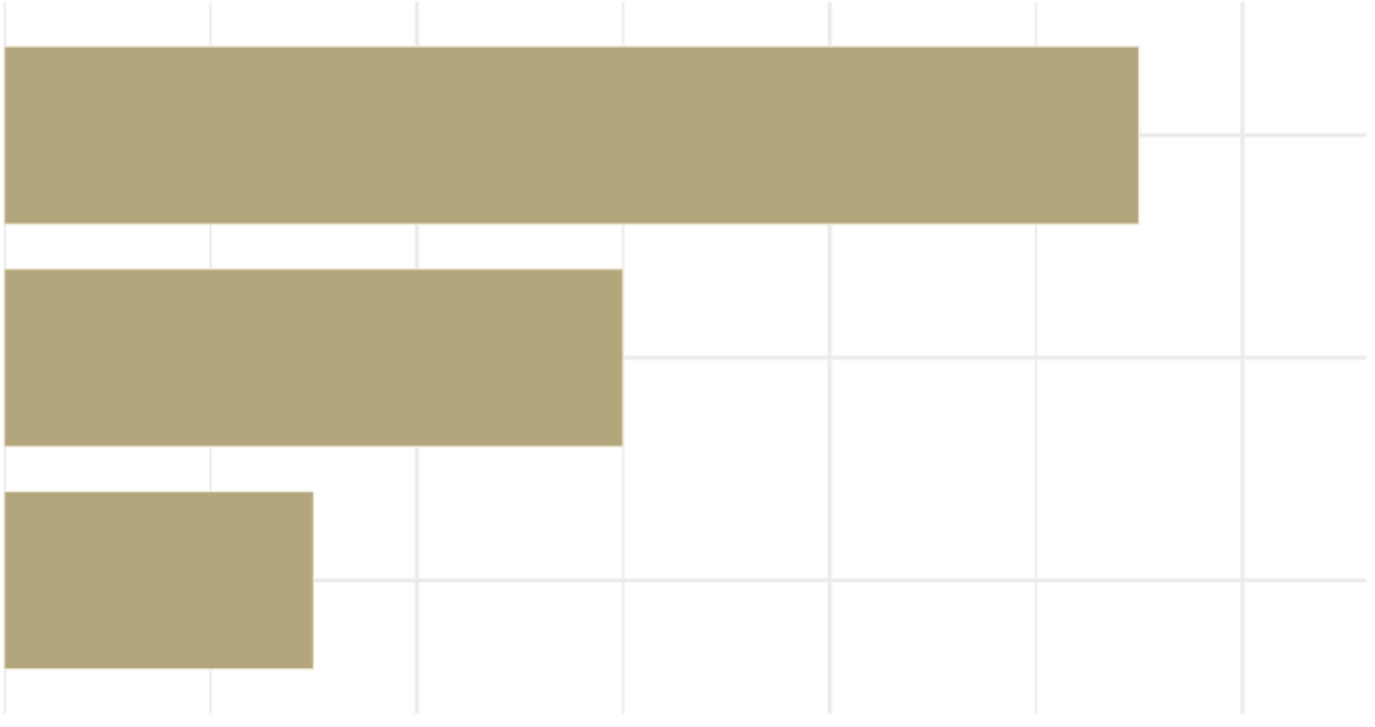
Kat? Ziyuan?

