

# Visualizing uncertainty

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Daniel Anderson

Week 6, Class 2

Reviewing

Homework 1

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# Data viz in the wild

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Raleigh

Maggie

Ann-Marie and Murat on Deck

# Agenda

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- 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

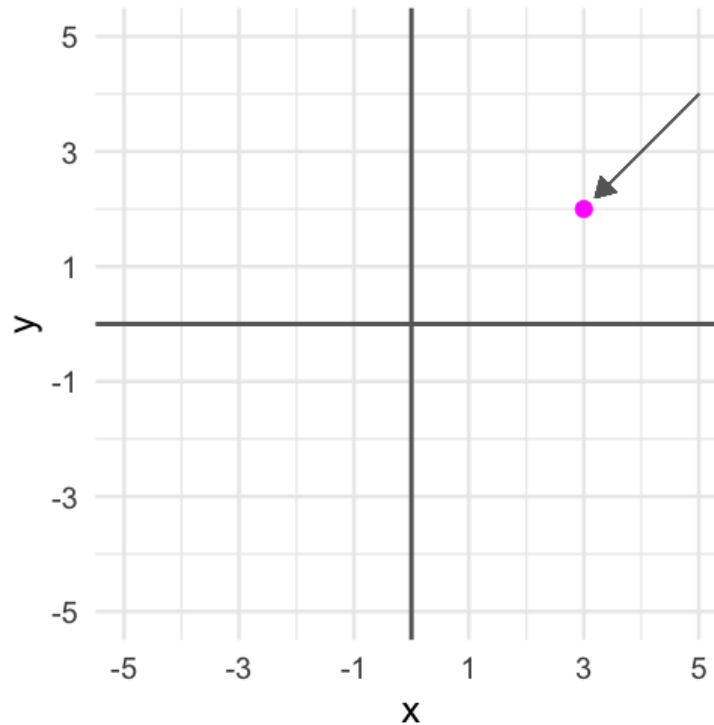
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1. Understand there are lots of different ways to visualize uncertainty, and the best method may often be non-standard.
2. Understand how to implement basic methods, and the resources available to you to implement more advanced methods

# The primary problem

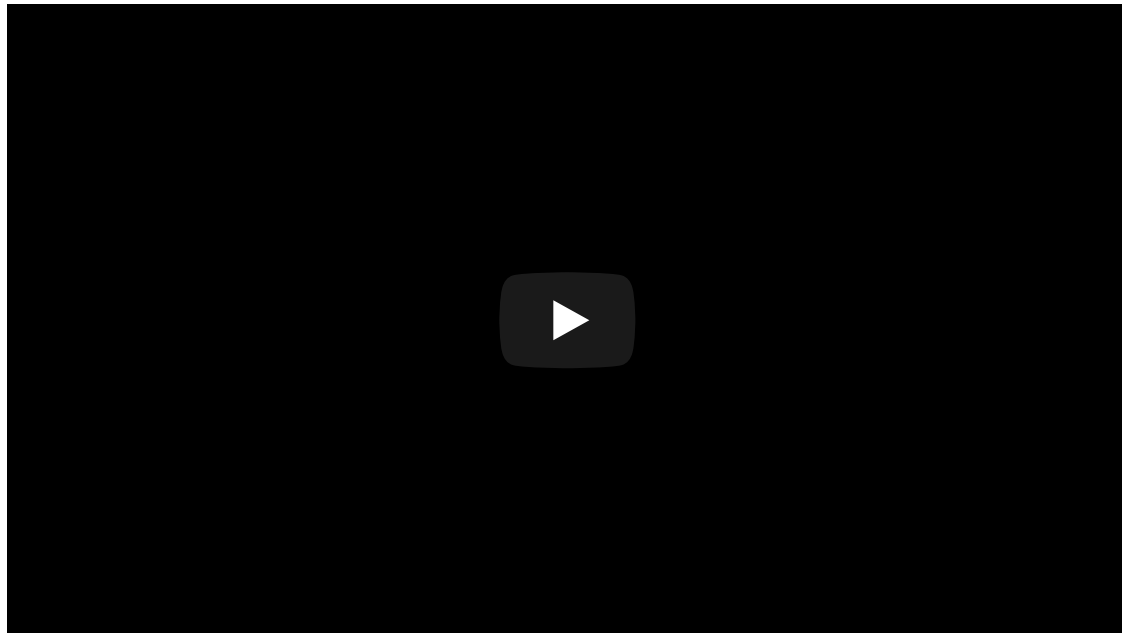
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- When we see a point on a plot, we interpret it as THE value.



# Let's have Dr. Kay explain

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# Some secondary problem

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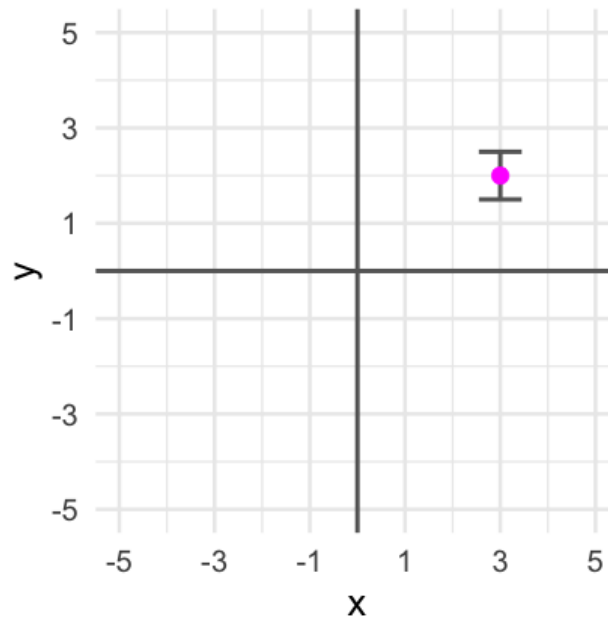
- We're not great at understanding probabilities
- We regularly round probabilities to 100% or 0%
- As probabilities move to the tails, we're generally worse



# How do we typically communicate uncertainty?

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- Error bars



# How?

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## 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`

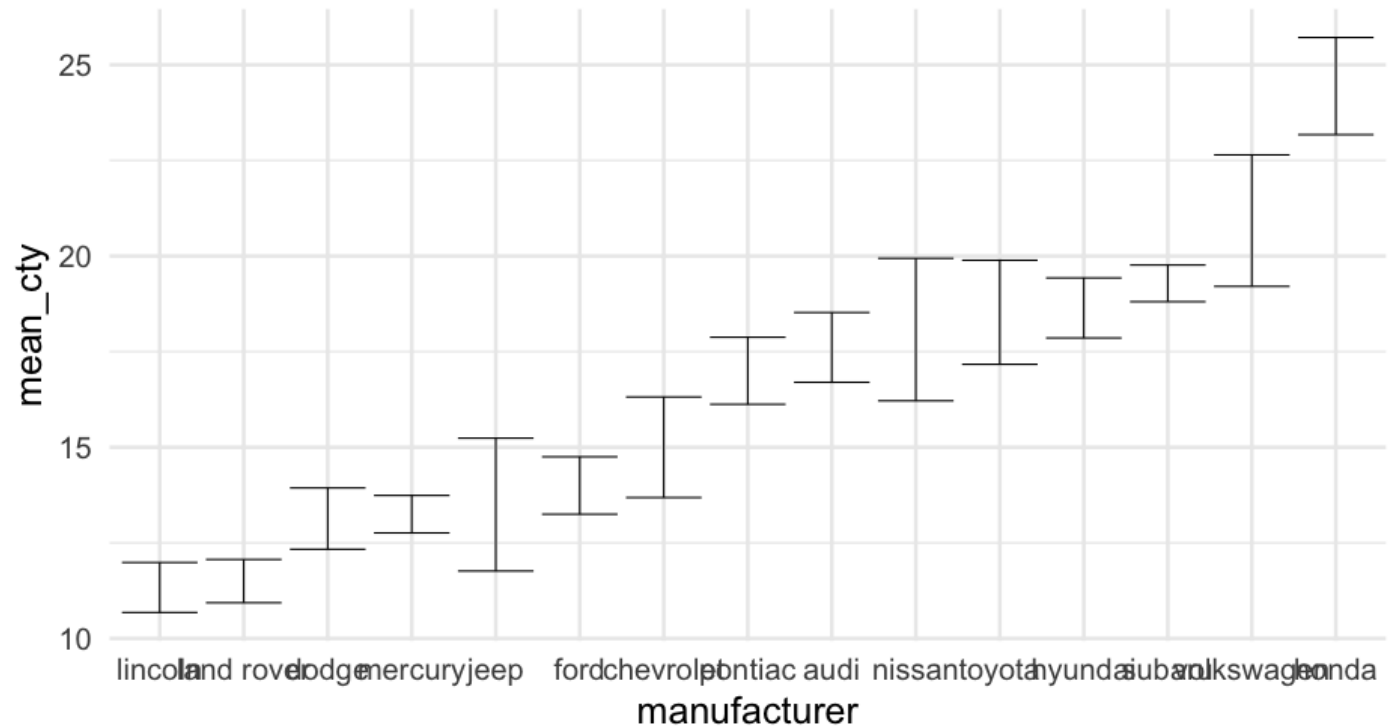
# Example

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```
mpg_by_man <- mpg %>%  
  group_by(manufacturer) %>%  
  summarize(mean_cty = mean(cty),  
             se_cty = sd(cty)/sqrt(n()))  
  
head(mpg_by_man)
```

```
## # A tibble: 6 x 3  
##   manufacturer mean_cty    se_cty  
##   <chr>         <dbl>    <dbl>  
## 1 audi          17.61111 0.4653967  
## 2 chevrolet      15         0.6710383  
## 3 dodge          13.13514 0.4085464  
## 4 ford           14         0.3829708  
## 5 honda          24.44444 0.6478835  
## 6 hyundai        18.64286 0.4006470
```

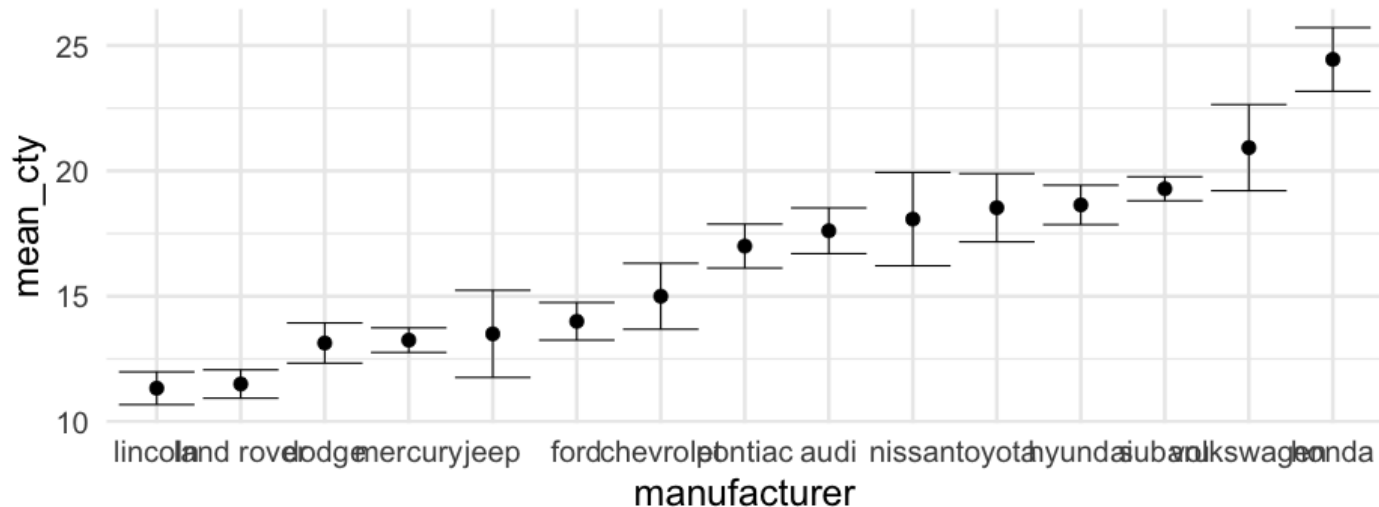
```
mpg_by_man %>%
  mutate(manufacturer = fct_reorder(manufacturer, mean_cty)) %>%
  ggplot(aes(manufacturer, mean_cty)) +
  geom_errorbar(aes(ymin = mean_cty + qnorm(0.025)*se_cty,
                    ymax = mean_cty + qnorm(0.975)*se_cty))
```



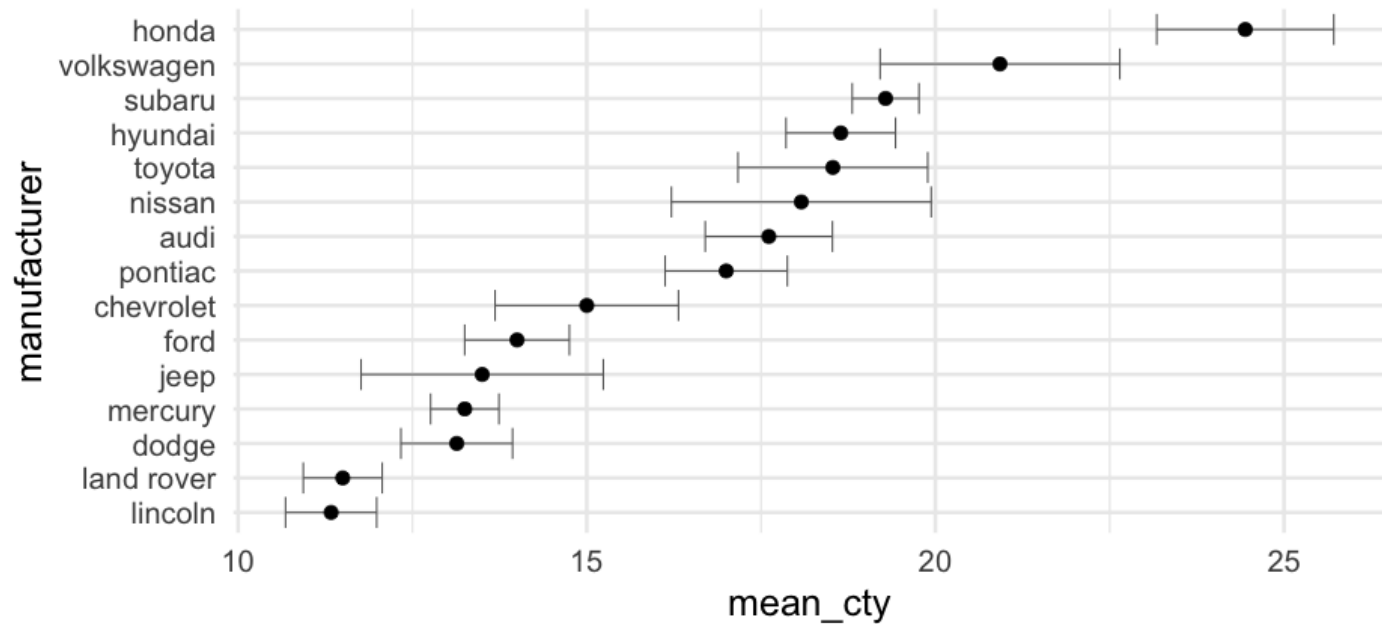
# Put points on top

Not under

