Visualizing uncertainty

Daniel Anderson

Week 6, Class 2

Reviewing Homework 1

Data viz in the wild

Raleigh

Maggie

Ann-Marie and Murat on Deck

Agenda

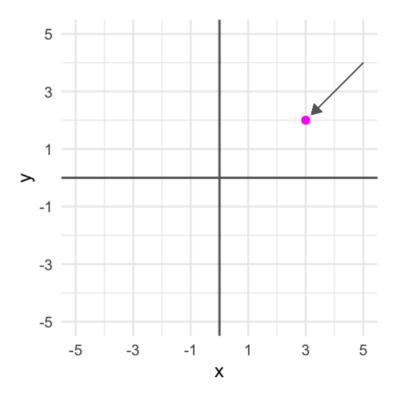
- Common ways of visualizing uncertainty
 - And how to implement them with {ggplot2}
- Framing uncertainty as relative frequencies
 - Discrete probabilities
 - Non-discrete probabilities
 - Understanding AUC calculations
- Understanding standard errors
 - Non-standard ways of visualizing SEs
- HOPs (briefly)
 - Also bootstrapping

Learning objectives

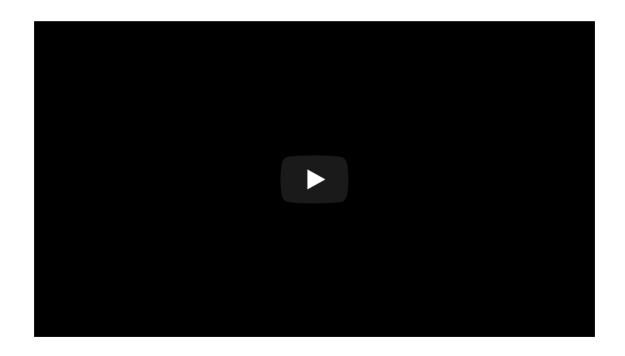
- 1. Understand there are lots of different ways to visualize uncertainty, and the best method may often be non-standard.
- 2. Understand how to implement basic methods, and the resources available to you to implement more advanced methods

The primary problem

• When we see a point on a plot, we interpret it as THE value.



Let's have Dr. Kay explain

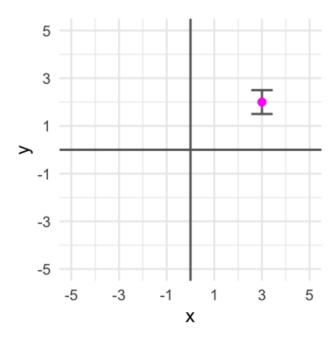


Some secondary problem

- We're not great at understanding probabilities
- We regularly round probabilities to 100% or 0%
- As probabilities move to the tails, we're generally worse

How do we typically communicate uncertainty?

Error bars



HOW?

Vertical error bars

geom_errorbar

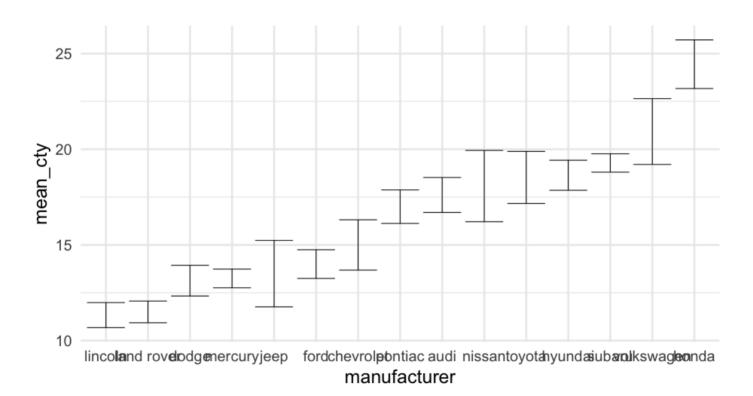
- Requires ymin and ymax aesthetics
- You have to supply these no calculation for you