Visualizing amounts

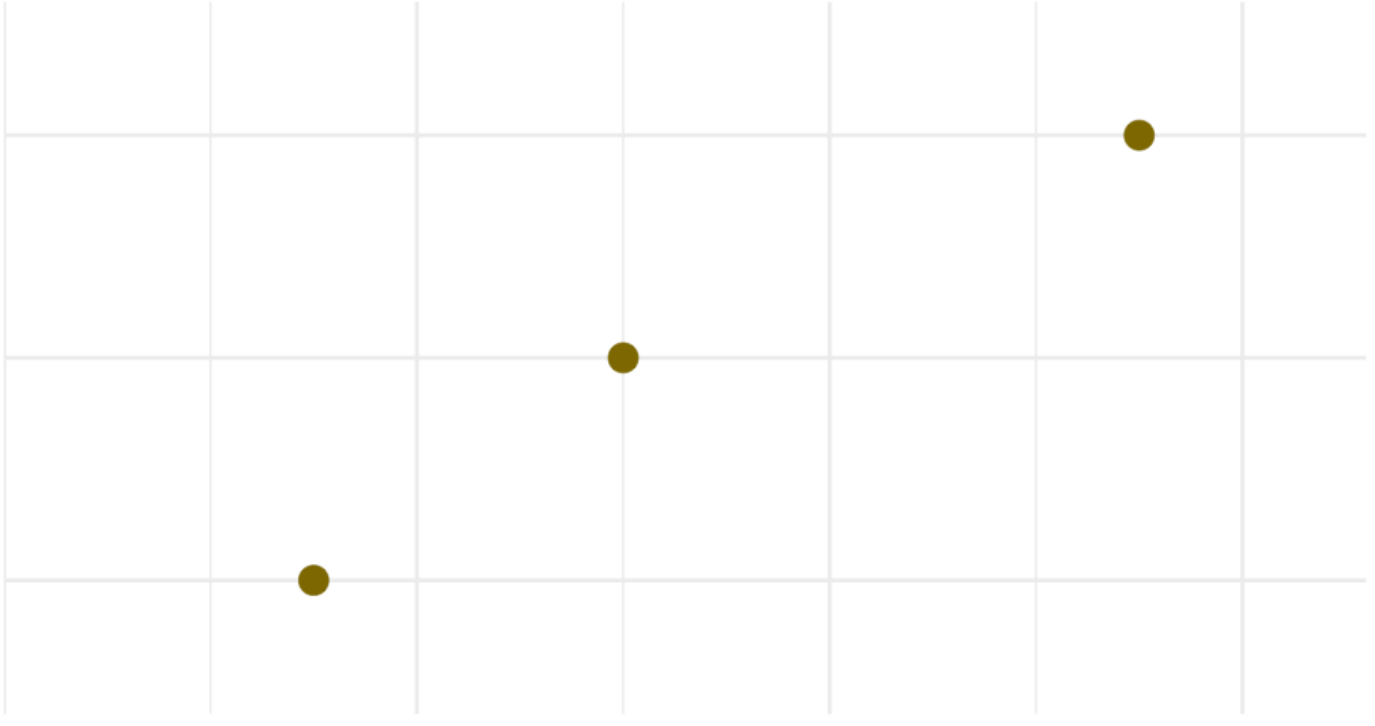
Bar plots



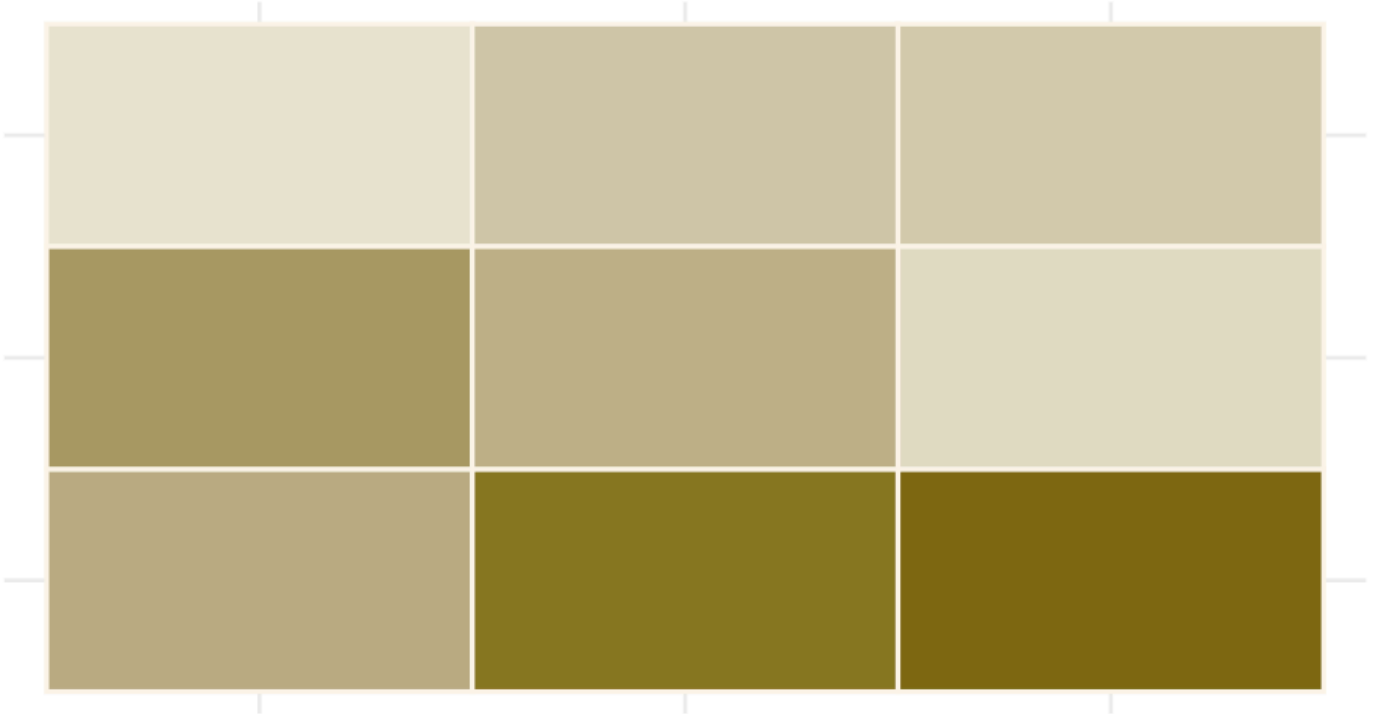
Flipped bars



Dotplot



Heatmap



Empirical examples

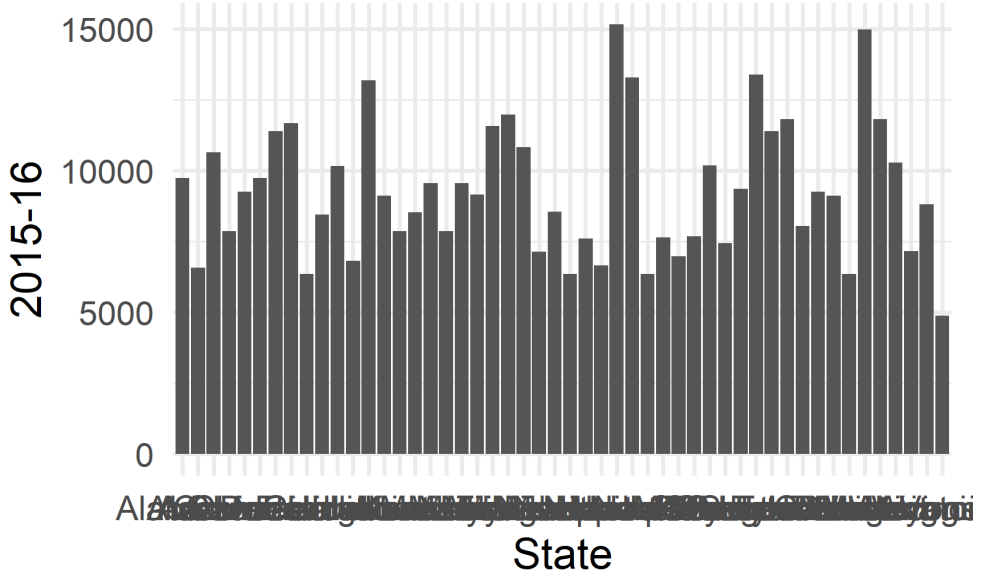
How much does college cost?

```
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` `2007-08` `2008-09` `2009-10` `2010-
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <d
## 1 Alabama        5683.     5841.     5753.     6008.     6475.     7189.     80
## 2 Alaska         4328.     4633.     4919.     5070.     5075.     5455.     57
## 3 Arizona        5138.     5416.     5481.     5682.     6058.     7263.     88
## 4 Arkansas       5772.     6082.     6232.     6415.     6417.     6627.     69
## 5 California     5286.     5528.     5335.     5672.     5898.     7259.     81
## 6 Colorado       4704.     5407.     5596.     6227.     6284.     6948.     77
```