```
mpg_by_man %>%  
  mutate(manufacturer = fct_reorder(manufacturer, mean_cty)) %>%  
  ggplot(aes(manufacturer, mean_cty)) +  
  geom_errorbar(aes(ymin = mean_cty + qnorm(0.025)*se_cty,  
                    ymax = mean_cty + qnorm(0.975)*se_cty)) +  
  geom_point()
```



```
mpg_by_man %>%
  mutate(manufacturer = fct_reorder(manufacturer, mean_cty)) %>%
  ggplot(aes(mean_cty, manufacturer)) +
  geom_errorbarh(aes(xmin = mean_cty - 1.96*se_cty,
                    xmax = mean_cty + 1.96*se_cty),
                color = "gray40") +
  geom_point()
```



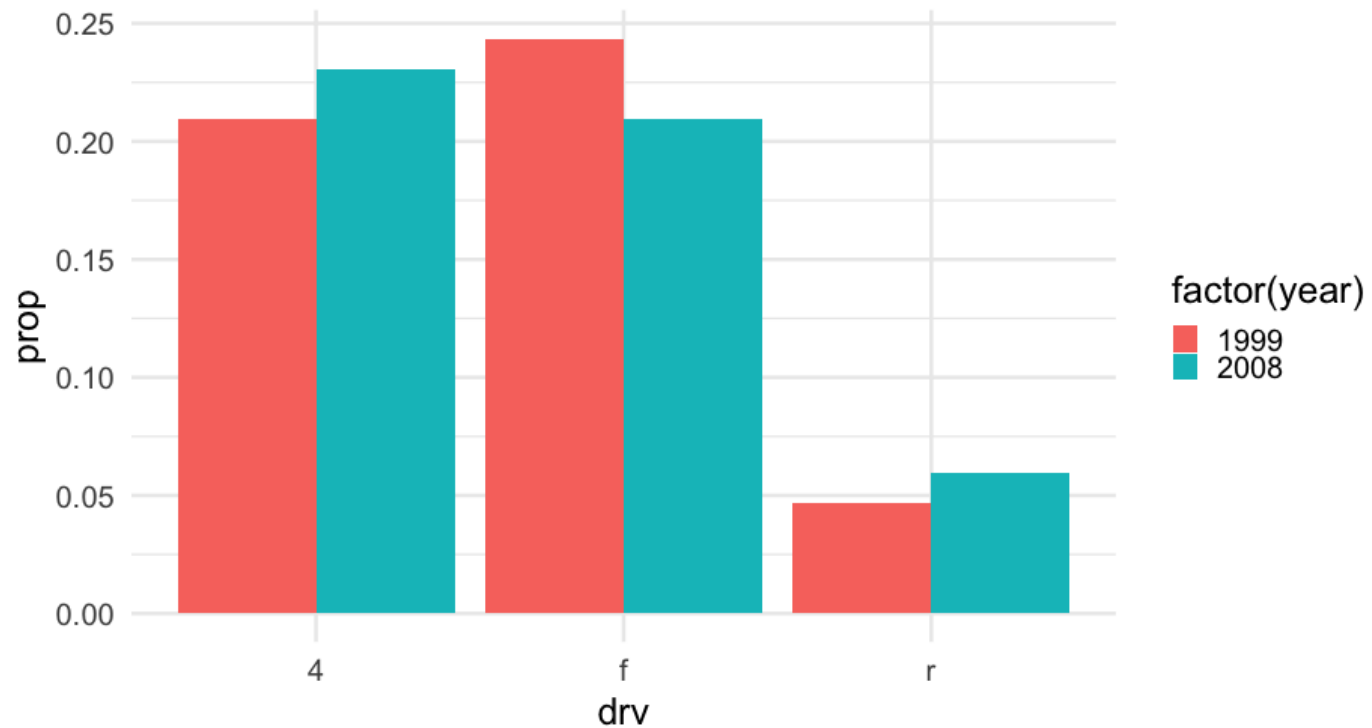
# Dodging

---

```
props <- mpg %>%  
  count(drv, year) %>%  
  mutate(prop = n/sum(n),  
         prop_se = sqrt((prop*(1-prop)) / n))  
  
head(props)
```

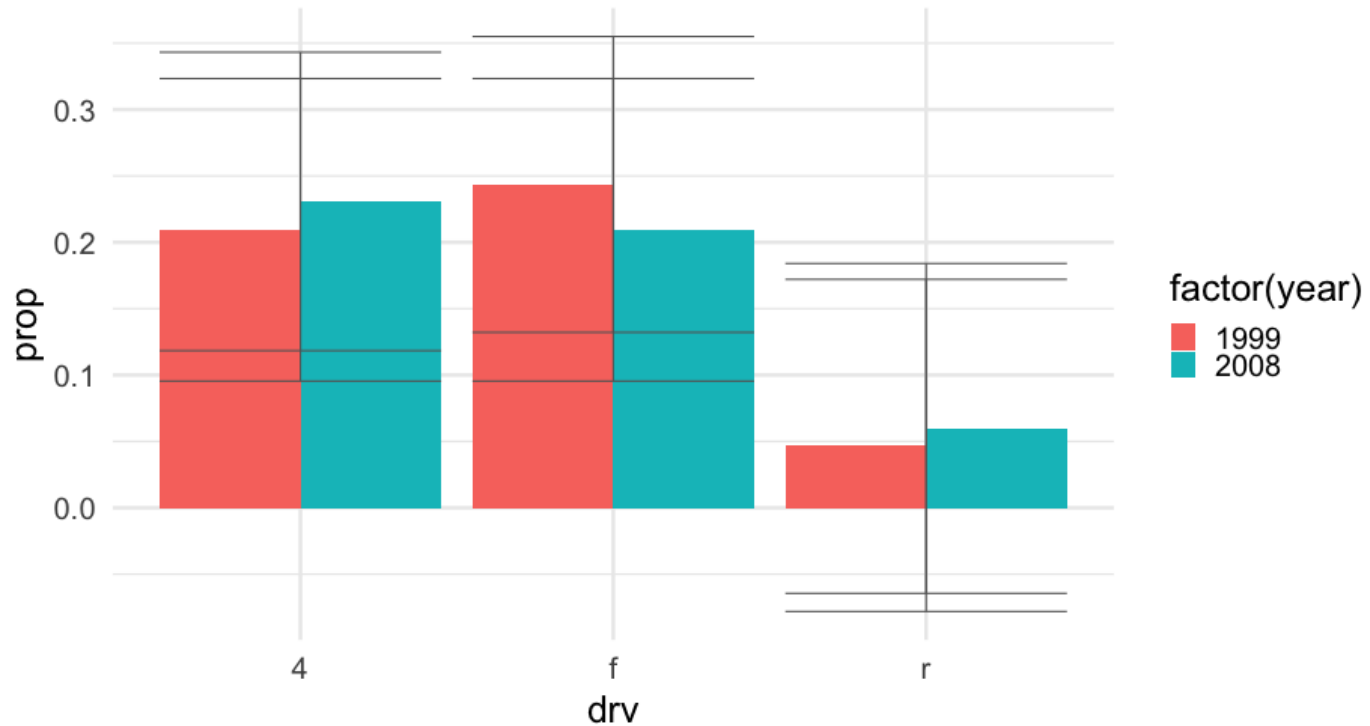
```
## # A tibble: 6 x 5  
##   drv      year      n      prop      prop_se  
##   <chr> <int> <int>    <dbl>    <dbl>  
## 1 4      1999     49 0.2094017 0.05812594  
## 2 4      2008     54 0.2307692 0.05733508  
## 3 f      1999     57 0.2435897 0.05685528  
## 4 f      2008     49 0.2094017 0.05812594  
## 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")
```

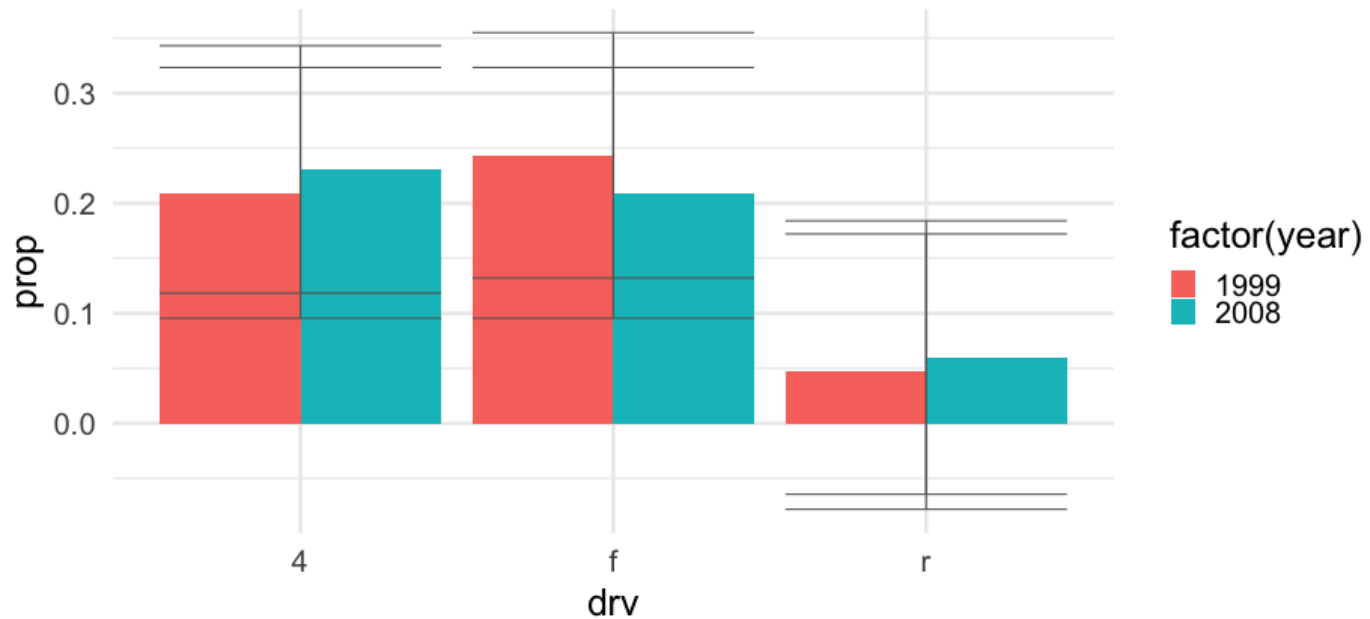




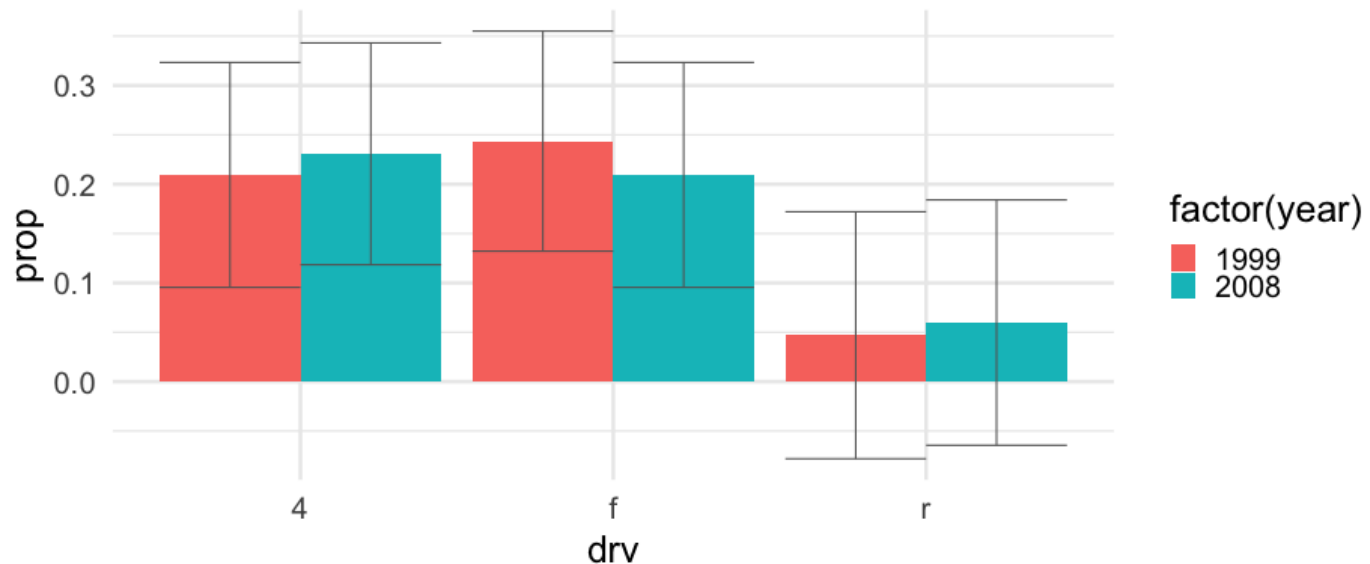
```
ggplot(props, aes(drv, prop)) +
  geom_col(aes(fill = factor(year)), position = "dodge") +
  geom_errorbar(aes(ymin = prop - 1.96*prop_se,
                    ymax = prop + 1.96*prop_se),
               color = "gray40")
```