Horizontal error bars

geom_errorbarh

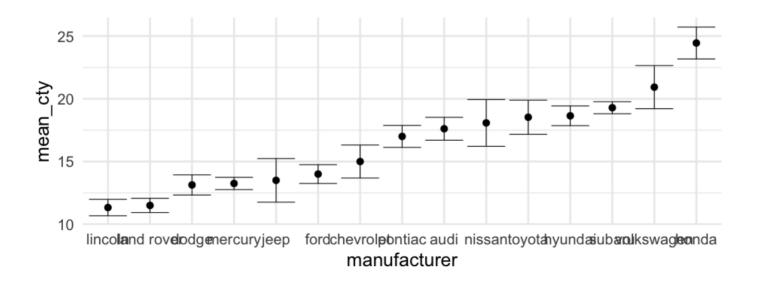
• Requires **xmin** and **xmax**

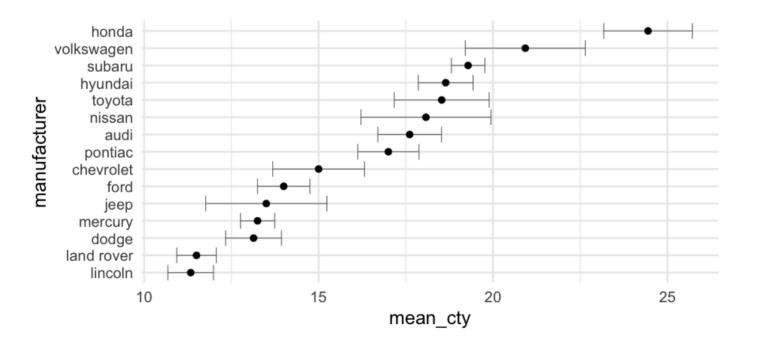
Example



Put points on top

Not under

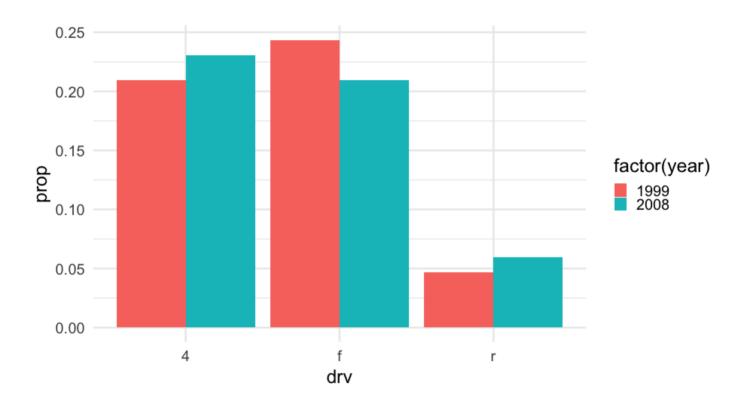


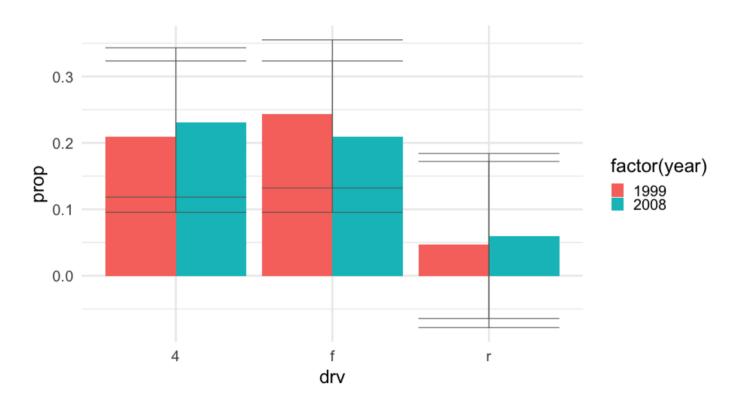


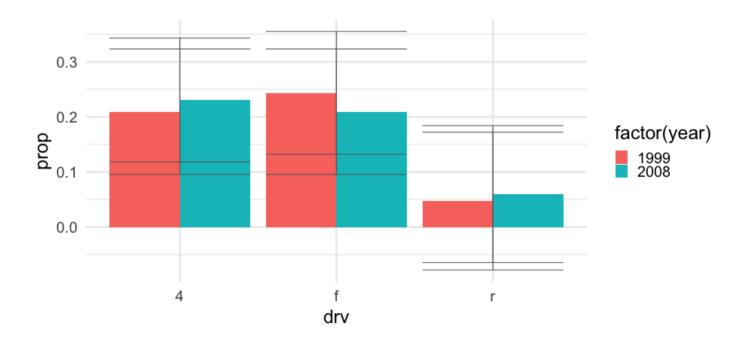
Dodging

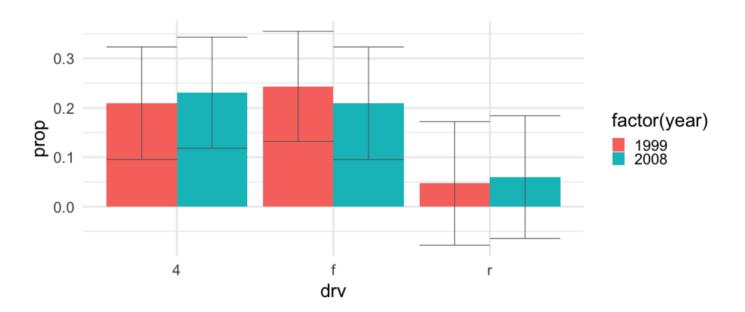
```
## # A tibble: 6 x 5
## drv year n prop prop_se
## <chr> <int> <int> <dbl> <dbl> <dbl> <dbl> 
## 1 4 1999 49 0.2094017 0.05812594
## 2 4 2008 54 0.2307692 0.05733508
## 3 f 1999 57 0.2435897 0.05685528
## 4 f 2008 49 0.2094017 0.05812594
## 5 r 1999 11 0.04700855 0.06381703
## 6 r 2008 14 0.05982906 0.06338631
```

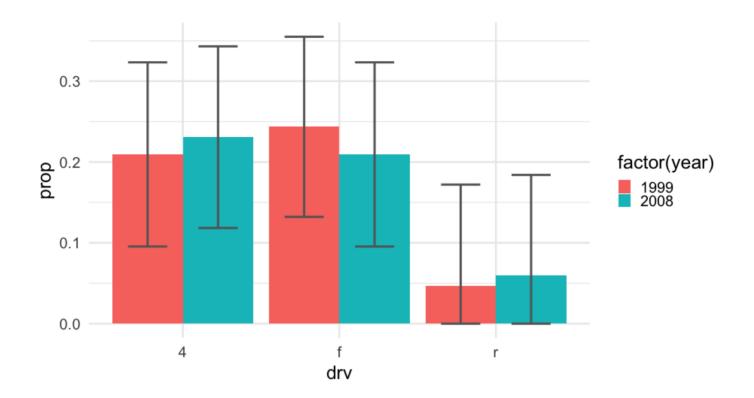
```
ggplot(props, aes(drv, prop)) +
  geom_col(aes(fill = factor(year)), position = "dodge")
```











Thinking about uncertainty

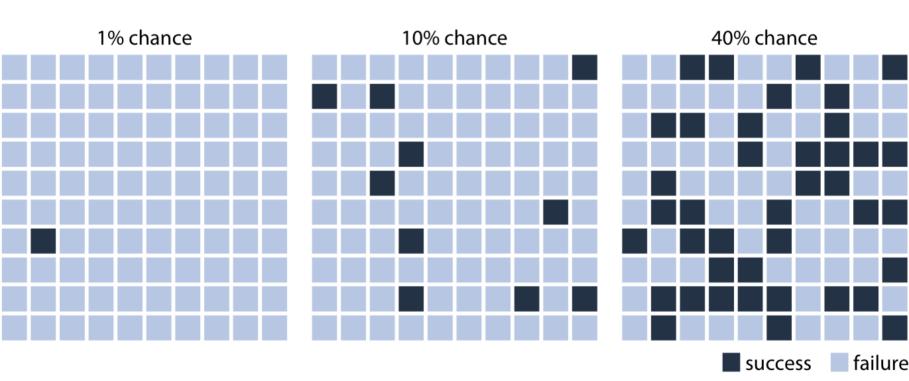
Uncertainty means exactly what it sounds like – we are not 100% sure.

- We are nearly always uncertain of future events (forecasting)
- We can also be uncertain about past events
 - I saw a parked car at 8 AM, but the next time I looked at 2PM it was gone. What time did it leave?

Quantifying uncertainty

- We quantify our uncertainty mathematically using probability
- Framing probabilities as frequencies is generally more intuitive

Framing a single uncertainty



How do we make these?

Start out by making a grid

tail(grid)

Look at the grid



Create occurrence rate

• For each sequence of x, create a variable that has the given occurrence rate

How?