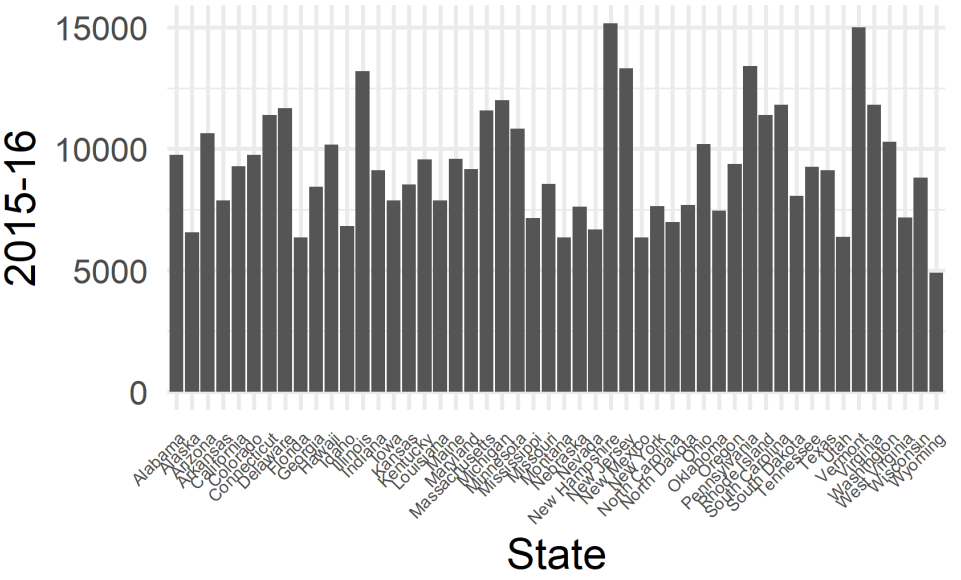
By state: 2015-16

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



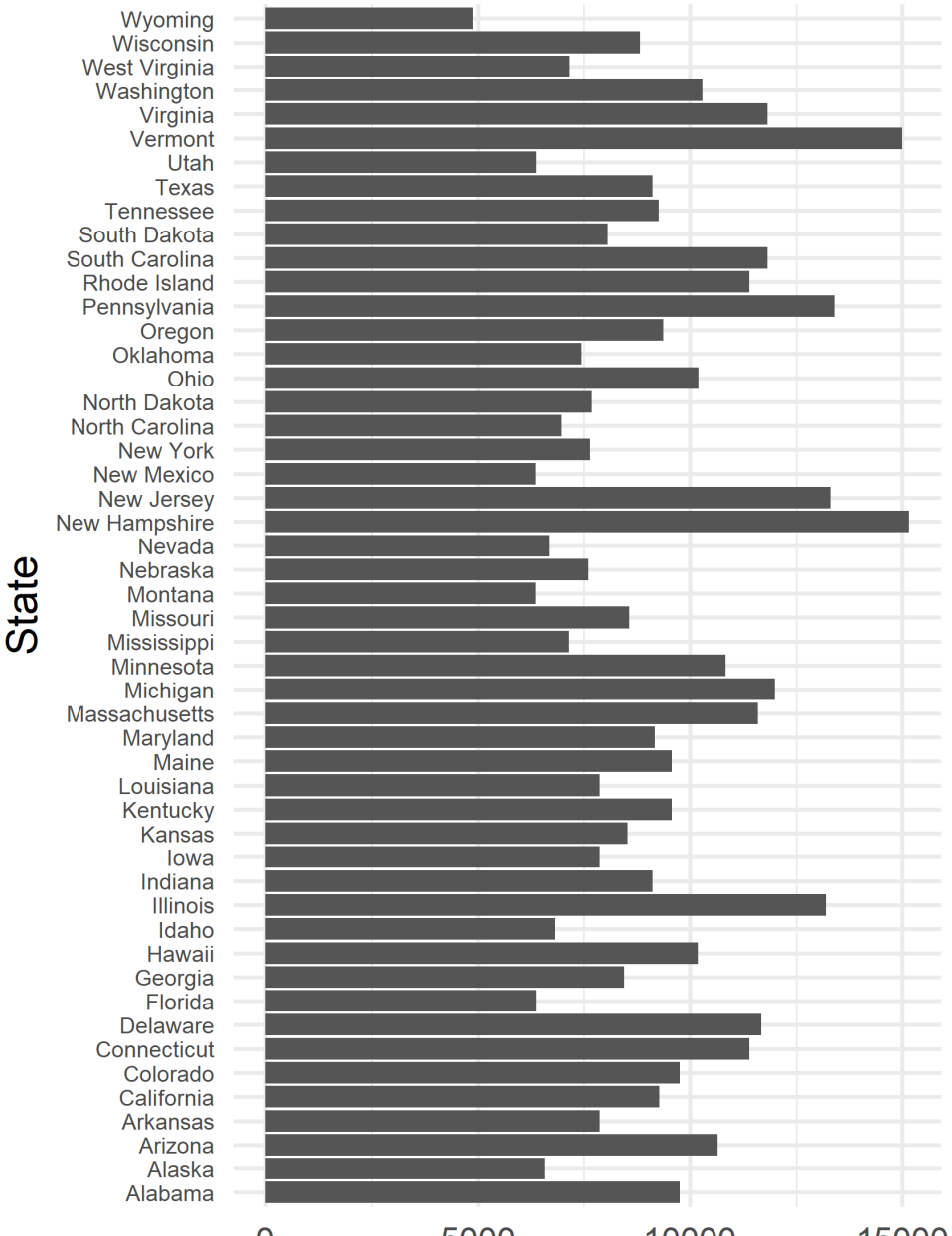
Two puke emoji version

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



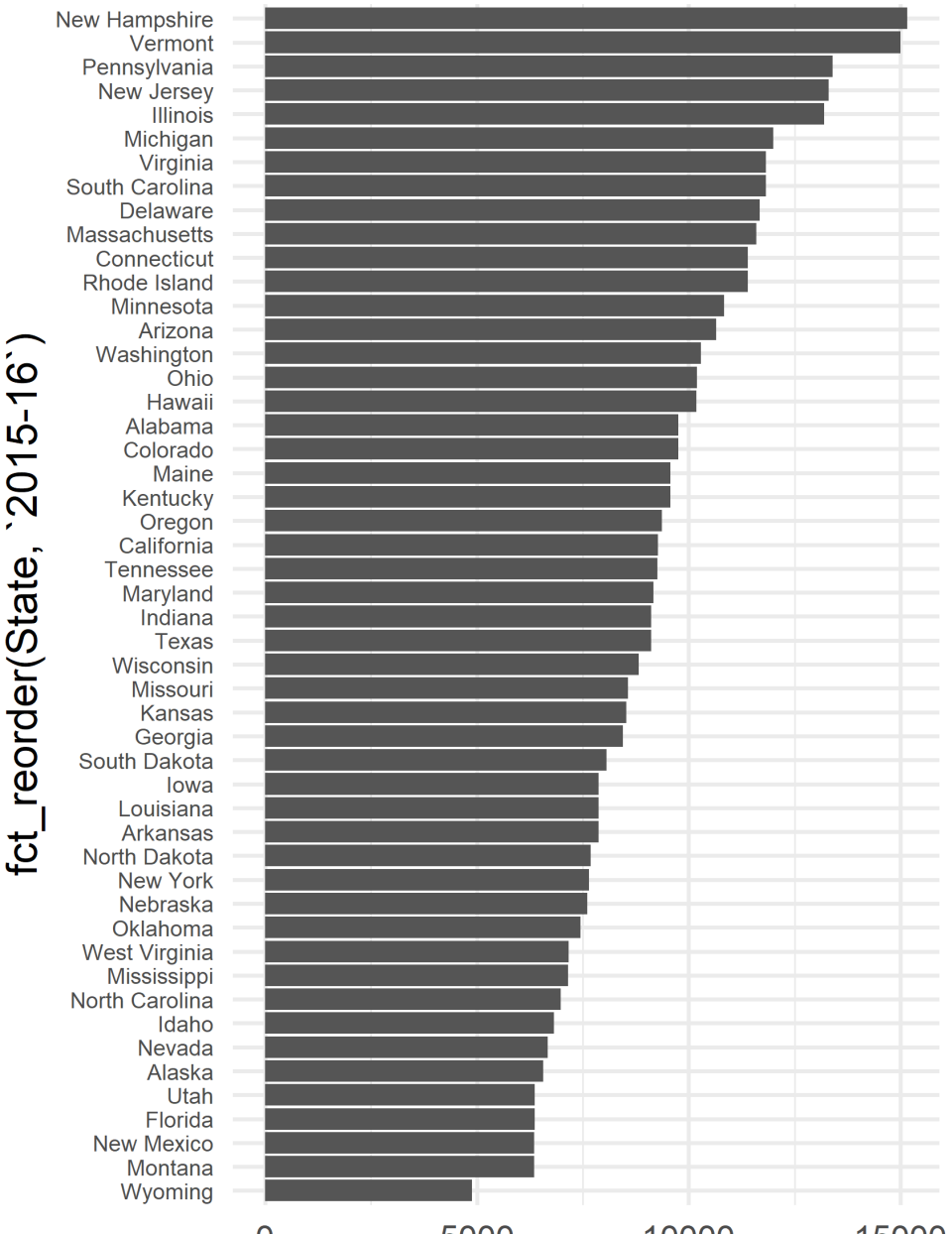
One puke emoji version

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


State
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

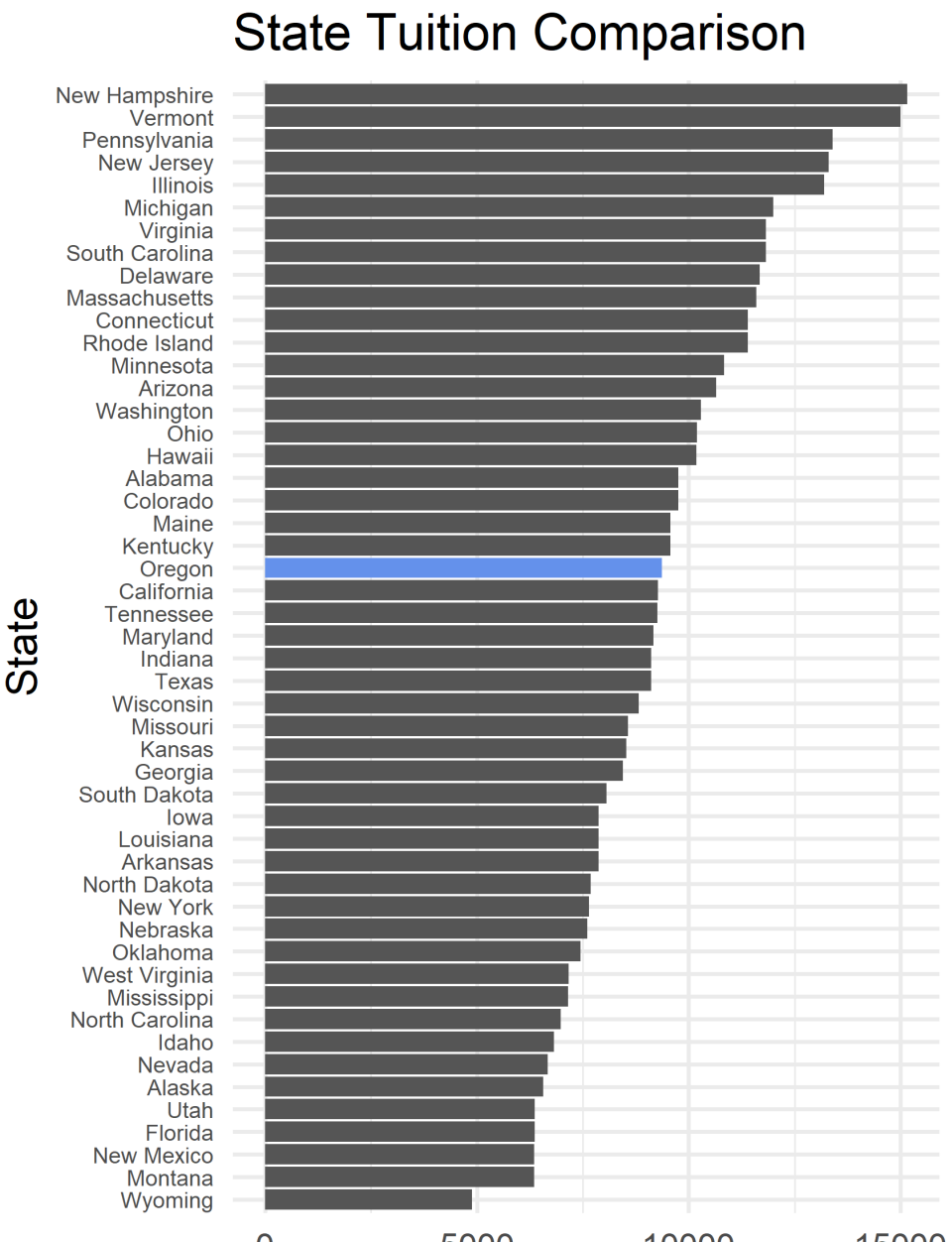
Kinda smiley version

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

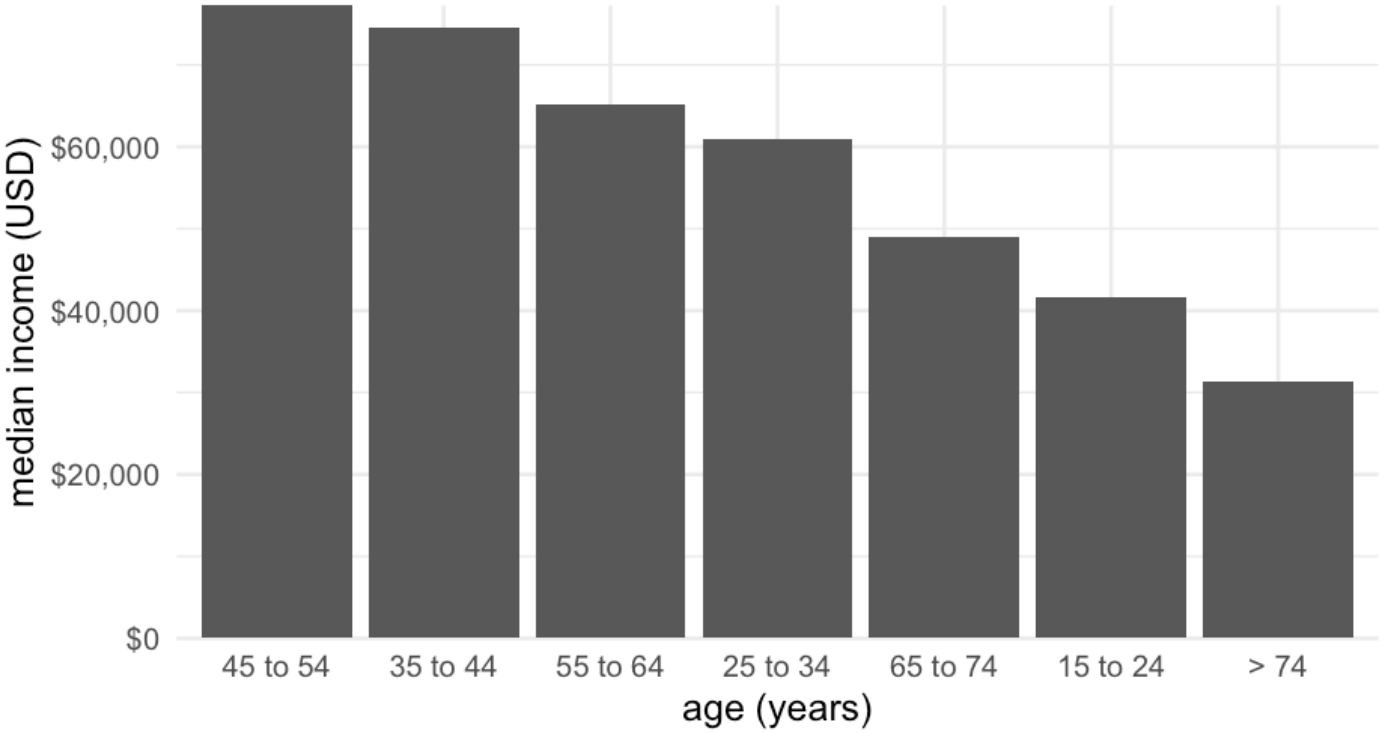

fct_reorder(State, `2015-16`)
New Hampshire
Vermont
Pennsylvania
New Jersey
Illinois
Michigan
Virginia
South Carolina
Delaware
Massachusetts
Connecticut
Rhode Island
Minnesota
Arizona
Washington
Ohio
Hawaii
Alabama
Colorado
Maine
Kentucky
Oregon
California
Tennessee
Maryland
Indiana
Texas
Wisconsin
Missouri
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
0
5000
10000
15000

Highlight Oregon

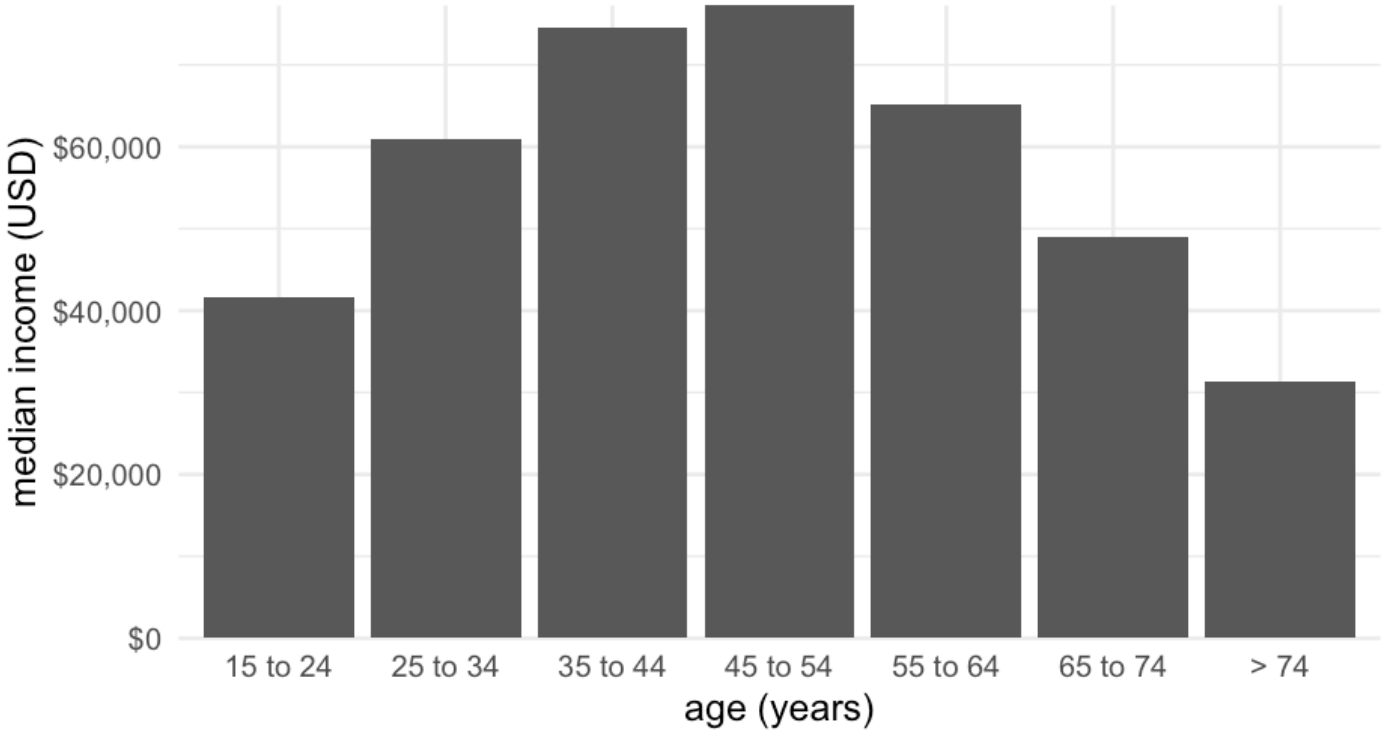
```
ggplot(tuition, aes(fct_reorder(State, `2015-16`), `2015-16`)) +
  geom_col() +
  geom_col(fill = "cornflowerblue",
           data = filter(tuition, State == "Oregon")) +
  coord_flip() +
  labs(x = "State",
       y = "Tuition (2015-16)")
```


State Tuition Comparison
State
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

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` `2007-08` `2008-09` `2009-10` `2010-
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <d
## 1 Alabama        5683.     5841.     5753.     6008.     6475.     7189.     80
## 2 Alaska         4328.     4633.     4919.     5070.     5075.     5455.     57
## 3 Arizona        5138.     5416.     5481.     5682.     6058.     7263.     88
## 4 Arkansas       5772.     6082.     6232.     6415.     6417.     6627.     69
## 5 California     5286.     5528.     5335.     5672.     5898.     7259.     81
## 6 Colorado       4704.     5407.     5596.     6227.     6284.     6948.     77
```

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       5683.
##  2 Alabama 2005-06       5841.
##  3 Alabama 2006-07       5753.
##  4 Alabama 2007-08       6008.
##  5 Alabama 2008-09       6475.
##  6 Alabama 2009-10       7189.
##  7 Alabama 2010-11       8071.
##  8 Alabama 2011-12       8452.
##  9 Alabama 2012-13       9098.
## 10 Alabama 2013-14       9359.
## # ℹ 590 more rows
```