```
pd <- position_dodge(.9)
ggplot(props, aes(drv, prop)) +
  geom_col(aes(fill = factor(year)), position = pd) +
  geom_errorbar(aes(ymin = prop - 1.96*prop_se,
                    ymax = prop + 1.96*prop_se),
               color = "gray40",
               position = pd)
```



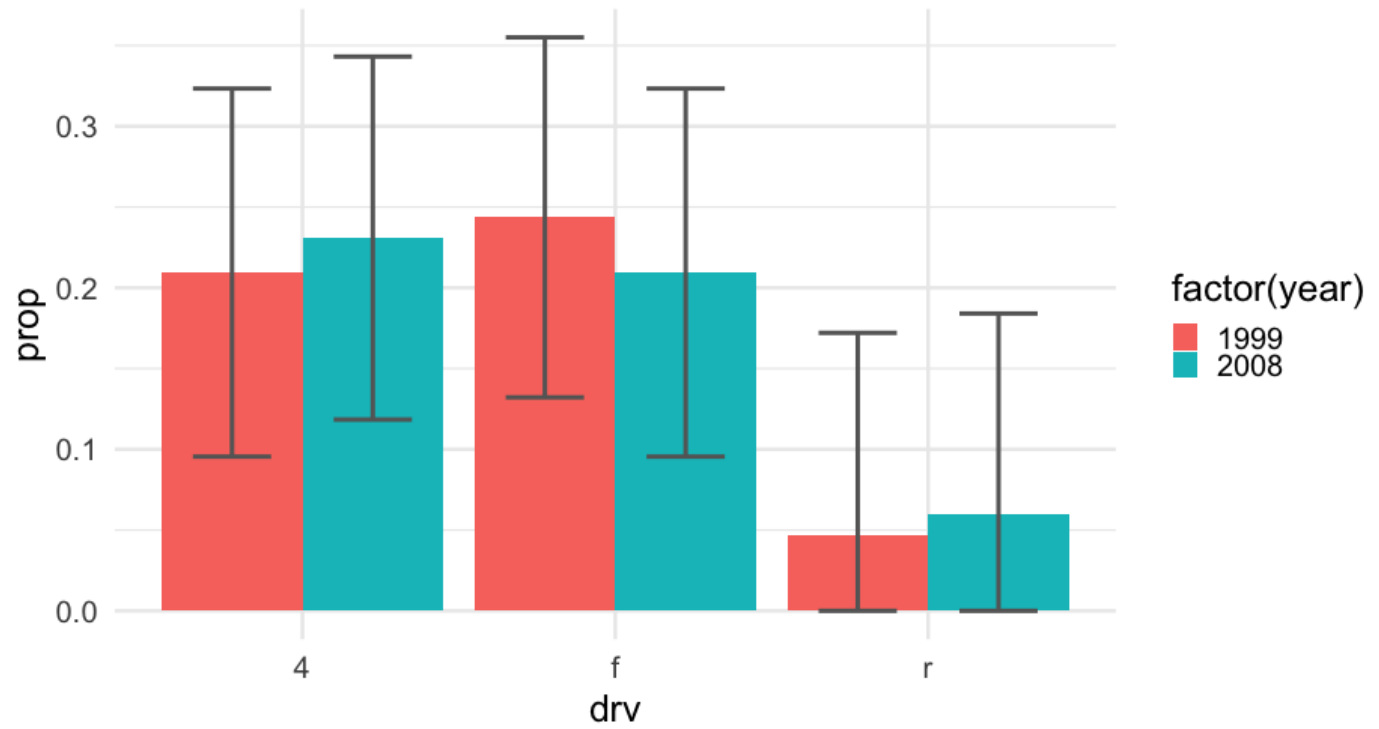
```
pd <- position_dodge(.9)
ggplot(props, aes(drv, prop)) +
  geom_col(aes(fill = factor(year)), position = pd) +
  geom_errorbar(aes(ymin = prop - 1.96*prop_se,
                    ymax = prop + 1.96*prop_se,
                    group = year),
               color = "gray40",
               position = pd)
```



```

pd <- position_dodge(.9)
ggplot(props, aes(drv, prop)) +
  geom_col(aes(fill = factor(year)), position = pd) +
  geom_errorbar(aes(ymin = ifelse(prop - 1.96*prop_se < 0,
                                0,
                                prop - 1.96*prop_se),
                    ymax = prop + 1.96*prop_se,
                    group = year),
               color = "gray40",
               position = pd,
               width = 0.5,
               size = 1.4)

```



# 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?

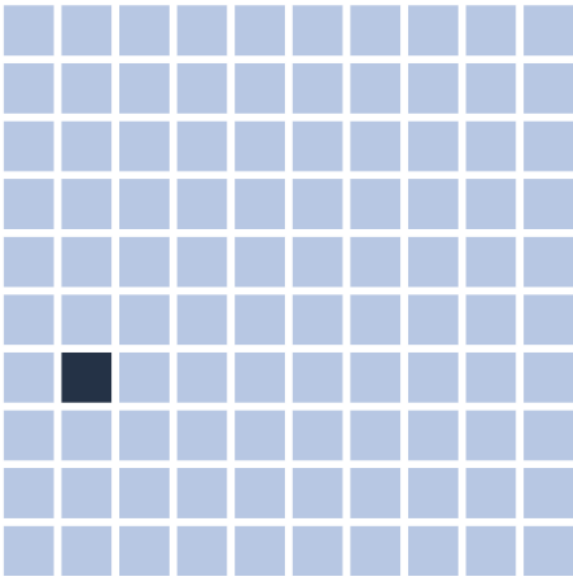
## Quantifying uncertainty

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

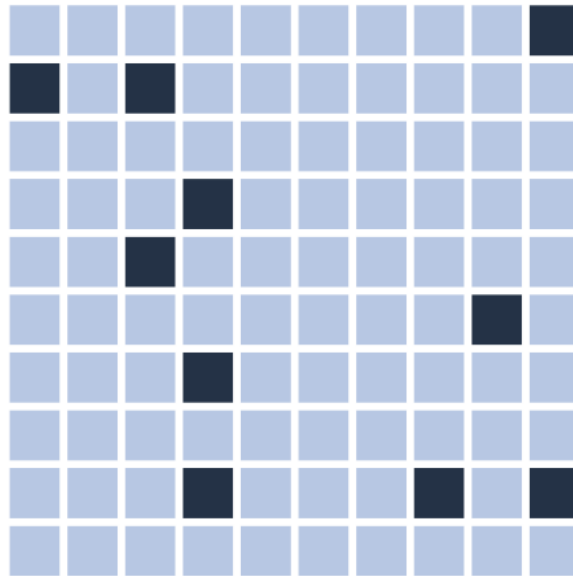
Framing a  
single  
uncertainty

---

1% chance



10% chance



40% chance



■ success ■ failure



# How do we make these?

---

- Start out by making a grid

```
grid <- expand.grid(x = 1:20, y = 1:20)
head(grid)
```

```
##      x y
##  1  1  1
##  2  2  1
##  3  3  1
##  4  4  1
##  5  5  1
##  6  6  1
```

```
tail(grid)
```

```
##      x y
## 395 15 20
## 396 16 20
## 397 17 20
## 398 18 20
## 399 19 20
## 400 20 20
```

# Look at the grid

---

```
ggplot(grid, aes(x, y)) +  
  geom_tile(color = "gray40",  
            fill = "white") +  
  theme_void()
```



# 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
```

# Create the variable

---

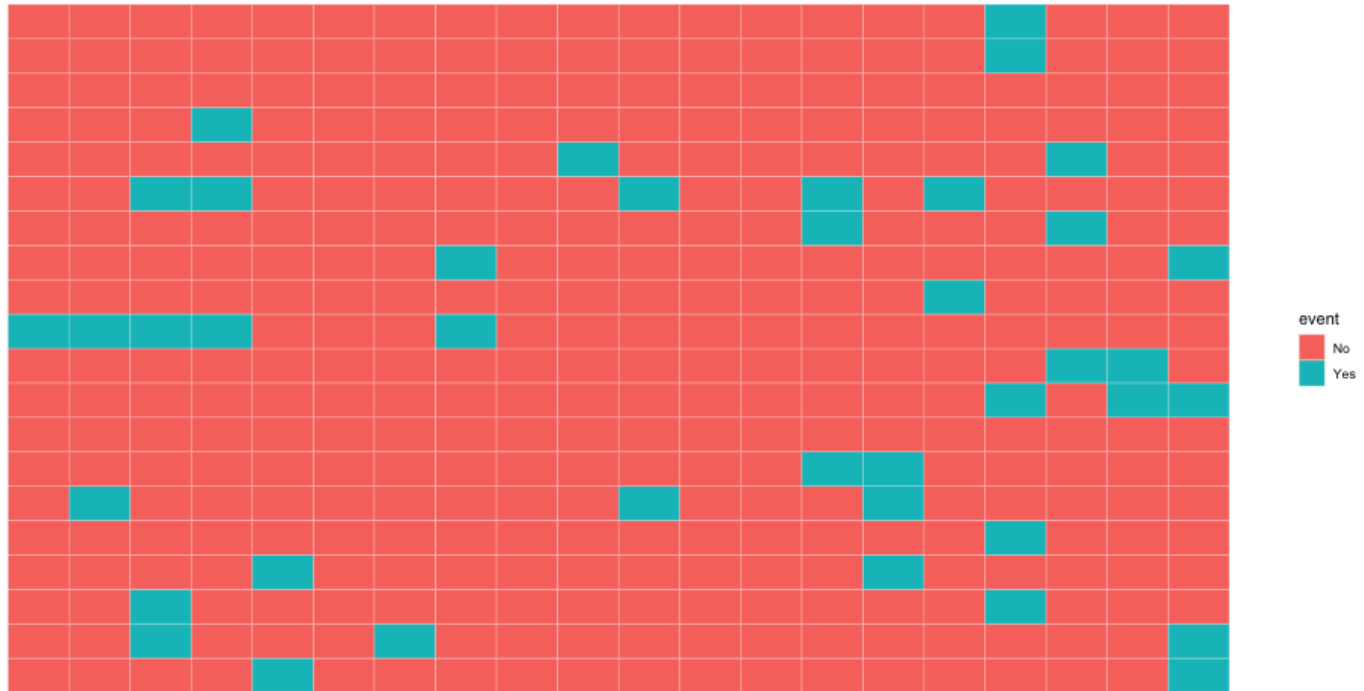
```
grid <- grid %>%  
  rownames_to_column("row_id") %>%  
  mutate(event = ifelse(row_id %in% samp, "Yes", "No"))  
head(grid)
```

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

# Fill in

---

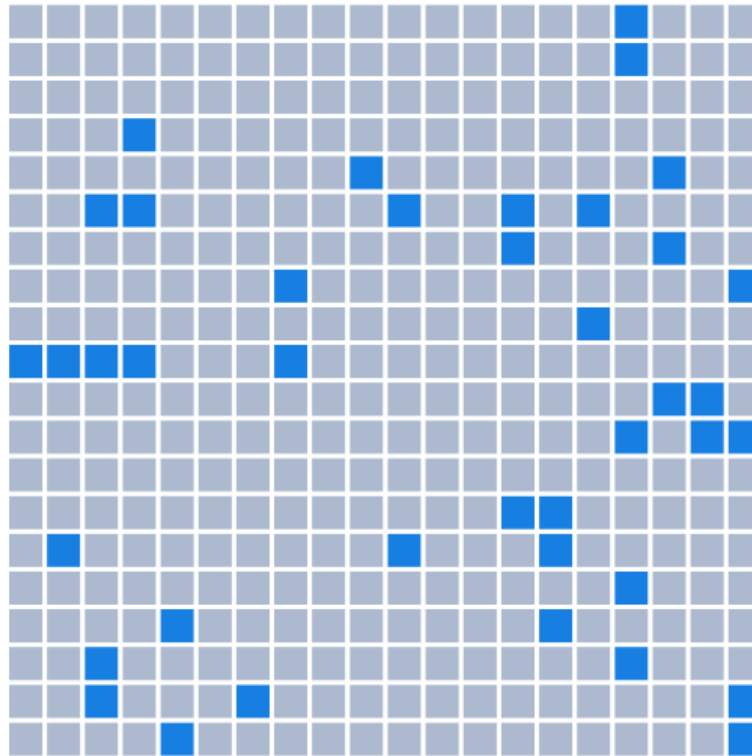
```
ggplot(grid, aes(x, y)) +  
  geom_tile(aes(fill = event), color = "white") +  
  theme_void()
```