• Plenty of options, here's one

Consider 10%

```
nrow(grid)*.10 # n to sample

## [1] 40

set.seed(86753098)
samp <- sample(seq_len(nrow(grid)), nrow(grid)*.10)
head(samp)

## [1] 318 134 180 283 177 248

length(samp)

## [1] 40</pre>
```

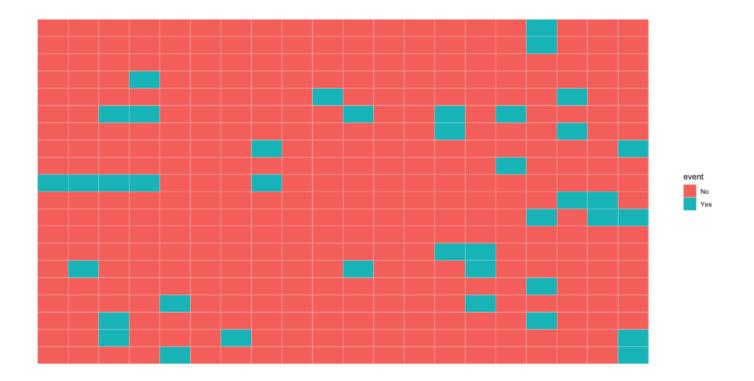
Create the variable

```
grid <- grid %>%
  rownames_to_column("row_id") %>%
  mutate(event = ifelse(row_id %in% samp, "Yes", "No"))
head(grid)
```

```
## 1 row_id x y event
## 1 1 1 1 No
## 2 2 2 1 No
## 3 3 1 No
## 4 4 1 No
## 5 5 5 1 Yes
## 6 6 6 1 No
```

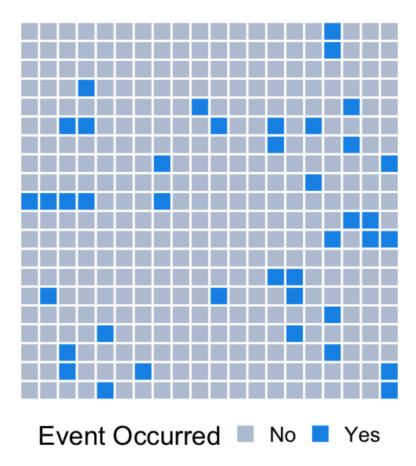
Fill in

```
ggplot(grid, aes(x, y)) +
  geom_tile(aes(fill = event), color = "white") +
  theme_void()
```

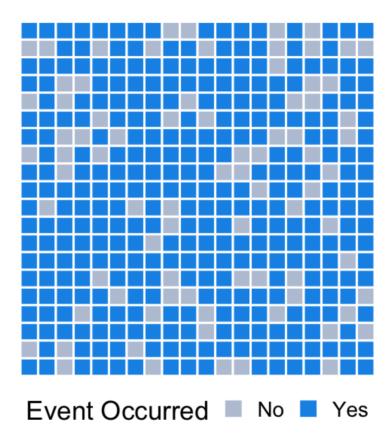


Customize

```
library(colorspace)
ggplot(grid, aes(x, y)) +
   geom_tile(aes(fill = event), color = "white", size = 1.4) +
   scale_fill_manual(
    name = "Event Occurred",
    values = c(desaturate(lighten("#1694E8", 0.5), 0.7), "#1694E8)) +
   coord_fixed() +
   theme_void() +
   theme(legend.position = c(0.75, 0),
        legend.direction = "horizontal",
        plot.margin = margin(b = 1, unit = "cm"))
```

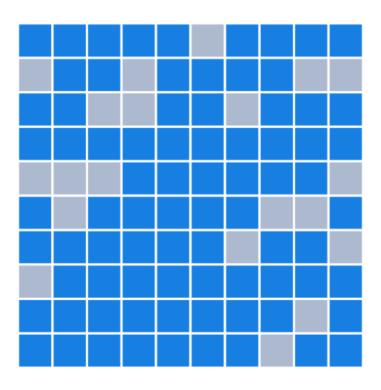


Chance of rain



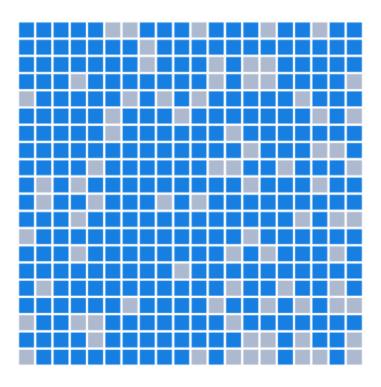
Vary grid size

10 x 10



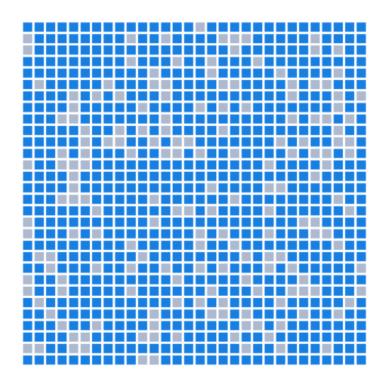
Vary grid size

 20×20



Vary grid size

 30×30



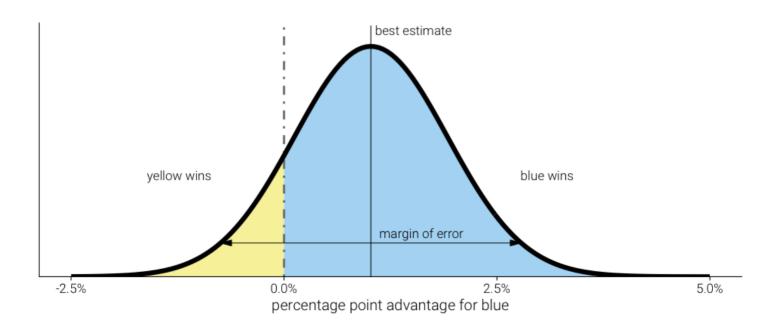
(probs too many)

Non-discrete probabilities

Hypothetical

Blue party has 1% advantage w/ margin of error of 1.76 points

Who will win?



A bit of math

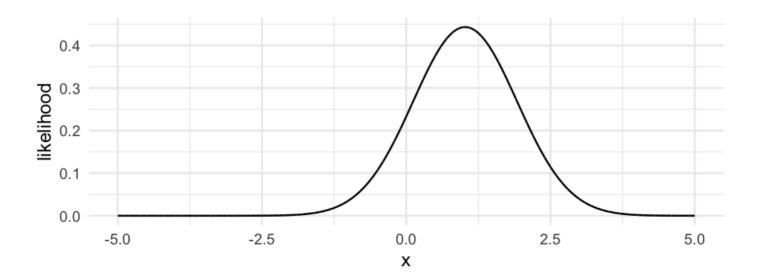
Our prior distribution was defined by $\mu=1.02$ and sd=0.9

• What's the chance the end result is below zero?