Compute summaries

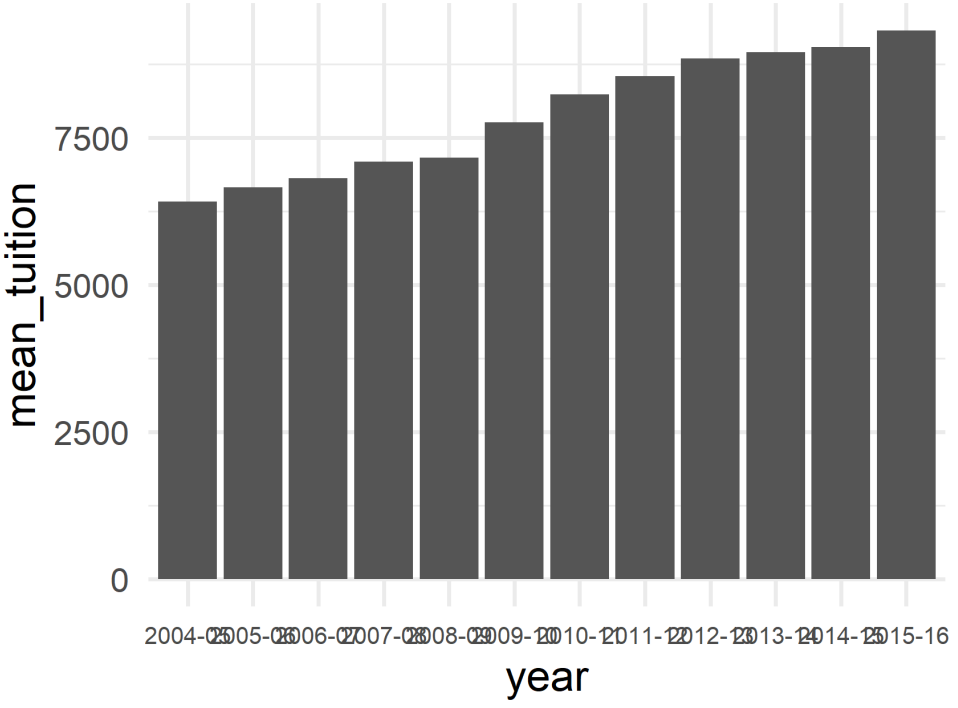
```
annual_means <- tuition %>%
  pivot_longer(`2004-05`:`2015-16`,
               names_to = "year",
               values_to = "avg_tuition")  %>%
  group_by(year) %>%
  summarize(mean_tuition = mean(avg_tuition))

annual_means
```

```
## # A tibble: 12 × 2
##    year    mean_tuition
##    <chr>          <dbl>
##  1 2004-05        6410.
##  2 2005-06        6654.
##  3 2006-07        6810.
##  4 2007-08        7086.
##  5 2008-09        7157.
##  6 2009-10        7762.
##  7 2010-11        8229.
##  8 2011-12        8539.
##  9 2012-13        8842.
## 10 2013-14        8948.
## 11 2014-15        9037.
## 12 2015-16        9318.
```

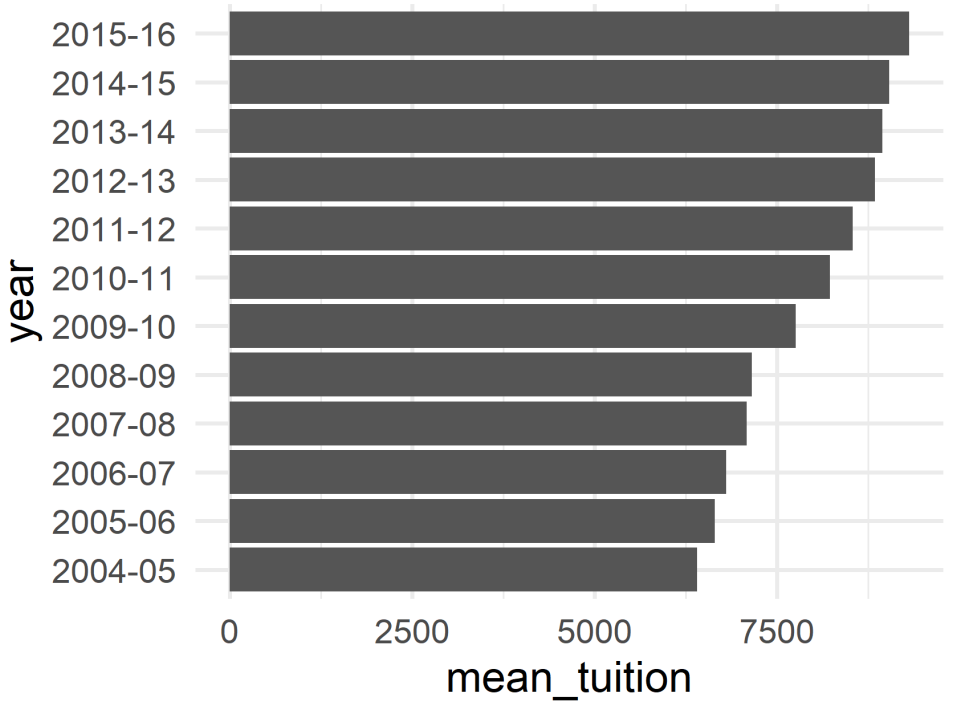
Good

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



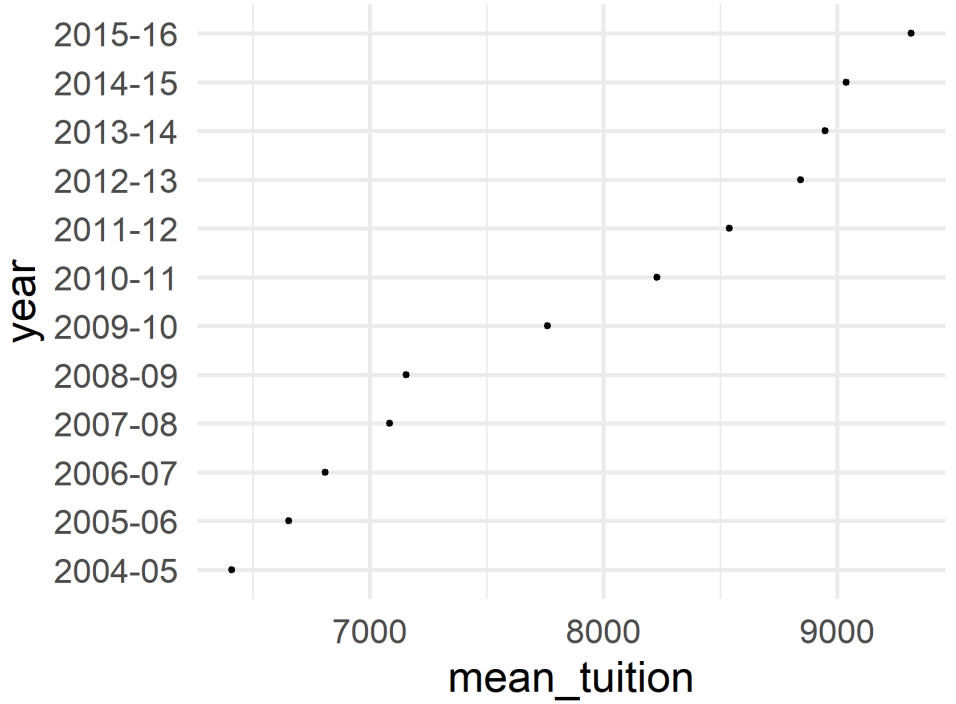
Better?