# 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"))
```

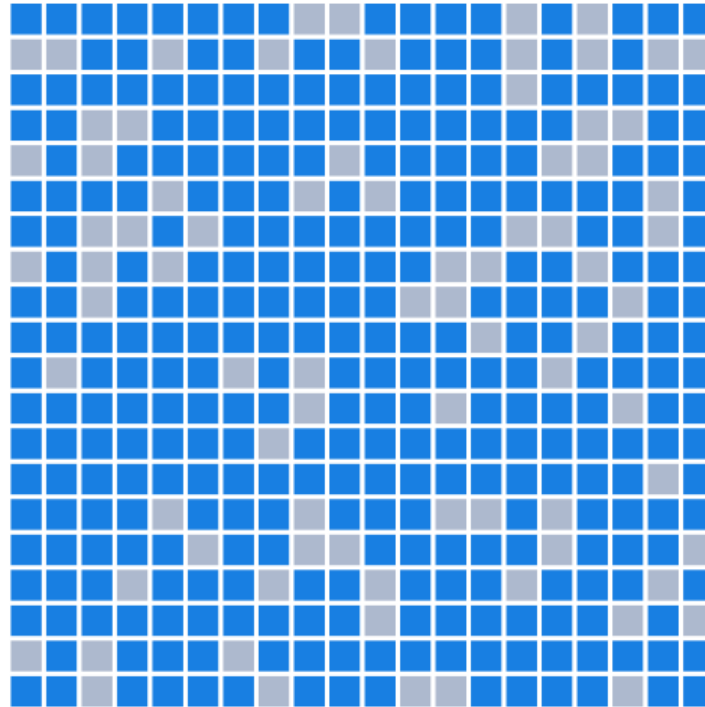


Event Occurred     No     Yes



# Chance of rain

---

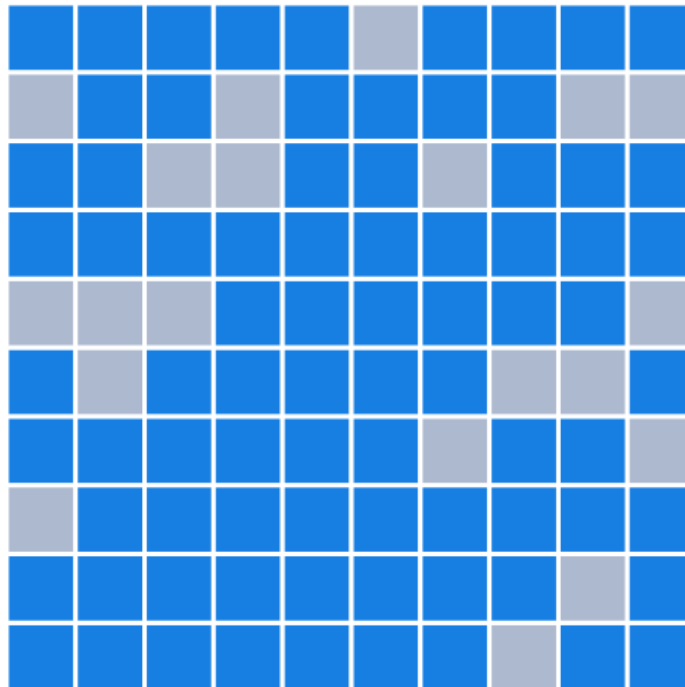


Event Occurred    ■ No    ■ Yes

# Vary grid size

---

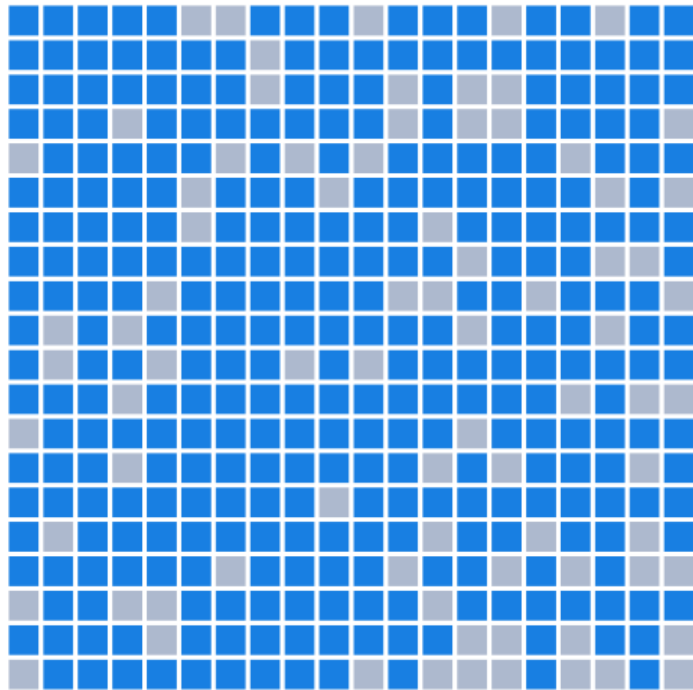
10 x 10



# Vary grid size

---

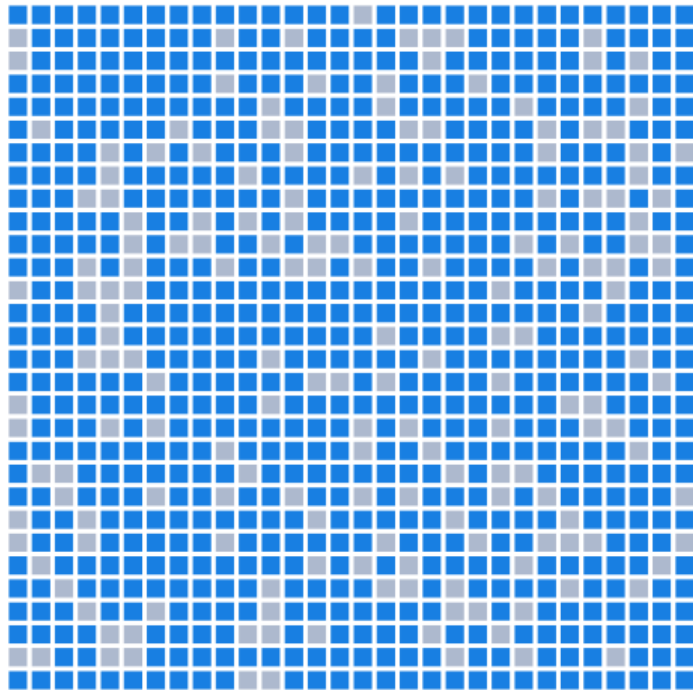
20 x 20



# Vary grid size

---

30 x 30



(probs too many)

Non-discrete  
probabilities

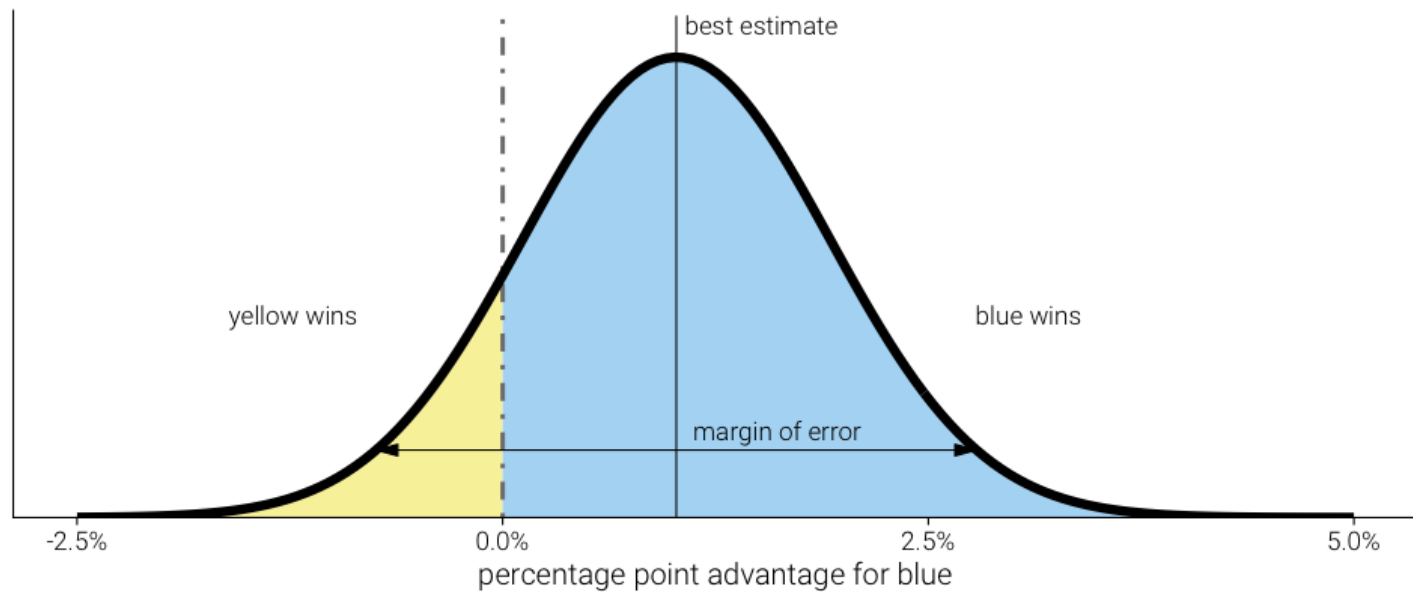
---

# Hypothetical

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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  $sd = 0.9$

.

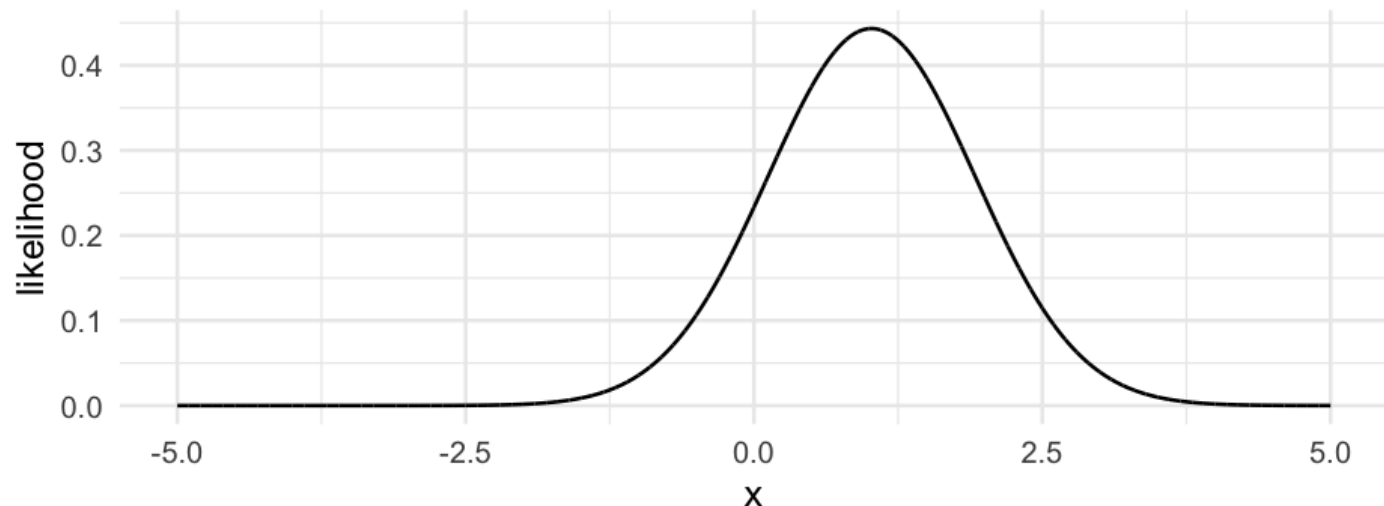
- What's the chance the end result is below zero?

# The hard way

---

Calculate the exact probability of data below zero under this distribution

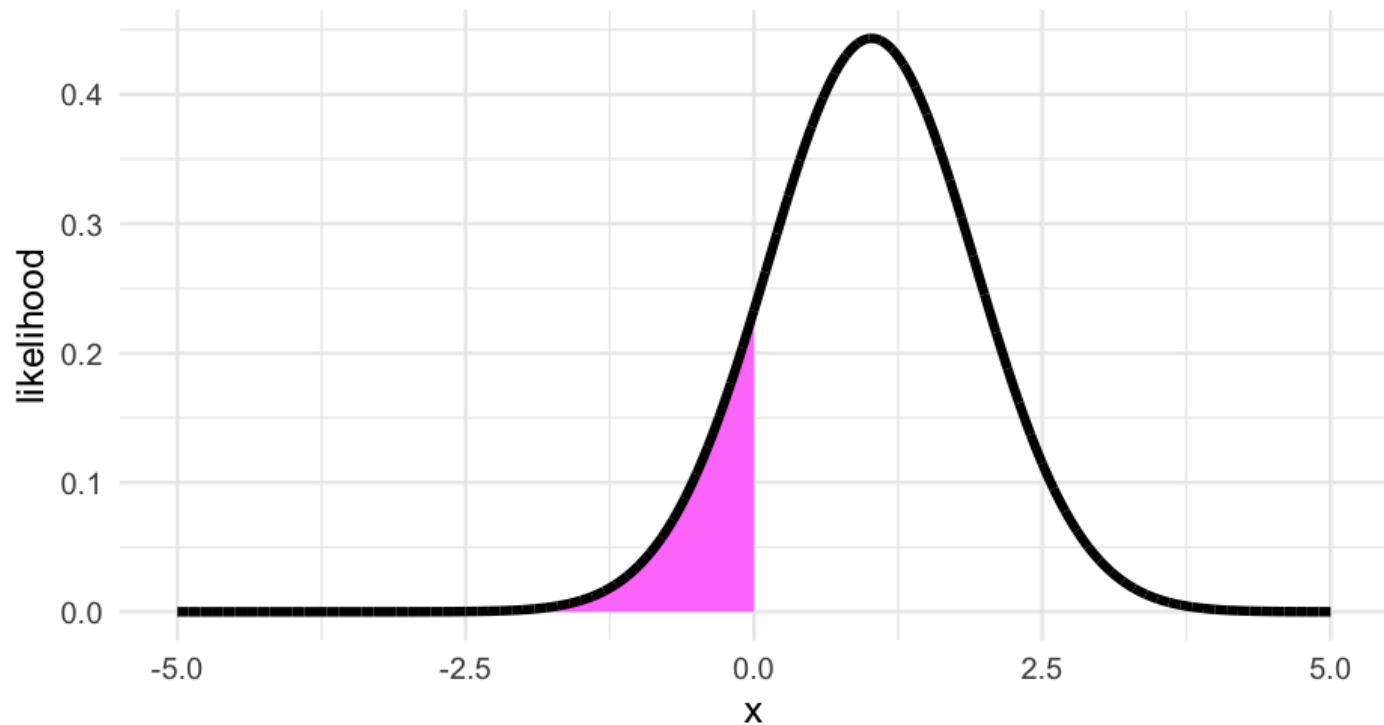
```
x <- seq(-5, 5, 0.001)
likelihood <- dnorm(x, 1.02, 0.9)
sim <- data.frame(x, likelihood)
ggplot(sim, aes(x, likelihood)) +
  geom_line(size = 1.2)
```





# How do we calculate this portion?

---



# Integrate

---

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