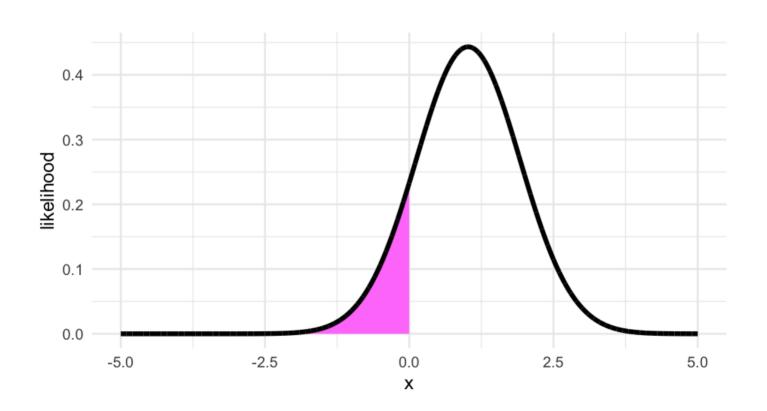
The hard way

Calculate the exact probability of data below zero under this distribution

```
x <- seq(-5, 5, 0.001)
likelihood <- dnorm(x, 1.02, 0.9)
sim <- data.frame(x, likelihood)
ggplot(sim, aes(x, likelihood)) +
  geom_line(size = 1.2)</pre>
```



How do we calculate this portion?



Integrate

```
zab <- filter(sim, x <= 0)
pracma::trapz(zab$x, zab$likelihood)</pre>
```

[1] 0.129

Easier: Simulate

0.13 0.87

```
random_draws <- rnorm(1e5, 1.02, 0.9)
table(random_draws > 0) / 1e5

##
## FALSE TRUE
```

Discretized plot

ppoints(50)

[28]

[37]

[46]

1.57153

2.22668

1.62704

2.34821

1.68496

2.50037

```
## [1] 0.01 0.03 0.05 0.07 0.09 0.11 0.13 0.15 0.17 0.19 0.21 0.23 0.25 0.
## [18] 0.35 0.37 0.39 0.41 0.43 0.45 0.47 0.49 0.51 0.53 0.55 0.57 0.59 0.
## [35] 0.69 0.71 0.73 0.75 0.77 0.79 0.81 0.83 0.85 0.87 0.89 0.91 0.93 0.

qnorm(ppoints(50), 1.02, 0.9)

## [1] -1.07371 -0.67271 -0.46037 -0.30821 -0.18668 -0.08388 0.00625 0.6
## [10] 0.22989 0.29422 0.35504 0.41296 0.46847 0.52195 0.57373 0.6
## [19] 0.72133 0.76861 0.81521 0.86126 0.90690 0.95226 0.99744 1.0
```

1.13310 1.17874 1.22479 1.27139 1.31867 1.36679 1.41592

2.71271

1.74578 1.81011

3.11371

1.87875

1.4

2.0

1.95279

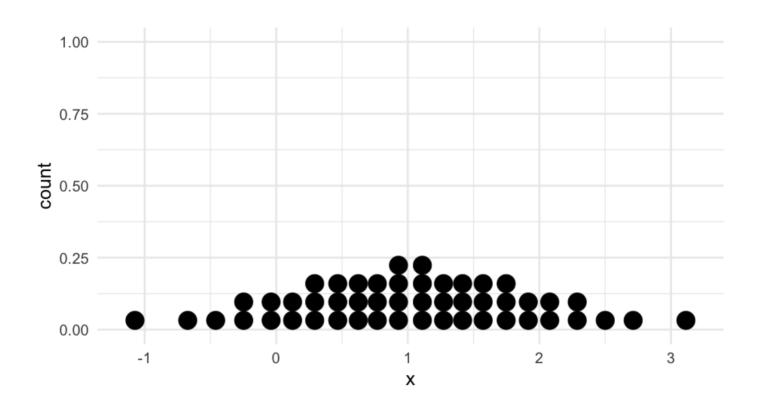
```
discretized <- data.frame(x = qnorm(ppoints(50), 1.02, 0.9)) %>%
  mutate(winner = ifelse(x <= 0, "#bldaf4", "#f8f1a9"))
head(discretized)</pre>
```

```
## x winner
## 1 -1.0737 #b1daf4
## 2 -0.6727 #b1daf4
## 3 -0.4604 #b1daf4
## 4 -0.3082 #b1daf4
## 5 -0.1867 #b1daf4
## 6 -0.0839 #b1daf4
```

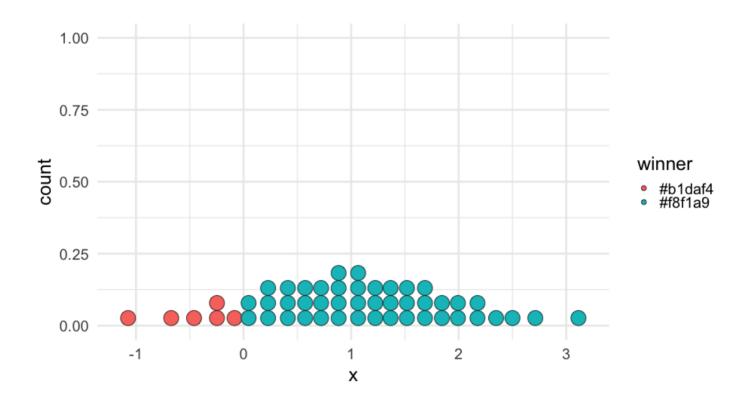
tail(discretized)

```
## x winner
## 45 2.12 #f8f1a9
## 46 2.23 #f8f1a9
## 47 2.35 #f8f1a9
## 48 2.50 #f8f1a9
## 49 2.71 #f8f1a9
## 50 3.11 #f8f1a9
```

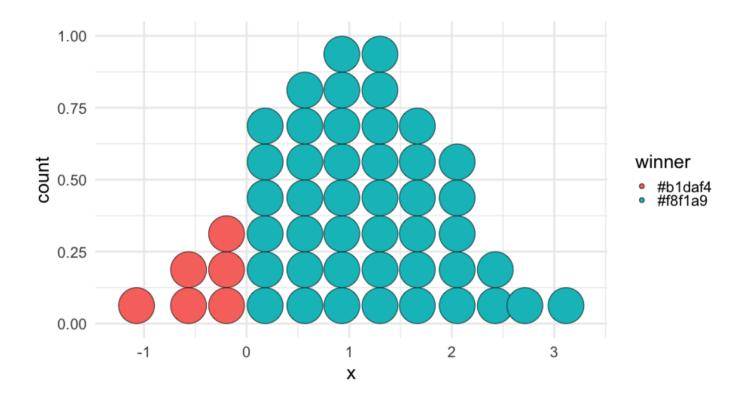
ggplot(discretized, aes(x)) + geom_dotplot()