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



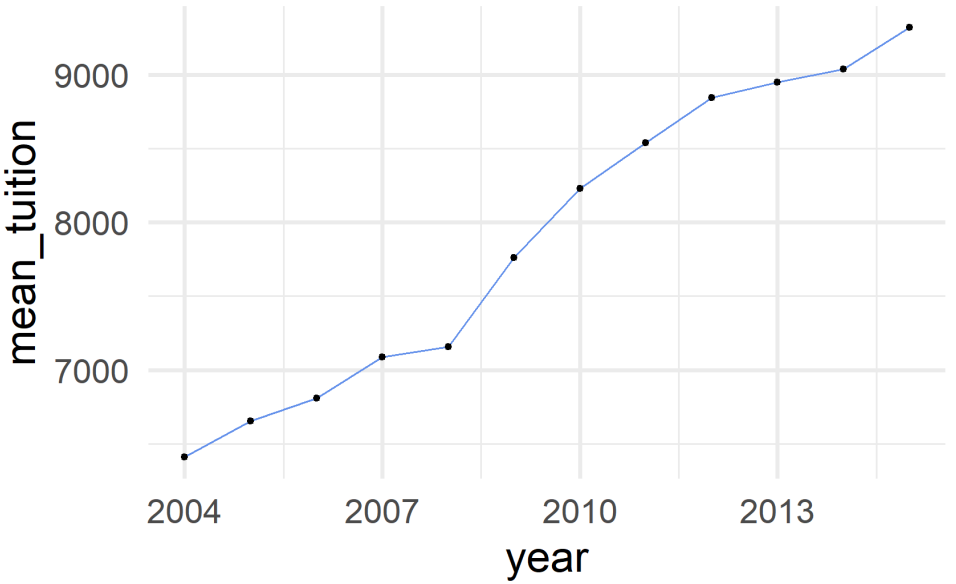
Better still?

```
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

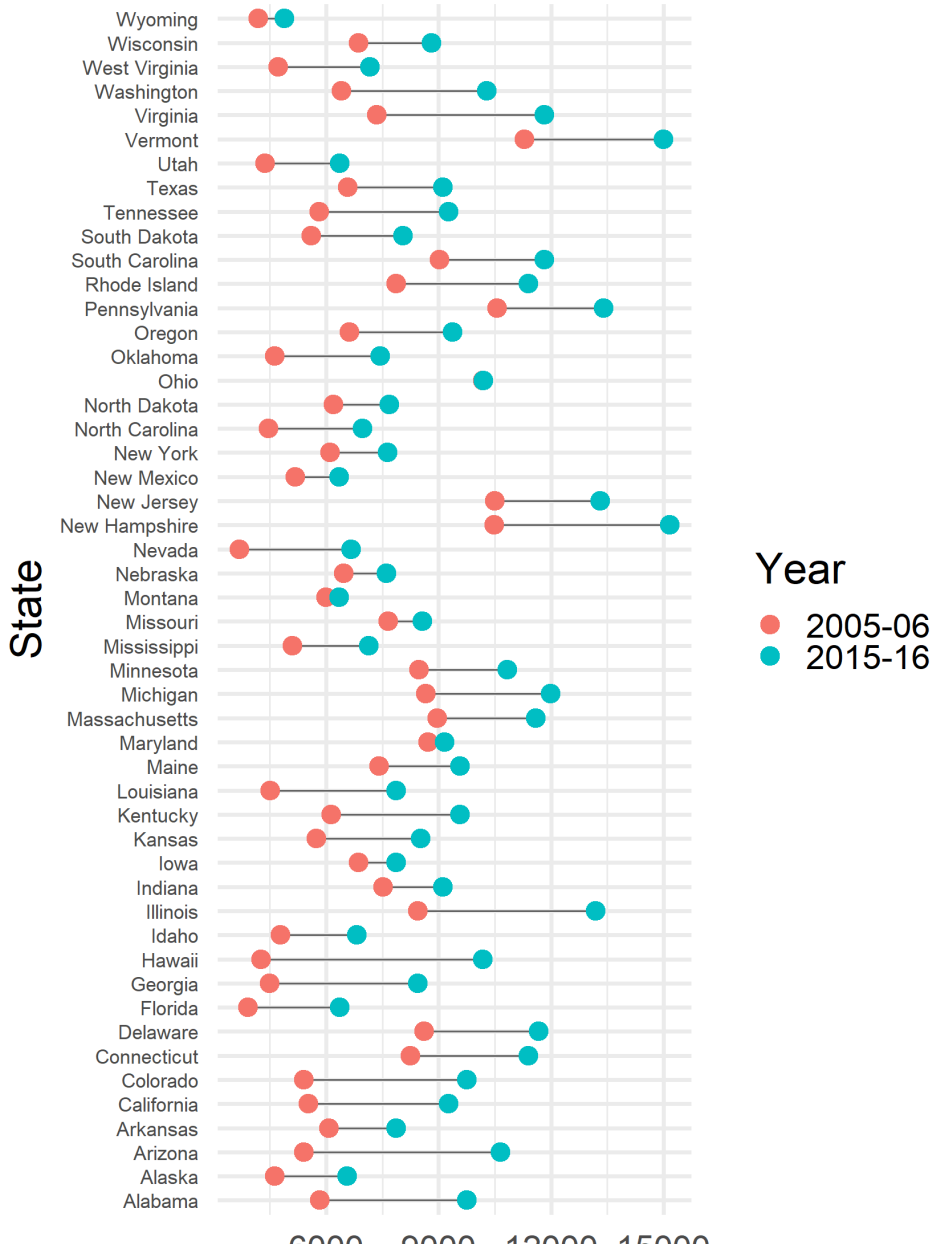
```
tuition %>%
  select(State, `2005-06`, `2015-16`)
```

```
## # A tibble: 50 × 3
##    State       `2005-06` `2015-16`
##    <chr>           <dbl>     <dbl>
##  1 Alabama         5841.     9751.
##  2 Alaska          4633.     6571.
##  3 Arizona         5416.    10646.
##  4 Arkansas        6082.     7867.
##  5 California      5528.     9270.
##  6 Colorado        5407.     9748.
##  7 Connecticut     8249.    11397.
##  8 Delaware        8611.    11676.
##  9 Florida         3924.     6360.
## 10 Georgia         4492.     8447.
## # ℹ 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   5841.
##  2 Alabama    2015-16   9751.
##  3 Alaska     2005-06   4633.
##  4 Alaska     2015-16   6571.
##  5 Arizona    2005-06   5416.
##  6 Arizona    2015-16  10646.
##  7 Arkansas   2005-06   6082.
##  8 Arkansas   2015-16   7867.
##  9 California 2005-06   5528.
## 10 California 2015-16   9270.
## # ℹ 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
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.

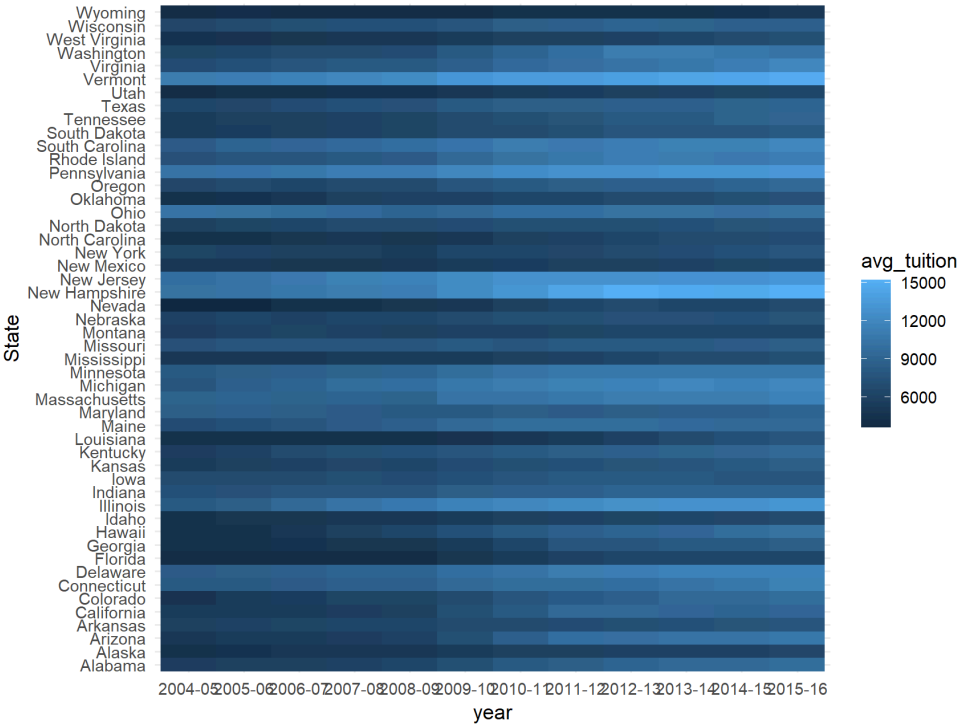
```
tuition_l <- tuition %>%
    pivot_longer(-State,
                 names_to = "year",
                 values_to = "avg_tuition")

tuition_l
```

```
## # A tibble: 600 × 3
##    State   year    avg_tuition
##    <chr>   <chr>         <dbl>
##  1 Alabama 2004-05       5683.
##  2 Alabama 2005-06       5841.
##  3 Alabama 2006-07       5753.
##  4 Alabama 2007-08       6008.
##  5 Alabama 2008-09       6475.
##  6 Alabama 2009-10       7189.
##  7 Alabama 2010-11       8071.
##  8 Alabama 2011-12       8452.
##  9 Alabama 2012-13       9098.
## 10 Alabama 2013-14       9359.
```