```
## [1] 0.129
```

# Easier: Simulate

---

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

```
##
## FALSE  TRUE
##  0.13  0.87
```

# Discretized plot

---

```
ppoints(50)
```

```
## [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 0.27 0.29 0.31 0.33 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 0.61 0.63 0.65 0.67 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 0.95 0.97 0.99
```

```
qnorm(ppoints(50), 1.02, 0.9)
```

```
## [1] -1.07371 -0.67271 -0.46037 -0.30821 -0.18668 -0.08388 0.00625 0.09875 0.19125 0.28375 0.37625 0.46875 0.56125 0.65375 0.74625 0.83875 0.93125 1.02375 1.11625 1.20875 1.30125 1.39375 1.48625 1.57875 1.67125 1.76375 1.85625 1.94875 2.04125 2.13375 2.22625 2.31875 2.41125 2.50375 2.59625 2.68875 2.78125 2.87375 2.96625 3.05875 3.15125 3.24375 3.33625 3.42875 3.52125 3.61375 3.70625 3.79875 3.89125 3.98375 4.07625 4.16875 4.26125 4.35375 4.44625 4.53875 4.63125 4.72375 4.81625 4.90875 5.00125 5.09375 5.18625 5.27875 5.37125 5.46375 5.55625 5.64875 5.74125 5.83375 5.92625 6.01875 6.11125 6.20375 6.29625 6.38875 6.48125 6.57375 6.66625 6.75875 6.85125 6.94375 7.03625 7.12875 7.22125 7.31375 7.40625 7.49875 7.59125 7.68375 7.77625 7.86875 7.96125 8.05375 8.14625 8.23875 8.33125 8.42375 8.51625 8.60875 8.70125 8.79375 8.88625 8.97875 9.07125 9.16375 9.25625 9.34875 9.44125 9.53375 9.62625 9.71875 9.81125 9.90375 10.0
```

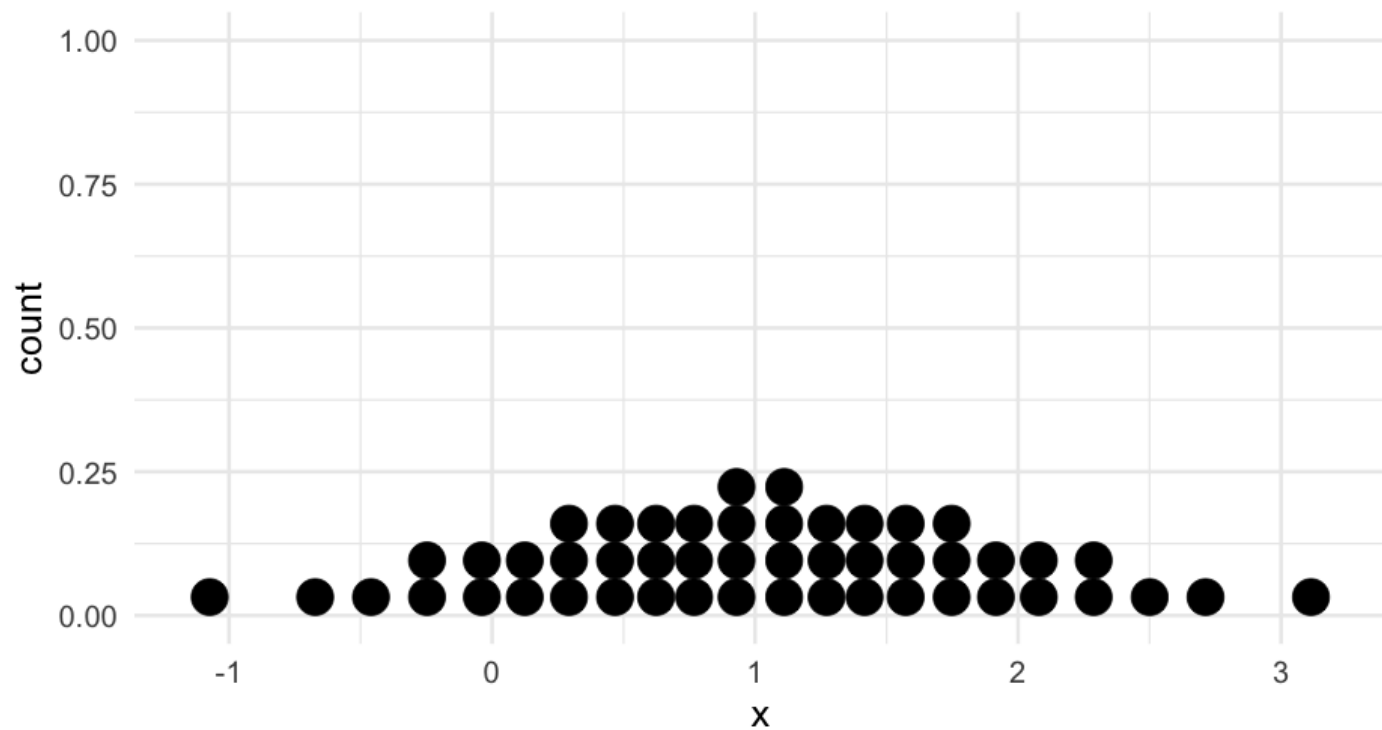
```
discretized <- data.frame(  
  x = qnorm(ppoints(50), 1.02, 0.9)  
  ) %>%  
  mutate(winner = ifelse(x <= 0, "#b1daf4", "#f8f1a9"))  
  
head(discretized)
```

```
##           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
```

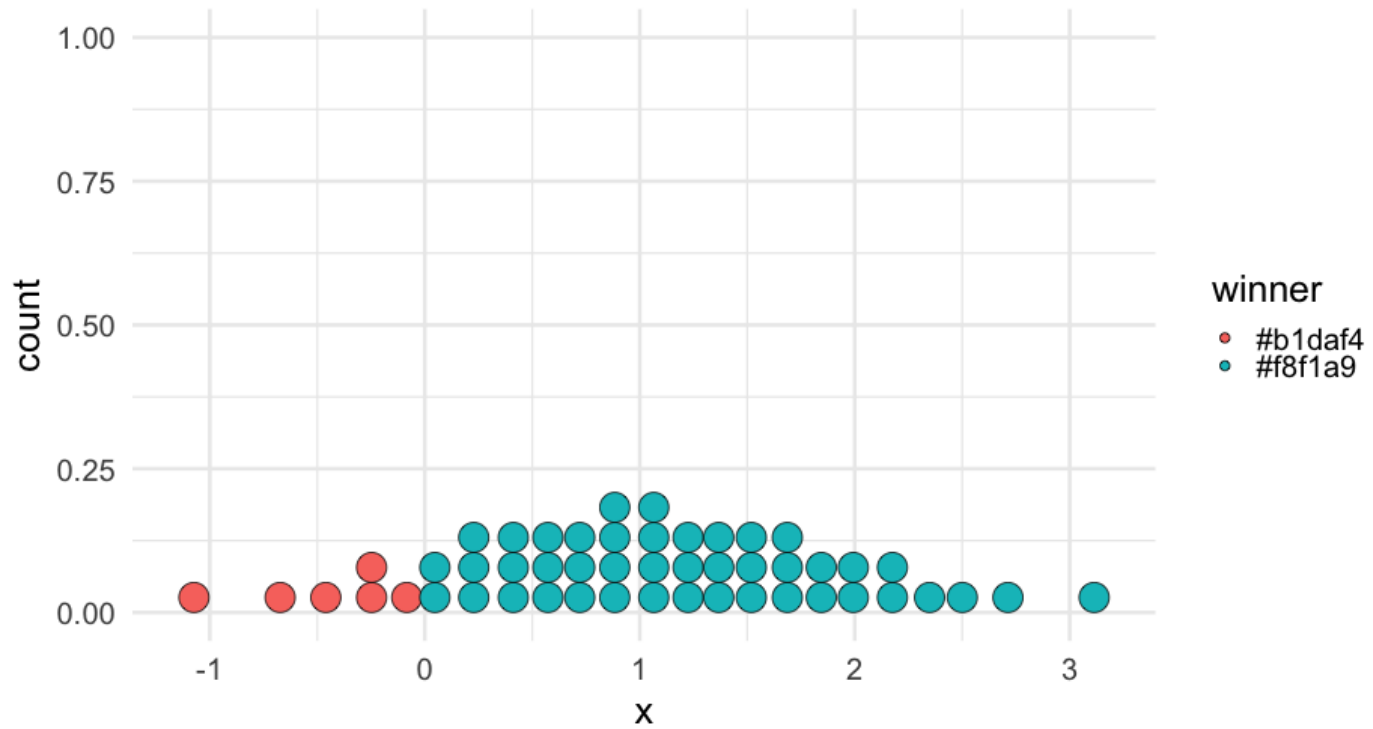
```
tail(discretized)
```