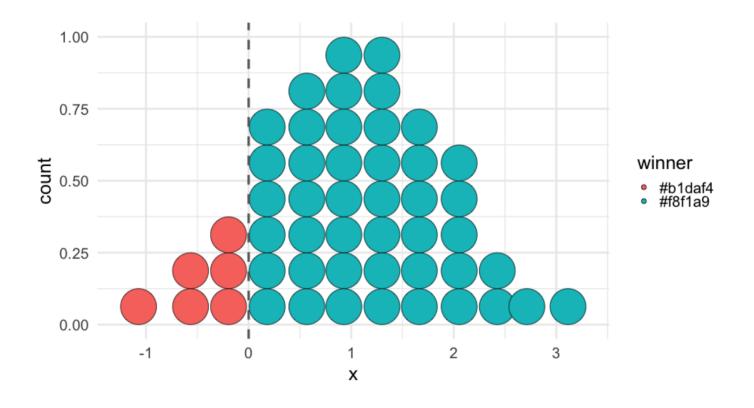
```
ggplot(discretized, aes(x)) +
  geom_dotplot(aes(fill = winner))
```

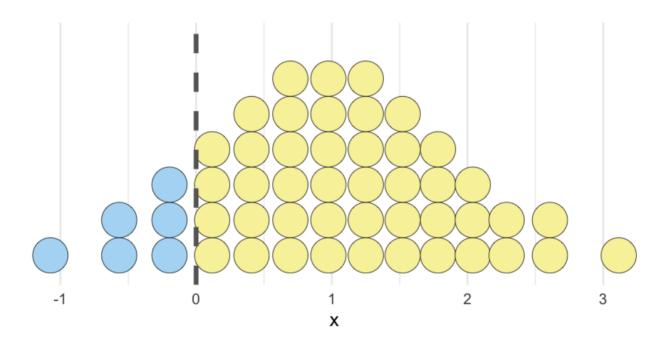


```
ggplot(discretized, aes(x)) +
  geom_dotplot(aes(fill = winner), binwidth = 0.35)
```

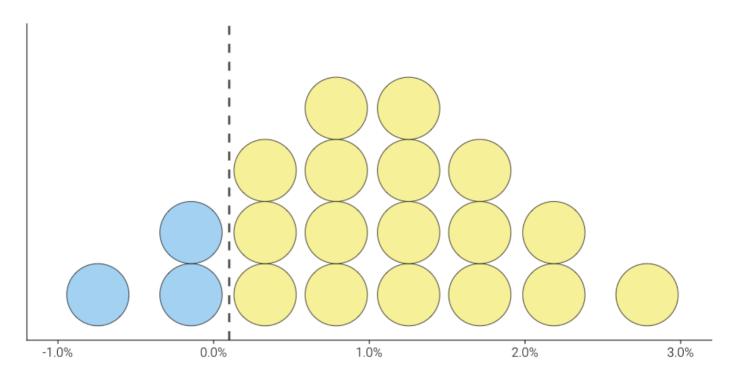


```
ggplot(discretized, aes(x)) +
  geom_dotplot(aes(fill = winner), binwidth = 0.35) +
  geom_vline(xintercept = 0, color = "gray40", linetype = "dashed")
```





Probs too many though



Each ball represents 5% probability

Uncertainty of point estimates

Quick review (hopefully a review)

- What is a standard error?
- Standard deviation of the sampling distribution
- What is the sampling distribution?
- Samples from the underlying, population—based, generative distribution
- What does this mean, exactly?
- Let's simulate to explore

Simulation

- ullet Imagine the "real" distribution has $\mu=100$ and $\sigma=10$.
- Let's draw a sample of 10 from this distribution

```
set.seed(123)
samp10a <- rnorm(n = 10, mean = 100, sd = 10)
samp10a</pre>
```

```
## [1] 94.4 97.7 115.6 100.7 101.3 117.2 104.6 87.3 93.1 95.5
```

Calculate the mean

```
mean(samp10a)
```

```
## [1] 101
```

Do it a second time

```
sampl0b <- rnorm(n = 10, mean = 100, sd = 10)
sampl0b

## [1] 112.2 103.6 104.0 101.1 94.4 117.9 105.0 80.3 107.0 95.3

mean(sampl0b)

## [1] 102</pre>
```

Do it a bunch of times

```
samples \leftarrow replicate(1000, rnorm(10, mean = 100, sd = 10),
                     simplify = FALSE)
samples
## [[1]]
   [1] 89.3 97.8 89.7 92.7 93.7 83.1 108.4 101.5 88.6 112.5
##
##
##
  [[2]]
   [1] 104.3 97.0 109.0 108.8 108.2 106.9 105.5 99.4 96.9 96.2
##
##
## [[3]]
   [1] 93.1 97.9 87.3 121.7 112.1 88.8 96.0 95.3 107.8 99.2
##
##
## [[4]]
   [1] 102.5 99.7 99.6 113.7 97.7 115.2 84.5 105.8 101.2 102.2
##
##
##
  [[5]]
   [1] 103.8 95.0 96.7 89.8 89.3 103.0 104.5 100.5 109.2 120.5
##
##
## [[6]]
##
   [1] 95.1 76.9 110.1 92.9 93.1 110.3 97.2 87.8 101.8 98.6
##
## [[7]]
   [1] 100.1 103.9 96.3 106.4 97.8 103.3 111.0 104.4 96.7 111.5
##
##
## [[8]]
```

Calculate all means

```
map_dbl(samples, mean) %>%
head()
```

```
## [1] 95.8 103.2 99.9 102.2 101.2 96.4
```

ullet What's the sd of these means? That's the standard error.

```
map_dbl(samples, mean) %>%
sd()
```

```
## [1] 3.14
```

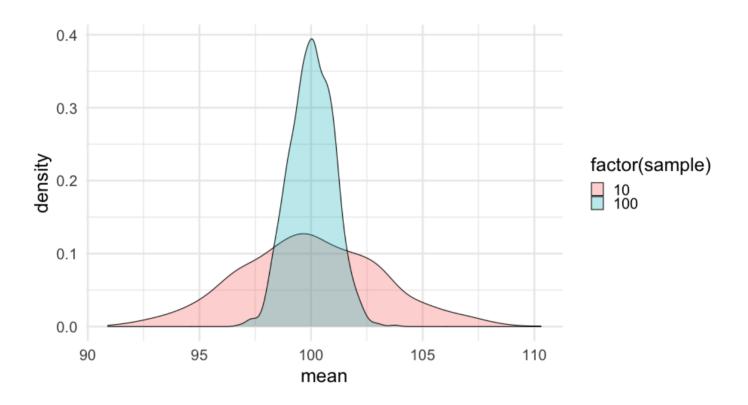
Sample size

Let's re-do this, pulling a sample of 100 each time.