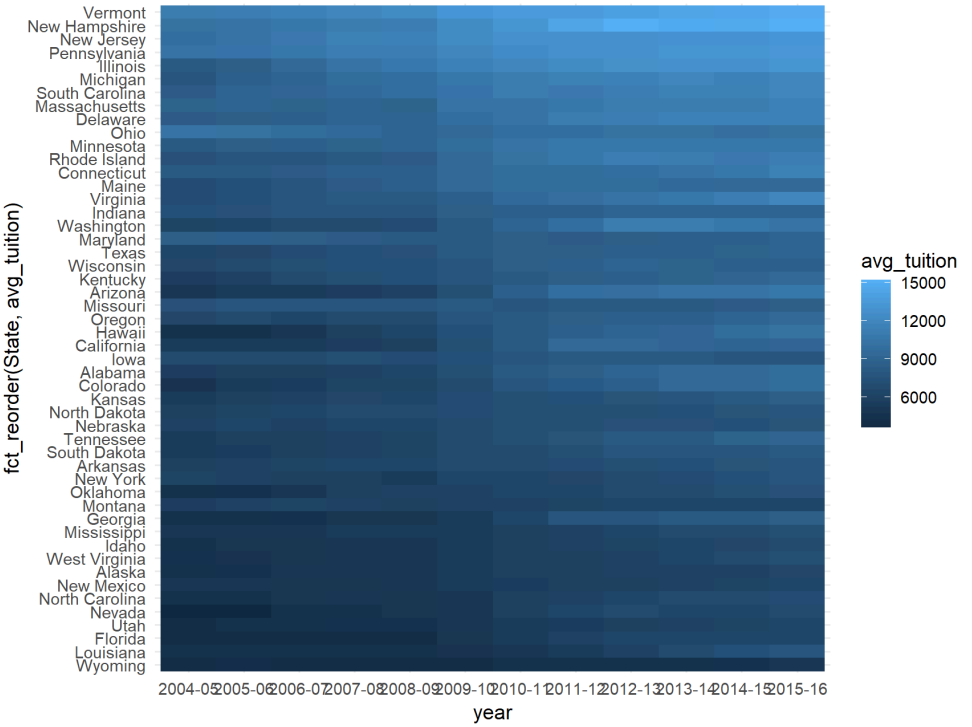
Heatmap

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



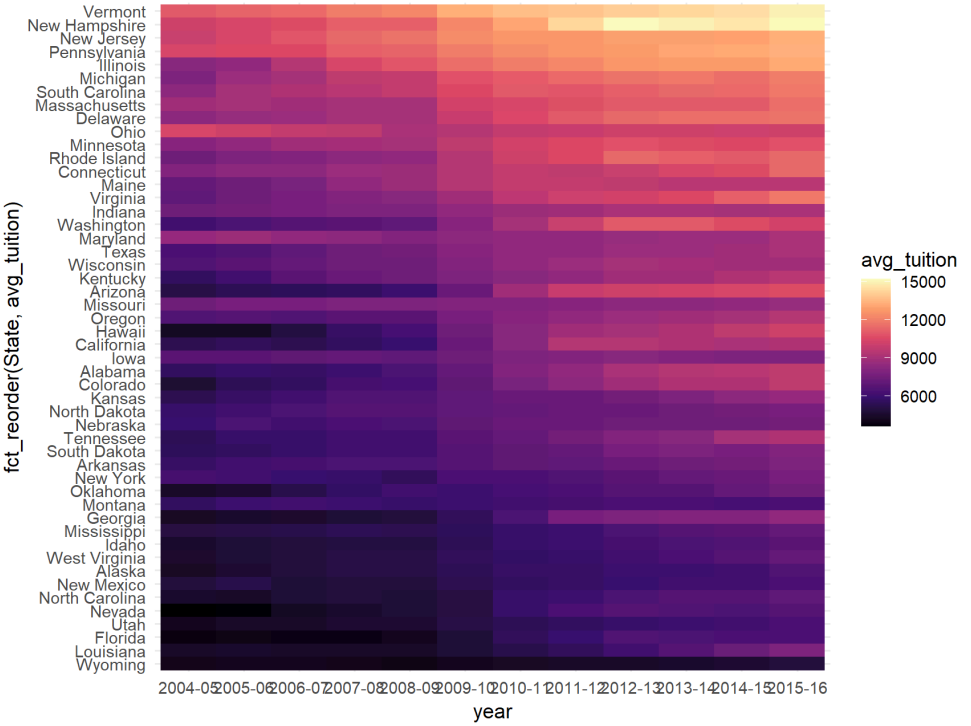
Better heatmap

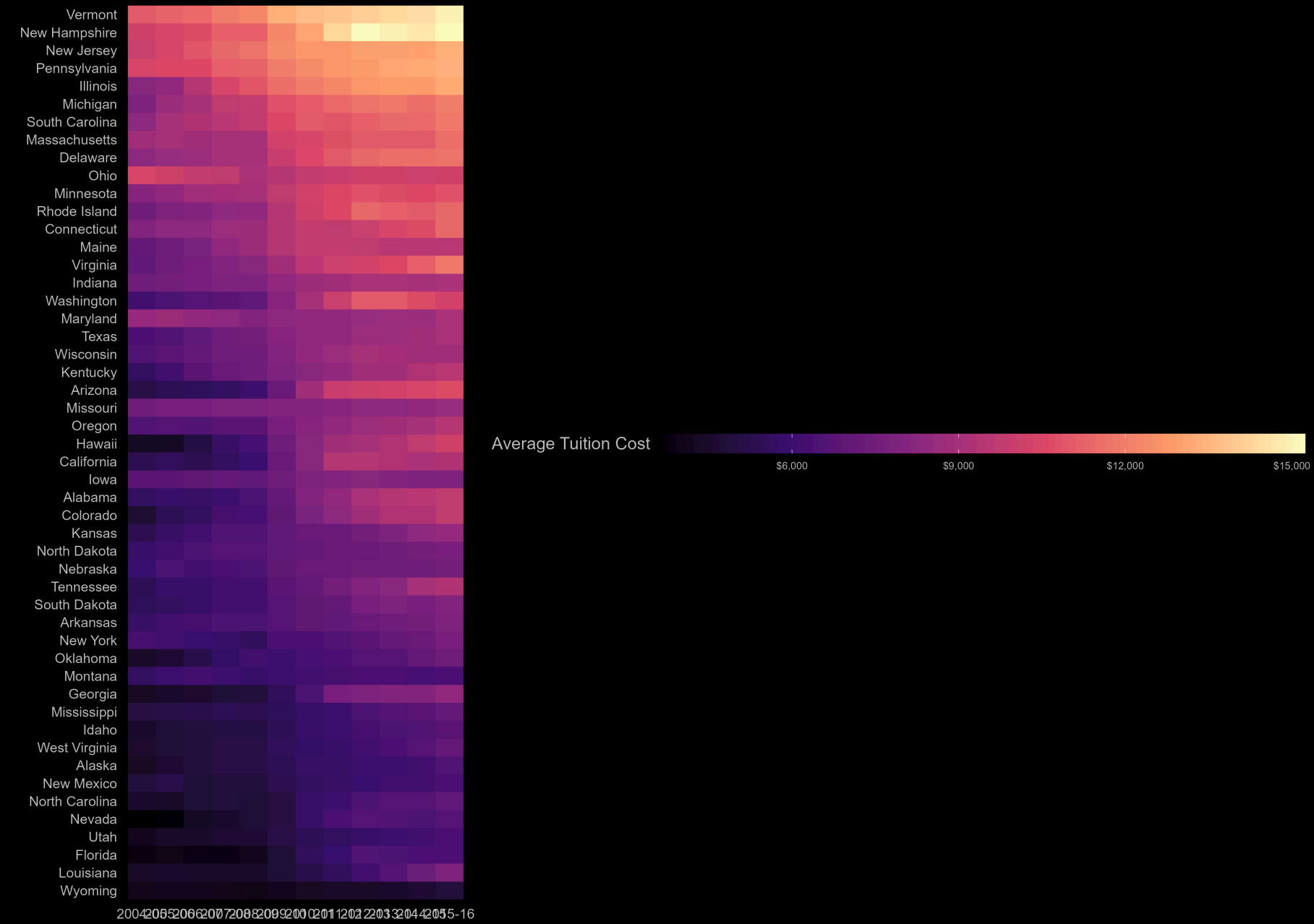
```
ggplot(tuition_l, aes(year, fct_reorder(State, avg_tuition))) +
  geom_tile(aes(fill = avg_tuition))
```