```
##           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
```

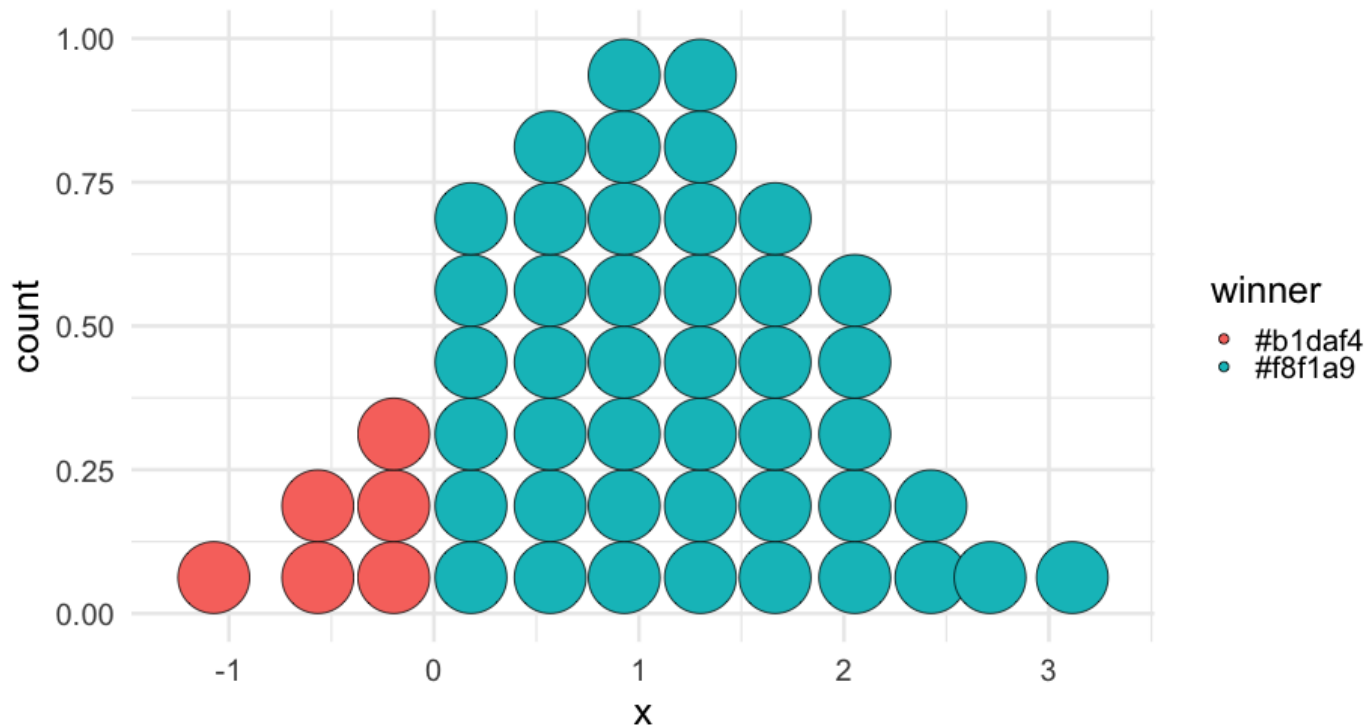
```
ggplot(discretized, aes(x)) +  
  geom_dotplot()
```



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

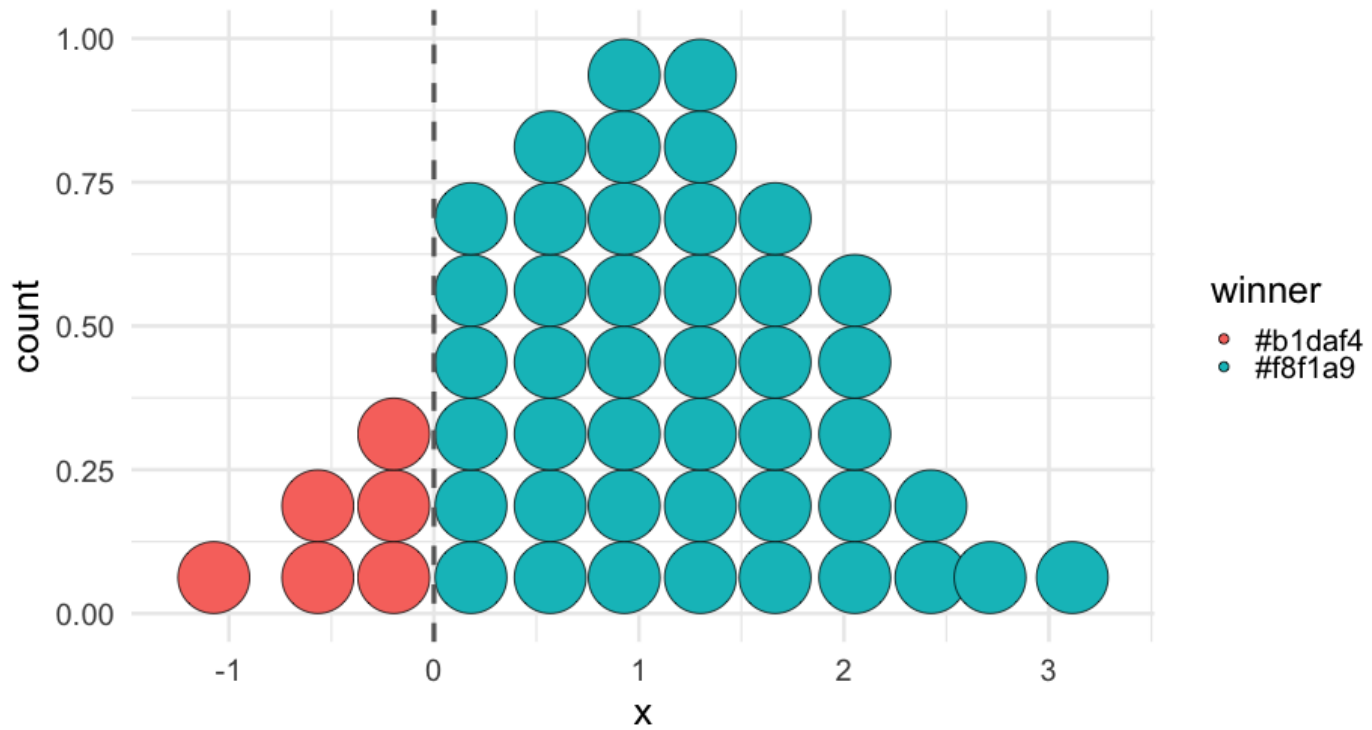


```
ggplot(discretized, aes(x)) +  
  geom_dotplot(aes(fill = winner), binwidth = 0.35)
```

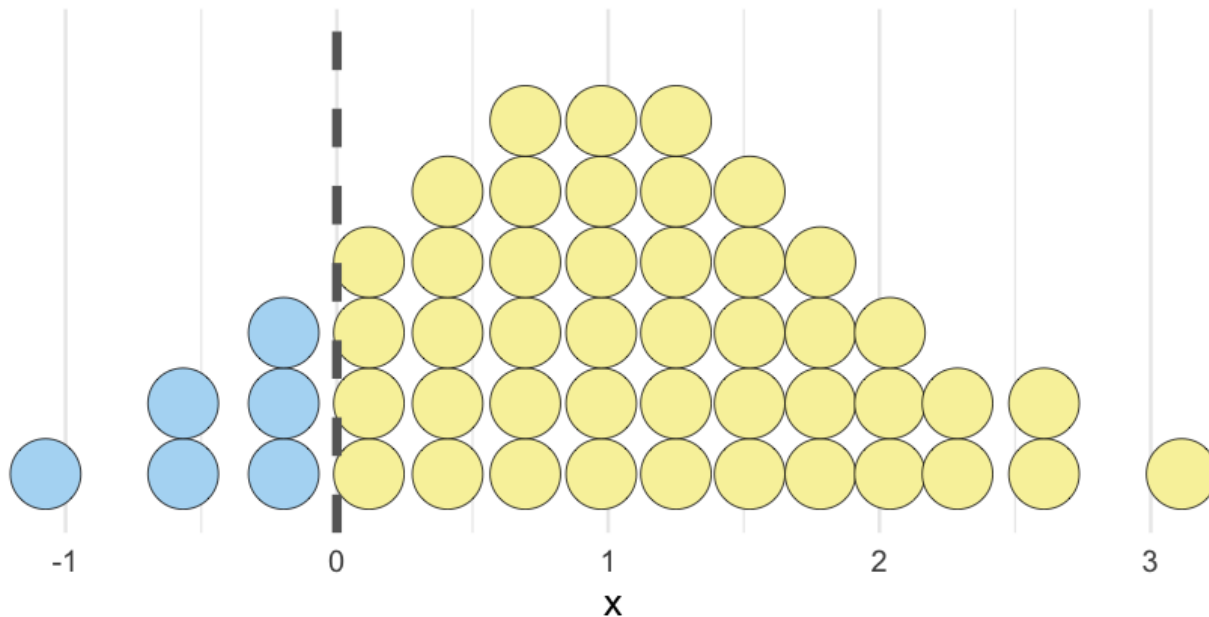




```
ggplot(discretized, aes(x)) +  
  geom_dotplot(aes(fill = winner), binwidth = 0.35) +  
  geom_vline(xintercept = 0,  
             color = "gray40",  
             linetype = "dashed",  
             size = 1.5)
```



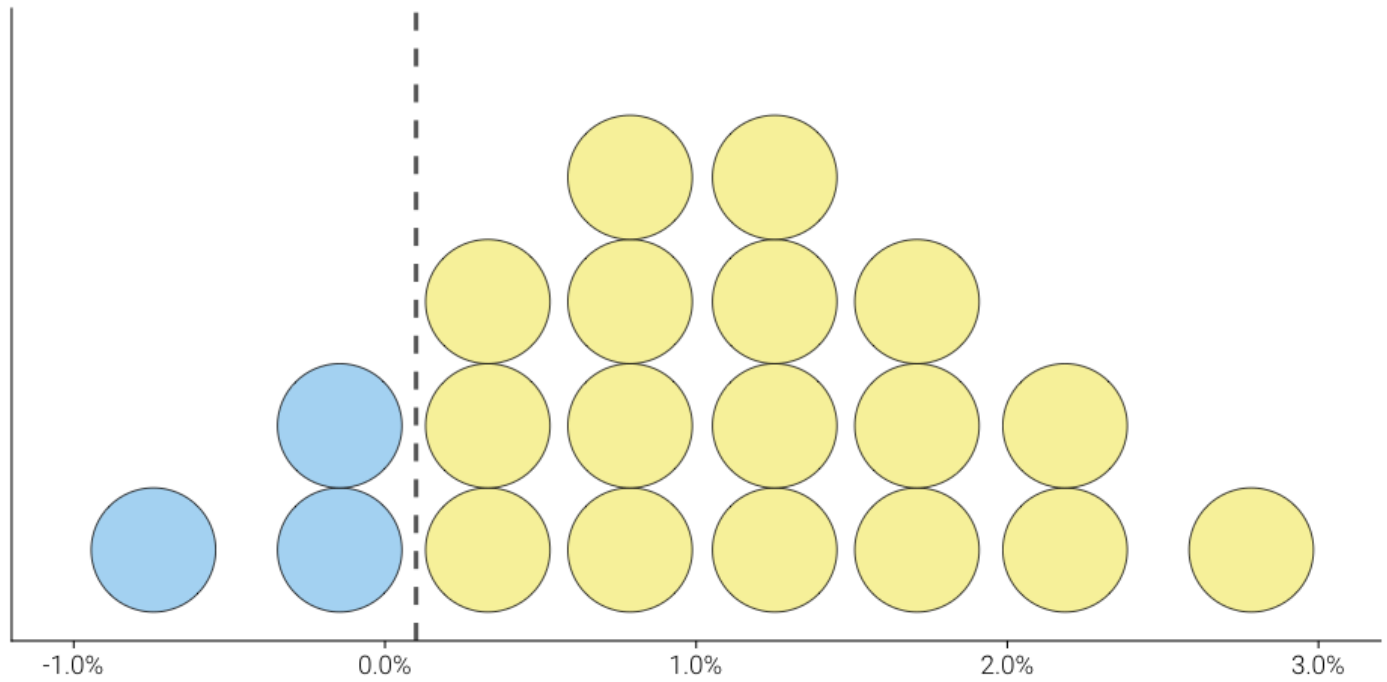
```
ggplot(discretized, aes(x)) +
  geom_dotplot(aes(fill = winner), binwidth = 0.26) +
  geom_vline(xintercept = 0,
             color = "gray40",
             linetype = 2,
             size = 3) +
  scale_fill_identity(guide = "none") +
  scale_y_continuous(name = "",
                     breaks = NULL)
```



# Probs too many though

---

```
discretized2 <- data.frame(  
  x = qnorm(ppoints(20), 1.02, 0.9)  
  ) %>%  
  mutate(winner = ifelse(x <= 0, "#b1daf4", "#f8f1a9"))  
  
ggplot(discretized2, aes(x)) +  
  geom_dotplot(aes(fill = winner), binwidth = 0.4) +  
  geom_vline(  
    xintercept = 0.1,  
    color = "gray40",  
    linetype = 2,  
    size = 1.4) +  
  scale_fill_identity(guide = "none") +  
  scale_x_continuous(  
    name = "",  
    limits = c(-1, 3),  
    labels = scales::percent_format(scale = 1)  
  ) +  
  theme_dviz_open(20, font_family = "Roboto Light") +  
  scale_y_continuous(breaks = NULL,  
                     name = "") +  
  labs(caption = "Each ball represents 5% probability")
```



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

---

- 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
```

```
## [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

---

```
samp10b <- rnorm(n = 10, mean = 100, sd = 10)  
samp10b
```

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

```
mean(samp10b)
```

```
## [1] 102
```



# Do it a bunch of times

---

```
samples <- 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
```

- 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.

```
samples2 <- replicate(1000, rnorm(100, mean = 100, sd = 10),  
                      simplify = FALSE)  
map_dbl(samples2, mean) %>%  
  sd()
```

```
## [1] 0.973
```

# Visualize the sampling distributions

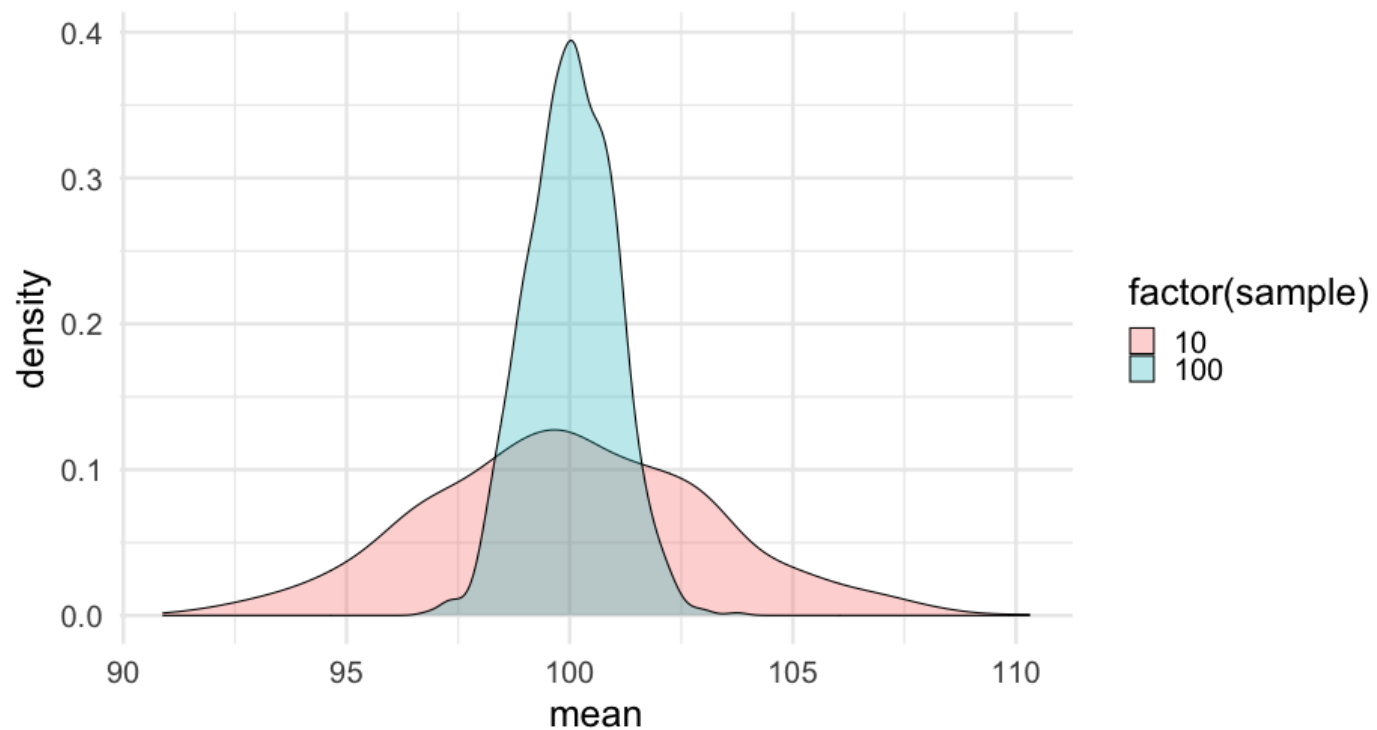
---