[1] 0.973

Visualize the sampling distributions

```
ggplot(sample_means, aes(mean)) +
  geom_density(aes(fill = factor(sample)), alpha = 0.3)
```

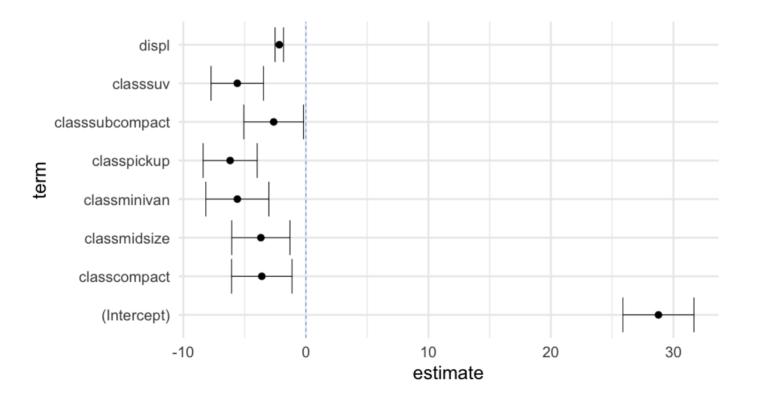


Fit a model

```
m <- lm(ctv ~ displ + class, mpg)</pre>
summary(m)
##
## Call:
## lm(formula = cty ~ displ + class, data = mpg)
##
## Residuals:
##
     Min
         10 Median 30 Max
## -5.269 -1.150 -0.016 1.034 12.978
##
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
                             1.473 19.54 < 2e-16 ***
## (Intercept)
                  28.777
                -2.172 0.175 -12.43 < 2e-16 ***
## displ
                             1.252 -2.87 0.0044 **
## classcompact -3.599
                             1.206 -3.05 0.0026 **
                -3.676
## classmidsize
## classminivan -5.595 1.306 -4.28 2.7e-05 ***
              -6.182 1.121 -5.51 9.6e-08 ***
## classpickup
## classsubcompact -2.629 1.237 -2.13 0.0346 *
           -5.599
                             1.087 -5.15 5.7e-07 ***
## classsuv
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.25 on 226 degrees of freedom
## Multiple R-squared: 0.729, Adjusted R-squared: 0.721
```

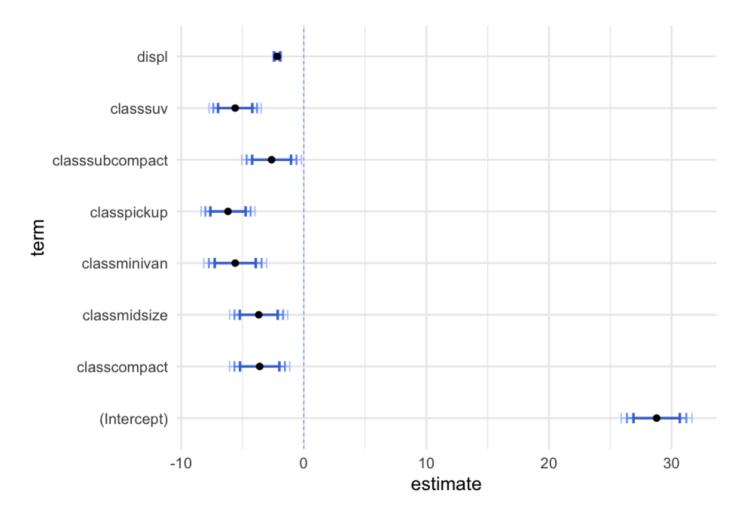
Visualize with standard errors

```
tidied_m <- broom::tidy(m, conf.int = TRUE)</pre>
tidied m
## # A tibble: 8 x 7
## term estimate std.error statistic p.value conf.low cor
## <chr>
                             <dbl> <dbl>
                   <dbl>
                                                   <dbl>
                                                             <dbl>
## 1 (Intercept) 28.77682 1.472892 19.53763 1.905873e-50 25.87446 31.
## 2 displ -2.171562 0.1746638 -12.43281 2.197130e-27 -2.515740 -1.
## 3 classcompact -3.599125 1.252190 -2.874265 4.436052e- 3 -6.066585 -1.
## 4 classmidsize -3.675526 1.206253 -3.047061 2.585762e- 3 -6.052466 -1.
## 5 classminivan -5.595070 1.305993 -4.284151 2.714490e- 5 -8.168550 -3.
## 6 classpickup -6.182466 1.121448 -5.512931 9.600087e- 8 -8.392297 -3.
## # ... with 2 more rows
```