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")
```




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
Average Tuition Cost
$6,000
$9,000
$12,000
$15,000

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 subregion  2004-05 2005-06  2006-07  2
## 1 -87.46201 30.38968     1     1 alabama      <NA> 5682.838 5840.55 5753.496 60
## 2 -87.48493 30.37249     1     2 alabama      <NA> 5682.838 5840.55 5753.496 60
## 3 -87.52503 30.37249     1     3 alabama      <NA> 5682.838 5840.55 5753.496 60
## 4 -87.53076 30.33239     1     4 alabama      <NA> 5682.838 5840.55 5753.496 60
## 5 -87.57087 30.32665     1     5 alabama      <NA> 5682.838 5840.55 5753.496 60
## 6 -87.58806 30.32665     1     6 alabama      <NA> 5682.838 5840.55 5753.496 60
```

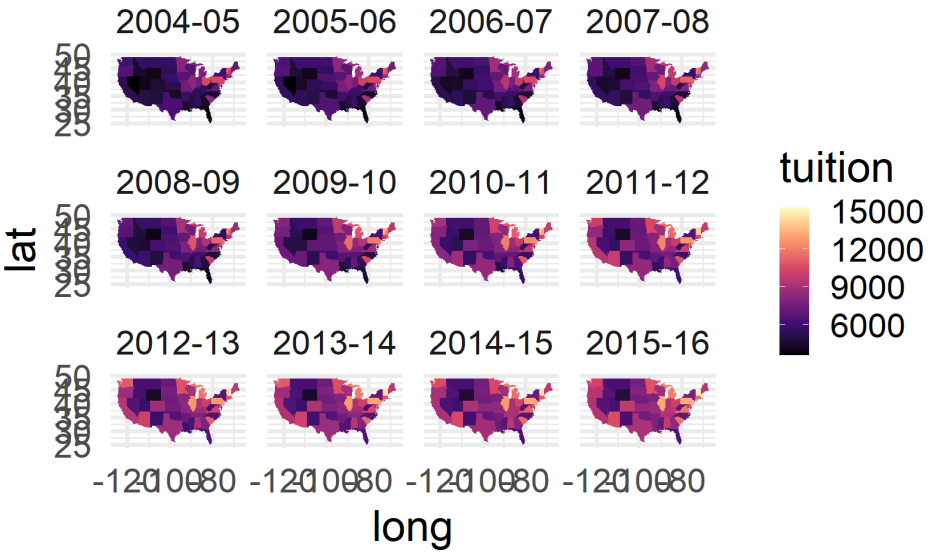
Rearrange

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

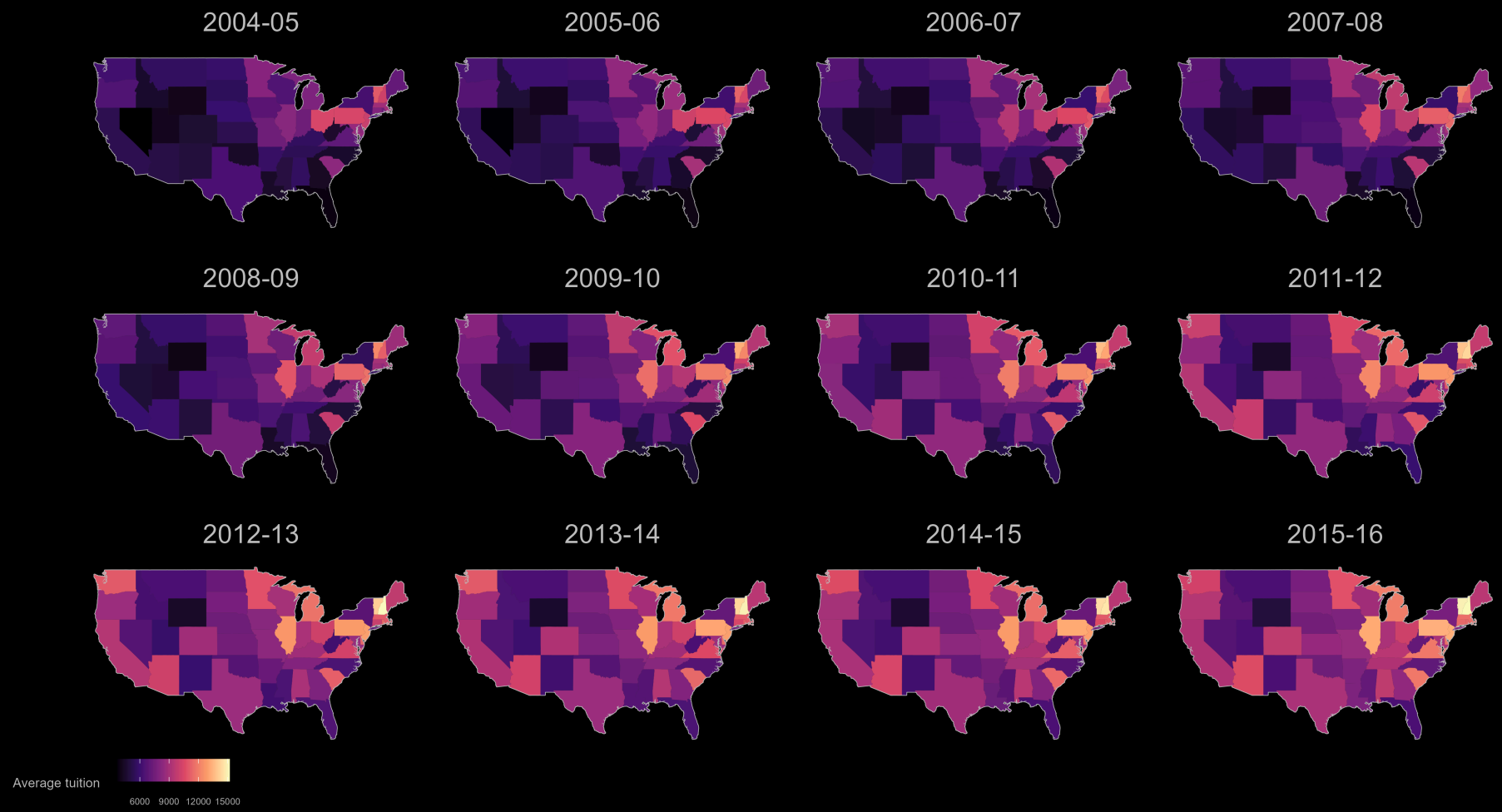
```
##        long      lat group order   State subregion    year  tuition
## 1 -87.46201 30.38968     1     1 alabama      <NA> 2004-05 5682.838
## 2 -87.48493 30.37249     1     2 alabama      <NA> 2004-05 5682.838
## 3 -87.52503 30.37249     1     3 alabama      <NA> 2004-05 5682.838
## 4 -87.53076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




```
ggplot(states, aes(long, lat, group = group, fill = tuition)) +
```


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

Data viz in the wild2

Intro to textual data and 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         29
##  2 Agender         26
##  3 F               24
##  4 FEMALE          25
##  5 Fem             27
##  6 Female          27
##  7 M               34
##  8 MALE            27
##  9 Male            37
## 10 NB              27
## 11 No response     21
## 12 agender         25
## 13 f               24
## 14 fluid           28
## 15 gender-fluid    28
## 16 m               29
## 17 nb              36
## 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          29
##  2 Agender          26
##  3 F                24
##  4 FEMALE           25
##  5 Fem              27
##  6 Female           27
##  7 M                34
##  8 MALE             27
##  9 Male             37
## 10 NB               27
## 11 No response      21
## 12 agender          25
## 13 f                24
## 14 fluid            28
## 15 gender-fluid     28
```

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 logical) 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", ex$gender)
str_detect(ex$gender, "fluid")
```

```
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"

```r
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")
```

```
##
  |
  |
  |
  |=
  |
  |==
  |
  |====
  |
  |=======
  |
  |==========
  |
  |============
  |
  |=============
  |
  |====================
  |
  |====================
```

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?

```
library(tidyverse)
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
## # ℹ 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
## # ℹ 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 `\`.

Wrapping up

This was a quick intro to string manipulations and basic visualizations for continuous measures, still a lot we didn't get to

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

We will walk through a quick refresher of R Markdowns, learn a bit about APIs, downloading data, and then jump to Lab 2!!

R-Markdown Refresher

Let's just go to our core reading on this!

Downloading data using packages/setting API keys

Let's use another R Markdown to follow step-by-step how to download college data from Data.gov using an r package/API

Next time

Saloni Dattani's Guide to Data Viz Guest lecture Visual processing and perceptual rankings It seems like there are a lot of readings, so skim them and we will discuss more in class

Lab 2