```
sample_means <- tibble(iter = rep(1:1000, 2),  
                        sample = rep(c(10, 100), each = 1000),  
                        mean = c(map_dbl(samples, mean),  
                                map_dbl(samples2, mean))  
                        )
```

sample\_means

```
## # A tibble: 2,000 x 3  
##   iter sample      mean  
##   <int>  <dbl>    <dbl>  
## 1      1      10  95.75441  
## 2      2      10 103.2204  
## 3      3      10  99.91284  
## 4      4      10 102.2169  
## 5      5      10 101.2308  
## 6      6      10  96.37082  
## # ... with 1,994 more rows
```

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



# Fit a model

---

```
m <- lm(cty ~ displ + class, mpg)
summary(m)
```

```
##
## Call:
## lm(formula = cty ~ displ + class, data = mpg)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5.269  -1.150  -0.016   1.034  12.978
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    28.777     1.473   19.54 < 2e-16 ***
## displ         -2.172     0.175  -12.43 < 2e-16 ***
## classcompact   -3.599     1.252   -2.87  0.0044 **
## classmidsize   -3.676     1.206   -3.05  0.0026 **
## classminivan   -5.595     1.306   -4.28  2.7e-05 ***
## classpickup    -6.182     1.121   -5.51  9.6e-08 ***
## classsubcompact -2.629     1.237   -2.13  0.0346 *
## classsuvs      -5.599     1.087   -5.15  5.7e-07 ***
## ---
## 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

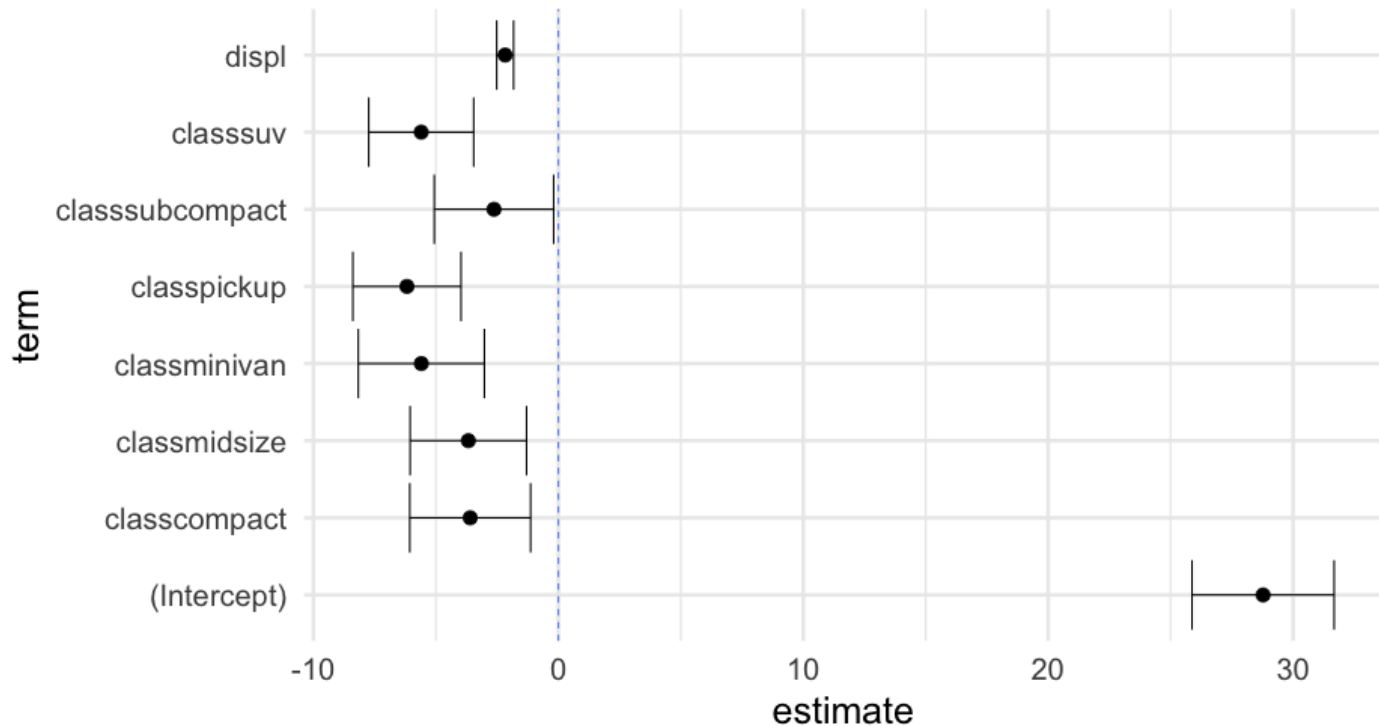
---

```
tidied_m <- broom::tidy(m, conf.int = TRUE)
```

```
tidied_m
```

```
## # A tibble: 8 x 7
##   term          estimate std.error statistic      p.value  conf.low conf.high
##   <chr>          <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
## 1 (Intercept)  28.77682  1.472892  19.53763 1.905873e-50 25.87446 31.67919
## 2 displ       -2.171562  0.1746638 -12.43281 2.197130e-27 -2.515740 -1.827384
## 3 classcompact -3.599125  1.252190   -2.874265 4.436052e- 3 -6.066585 -1.131665
## 4 classmidsize -3.675526  1.206253   -3.047061 2.585762e- 3 -6.052466 -1.298586
## 5 classminivan -5.595070  1.305993   -4.284151 2.714490e- 5 -8.168550 -3.021590
## 6 classpickup  -6.182466  1.121448   -5.512931 9.600087e- 8 -8.392297 -3.973035
## # ... with 2 more rows
```

```
ggplot(tidied_m, aes(term, estimate)) +
  geom_hline(yintercept = 0,
             color = "cornflowerblue",
             linetype = 2) +
  geom_errorbar(aes(ymin = conf.low, ymax = conf.high)) +
  geom_point() +
  coord_flip()
```

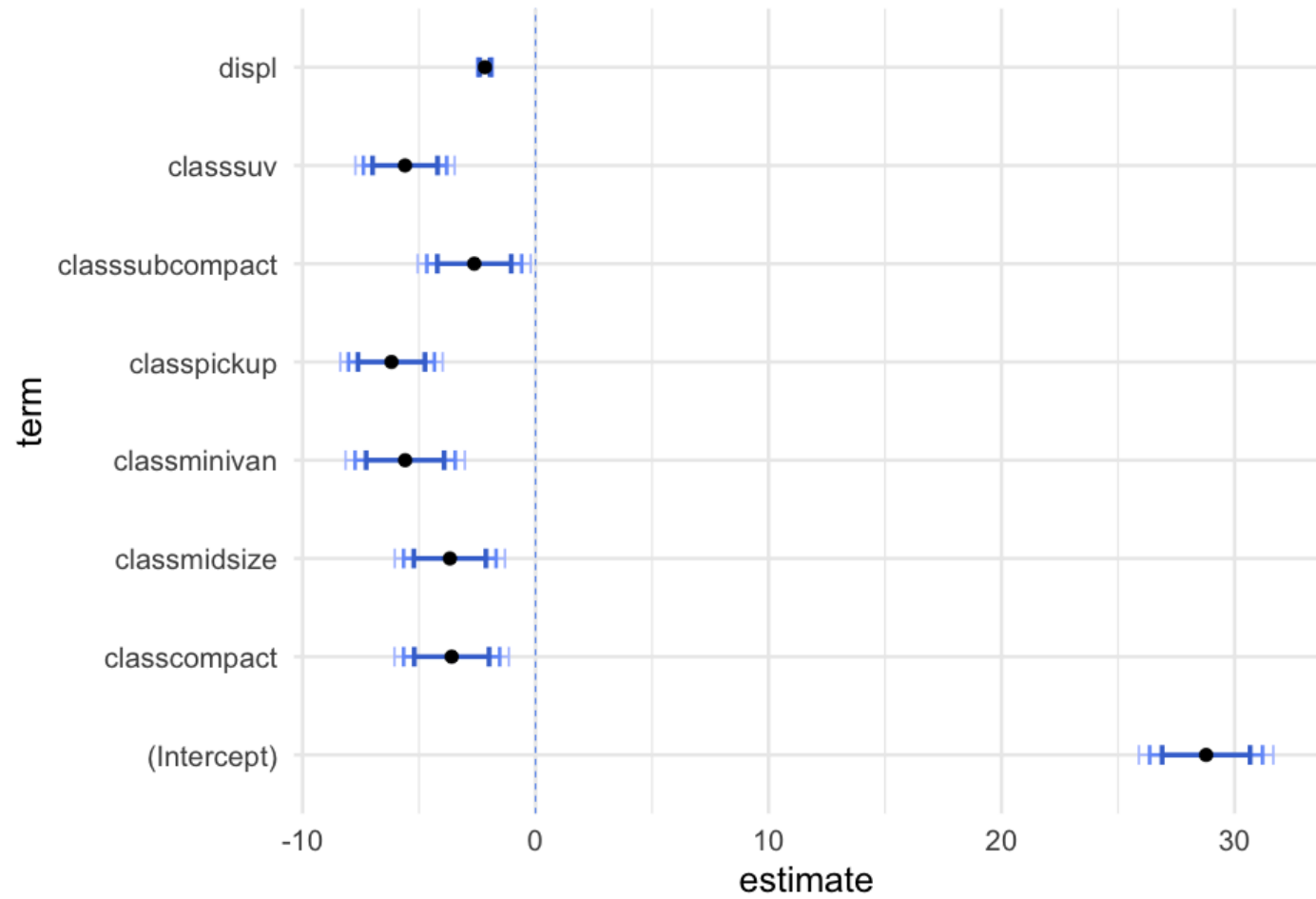




# Multiple error bars

---

```
library(colorspace)
ggplot(tidied_m, aes(term, estimate)) +
  geom_hline(yintercept = 0,
             color = "cornflowerblue",
             linetype = 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()
```