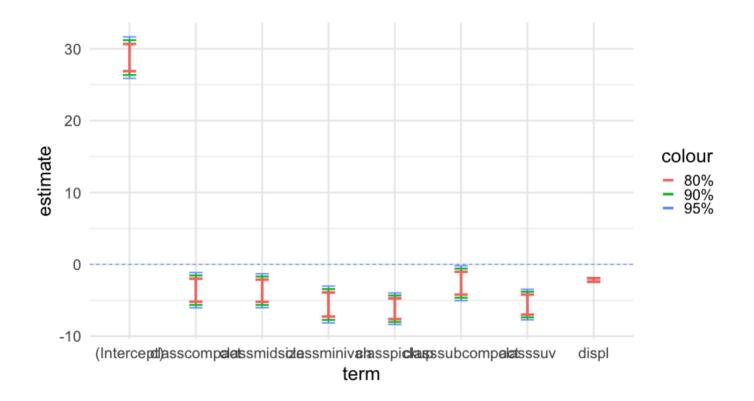
Multiple error bars

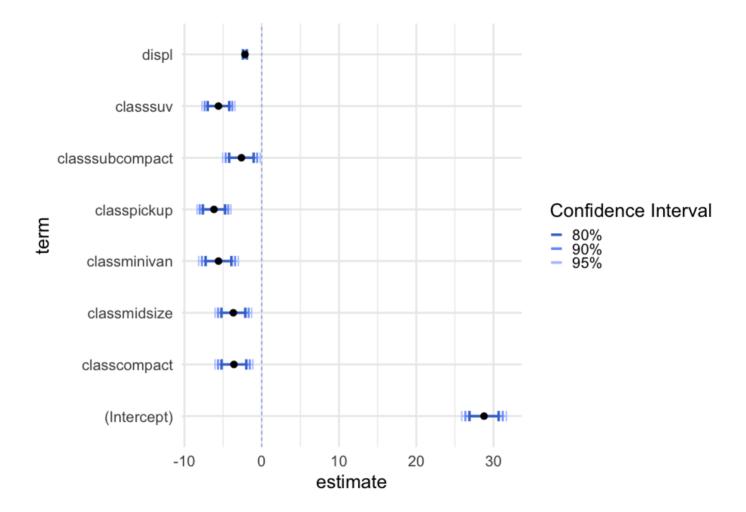
```
library(colorspace)
ggplot(tidied_m, aes(term, estimate)) +
  geom_hline(yintercept = 0,
             color = "cornflowerblue",
             linetvpe = 2) +
  geom_errorbar(aes(ymin = estimate + qnorm(.025)*std.error,
                    ymax = estimate + qnorm(.975)*std.error),
                color = lighten("#4375D3", .6),
                width = 0.2,
                size = 0.8) + # 95\% CI
  geom_errorbar(aes(ymin = estimate + qnorm(.05)*std.error,
                    ymax = estimate + qnorm(.95)*std.error),
                color = lighten("#4375D3", .3),
                width = 0.2,
                size = 1.2) + # 90% CI
  geom_errorbar(aes(ymin = estimate + qnorm(.1)*std.error,
                    ymax = estimate + qnorm(.9)*std.error),
                color = "#4375D3",
                width = 0.2,
                size = 1.6) + # 80\% CI
  geom_point() +
  coord_flip()
```



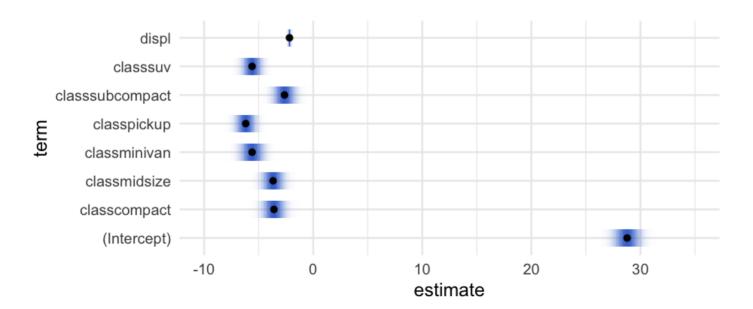
Add levels to legend

```
p <- ggplot(tidied_m, aes(term, estimate)) +</pre>
  geom_hline(yintercept = 0,
             color = "cornflowerblue",
             linetvpe = 2) +
  geom_errorbar(aes(ymin = estimate + qnorm(.025)*std.error,
                    ymax = estimate + qnorm(.975)*std.error,
                    color = "95%"),
                width = 0.2,
                size = 0.8) +
  geom_errorbar(aes(ymin = estimate + gnorm(.05)*std.error,
                    vmax = estimate + qnorm(.95)*std.error,
                    color = "90%"),
                width = 0.2,
                size = 1.2) +
  geom_errorbar(aes(ymin = estimate + qnorm(.1)*std.error,
                    ymax = estimate + qnorm(.9)*std.error,
                    color = "80%"),
                width = 0.2,
                size = 1.6)
```

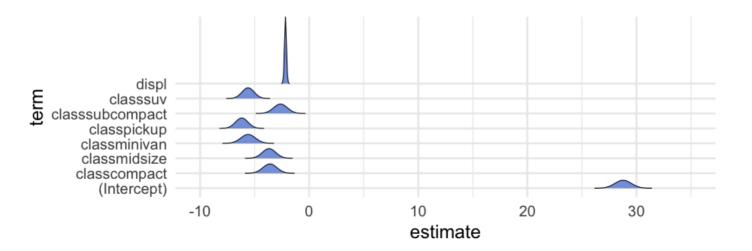




Density stripes



Actual densities

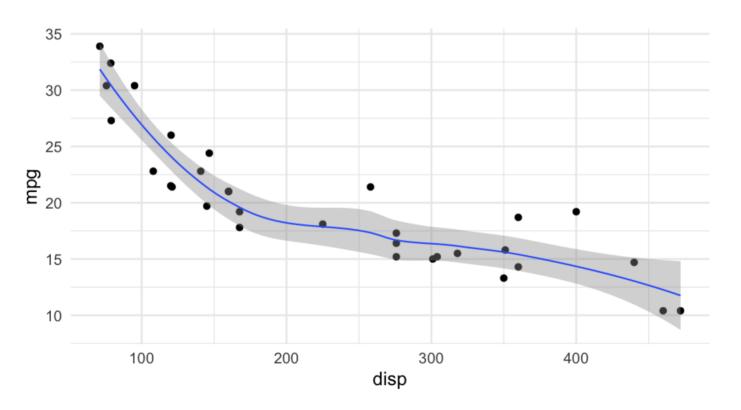


HOPS

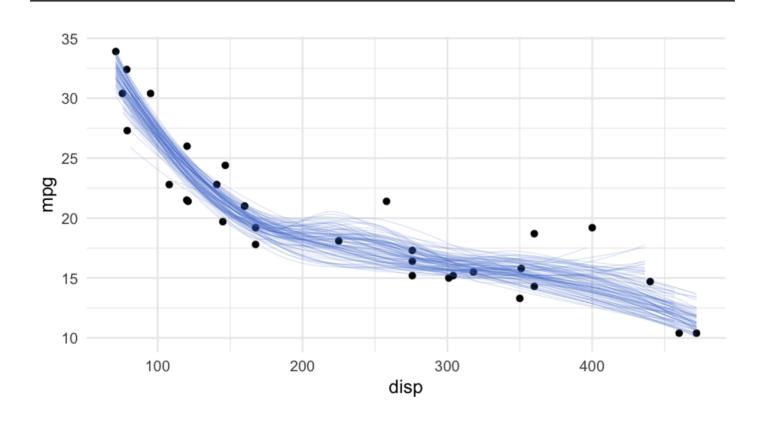
Hypothetical Outcome Plots (and related plots)

Standard regression plot

```
ggplot(mtcars, aes(disp, mpg)) +
  geom_point() +
  geom_smooth()
```



Alternative



How?

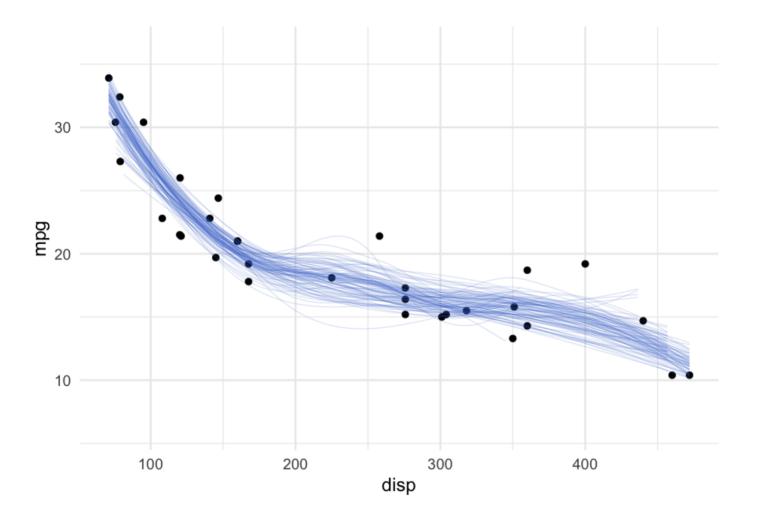
Bootstrapping

```
row_samps <- replicate(100,</pre>
                        sample(seq_len(nrow(mtcars)),
                               nrow(mtcars),
                               replace = TRUE),
                       simplify = FALSE)
row_samps
## [[1]]
  [1] 31 6 32 12 1 14 2 11 20 10 26 10 22 30 25 25 5 31 19 13 19 20 1
  [29] 20 21 16 23
##
##
## [[2]]
  [1] 11 23 14 1 24 20 10 30 27 24 22 23 25 1 18 18 25 8 8 16 25 19 3
##
  [29] 14 14 12 24
##
##
  [[3]]
   [1] 27 29 22 5 6 8 14 16 7 13 17 13 21 10 7 21 7 20 30 30 5 10
##
##
  [29] 27 23 19 7
##
## [[4]]
          7 8 28 3 17 13 26 8 30 3 32 20 10 2 6 19 21 11
##
                                                                  6 16 9 1
## [29] 19 21
```

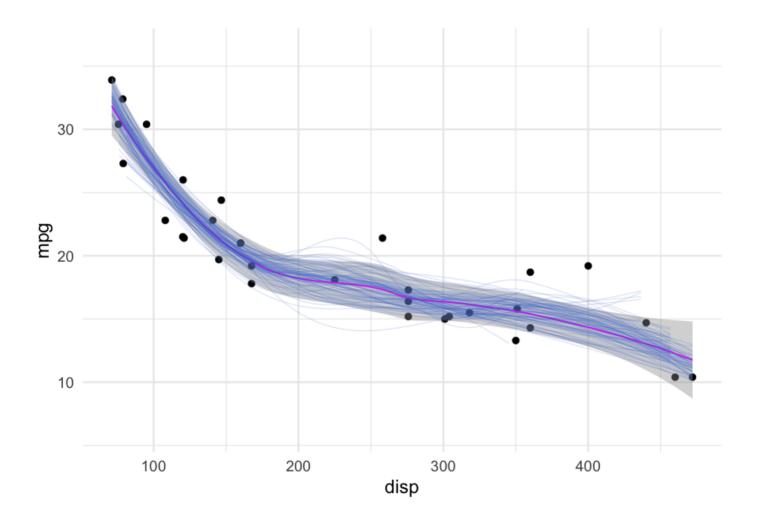
Extract samples

tail(d_samps)

Plot both data sources

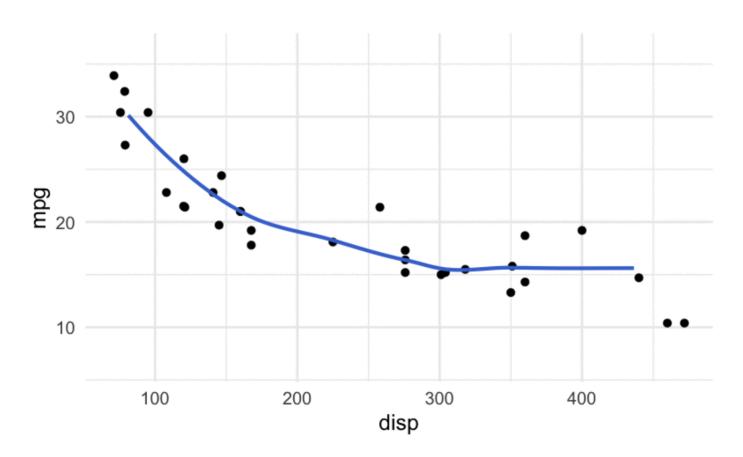


Note, they match up



HOPs

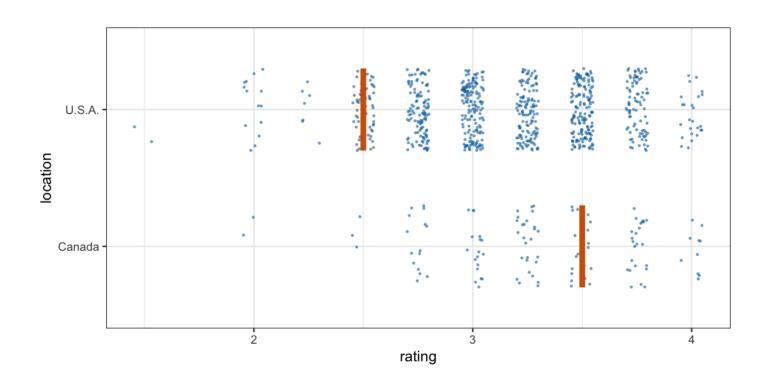
Hops animate the process, so you can't settle on one "truth"



How?

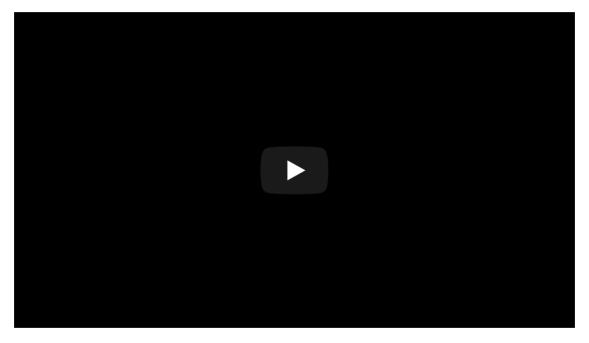
gganimate::transition_states

Another example



Another examples

From Dr. Kay again



Conclusions

- Lots of tools at your disposal (perhaps so many it can be difficult to choose)
- Do try to communicate uncertainty whenever possible
- I'd recommend checking out Clause Wilke's talk from rstudio::conf(2019L), where he talks about the ungeviz package.

Next time: Dashboards

Guest Lecturer: Akhila Nekkanti