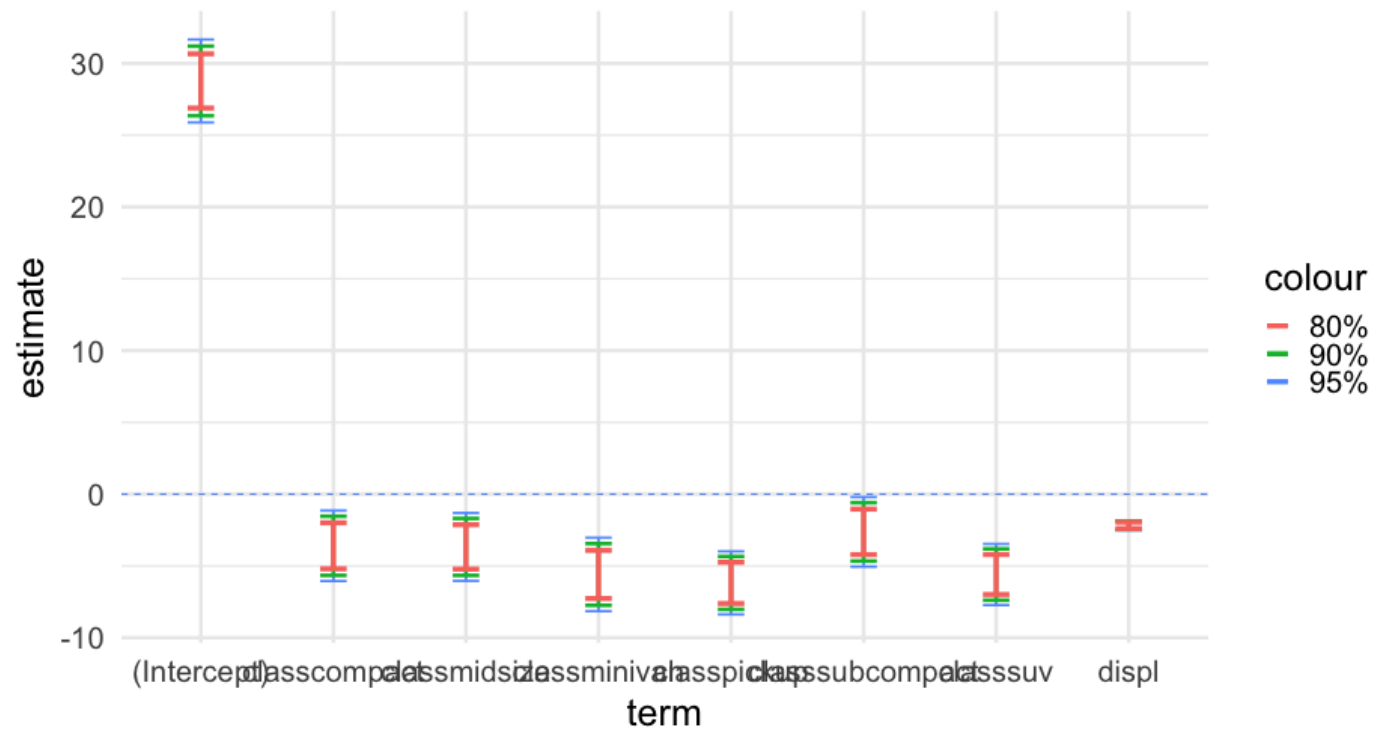


# Add levels to legend

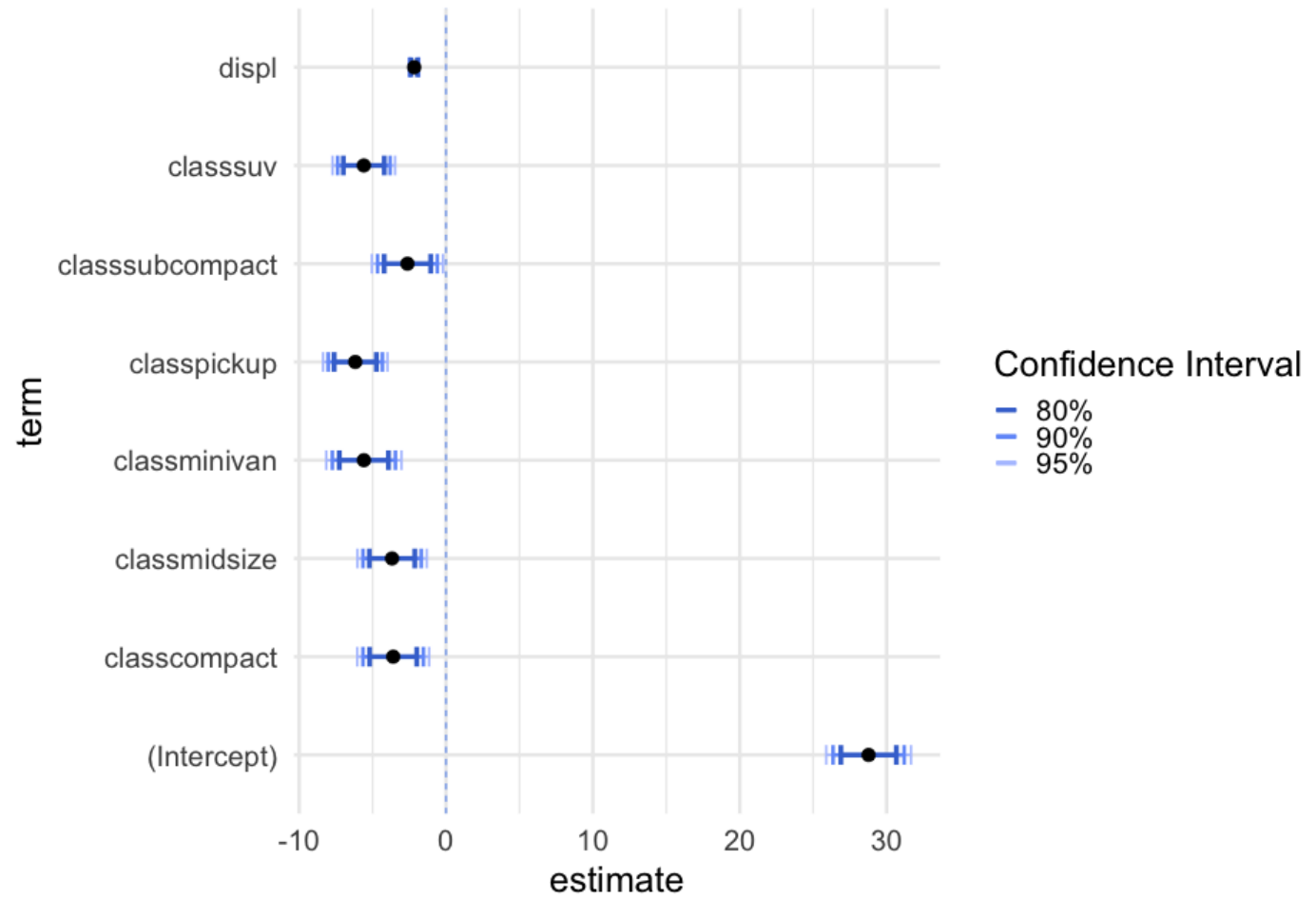
---

```
p <- ggplot(tidied_m, aes(term, estimate)) +  
  geom_hline(yintercept = 0,  
             color = "cornflowerblue",  
             linetype = 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 + qnorm(.05)*std.error,  
                   ymax = 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)
```

p

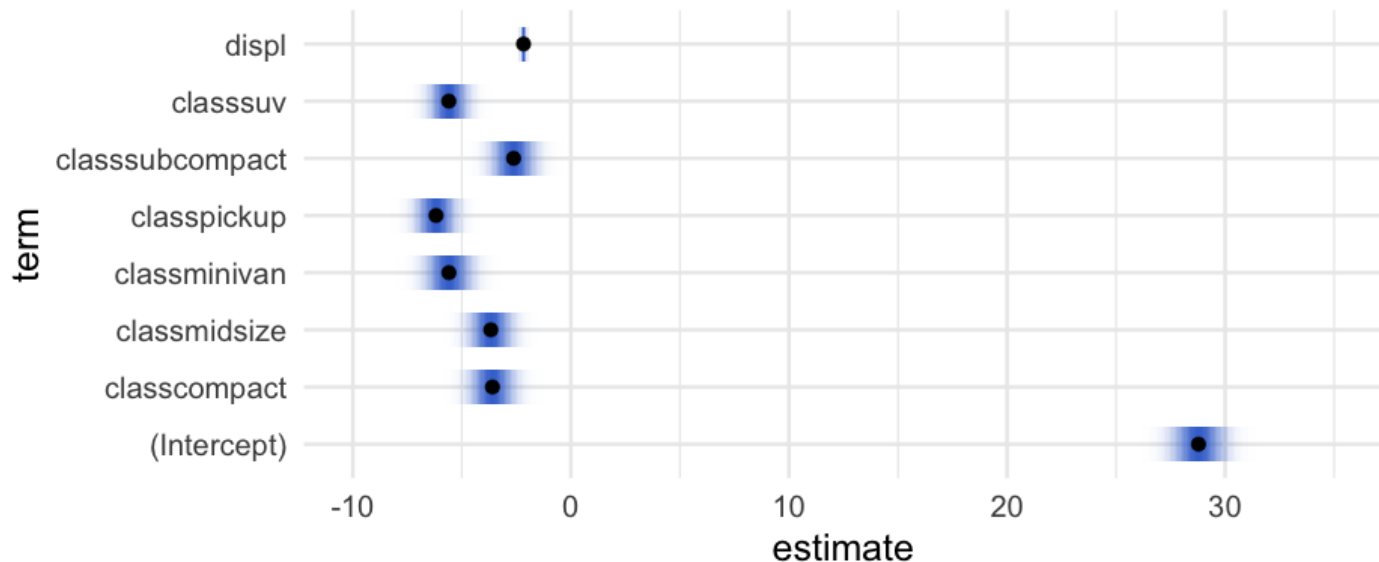


```
p +  
  scale_color_manual("Confidence Interval",  
                     values = c("#4375D3",  
                                lighten("#4375D3", .3),  
                                lighten("#4375D3", .6))) +  
  geom_point() +  
  coord_flip()
```



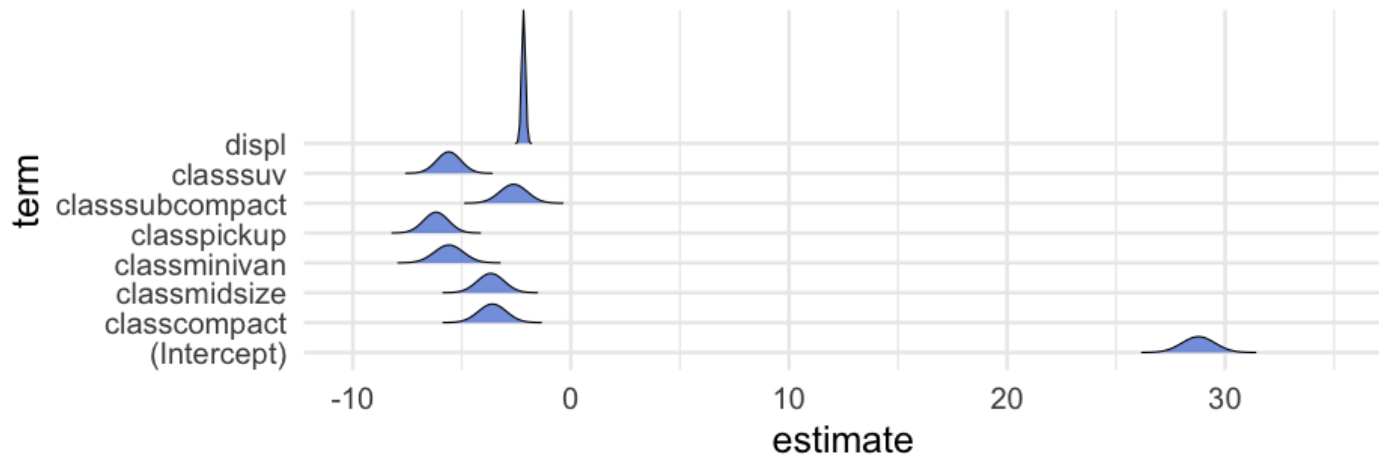
# Density stripes

```
#devtools::install_github("wilkelab/ungeviz")
library(ungeviz)
ggplot(tidied_m, aes(estimate, term)) +
  stat_confidence_density(aes(moe = std.error),
    fill = "#4375D3",
    height = 0.6) +
  xlim(-10, 35) +
  geom_point()
```



# Actual densities

```
library(ggribes)
ggplot(tidied_m, aes(estimate, term)) +
  stat_confidence_density(aes(moe = std.error,
                             height = stat(density)),
    geom = "ridgeline",
    confidence = 0.95,
    min_height = 0.001,
    alpha = 0.7,
    fill = "#4375D3") +
  xlim(-10, 35)
```





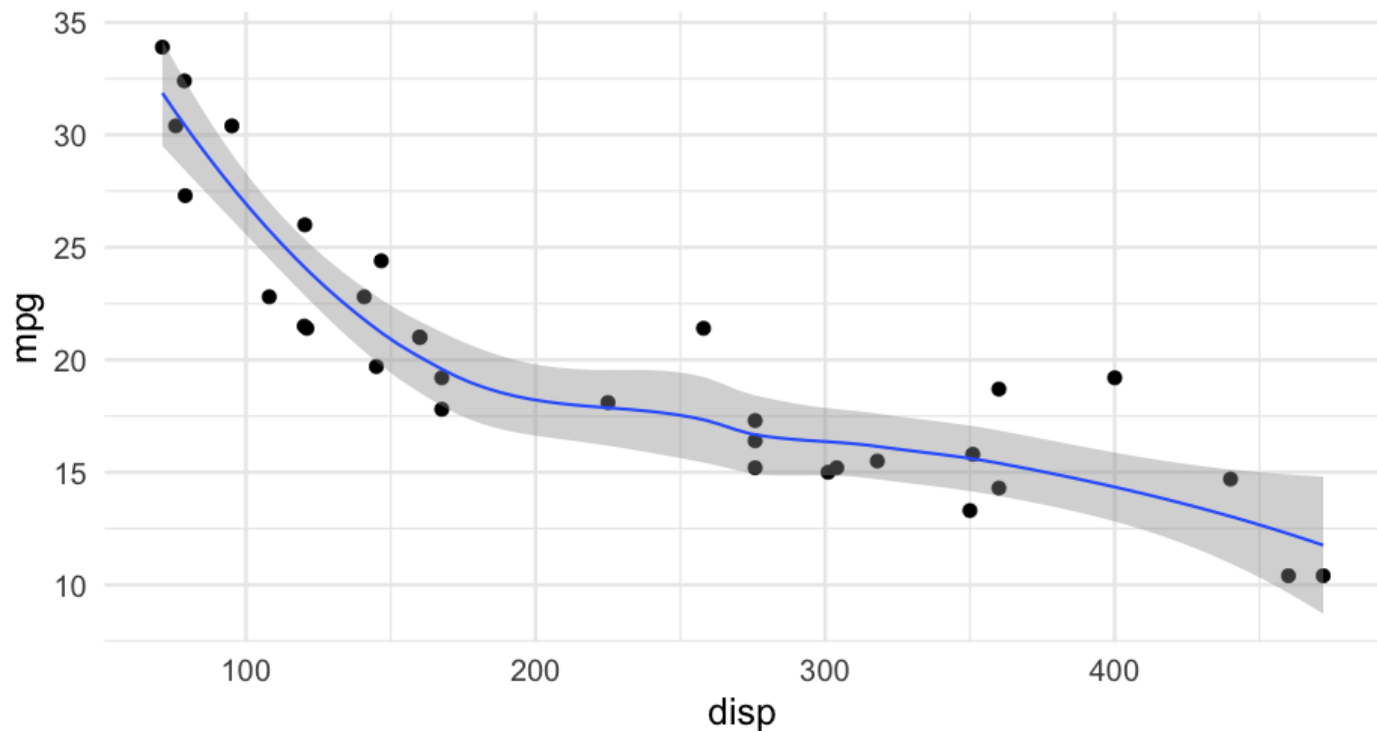
# HOPs

---

Hypothetical Outcome Plots (and related plots)

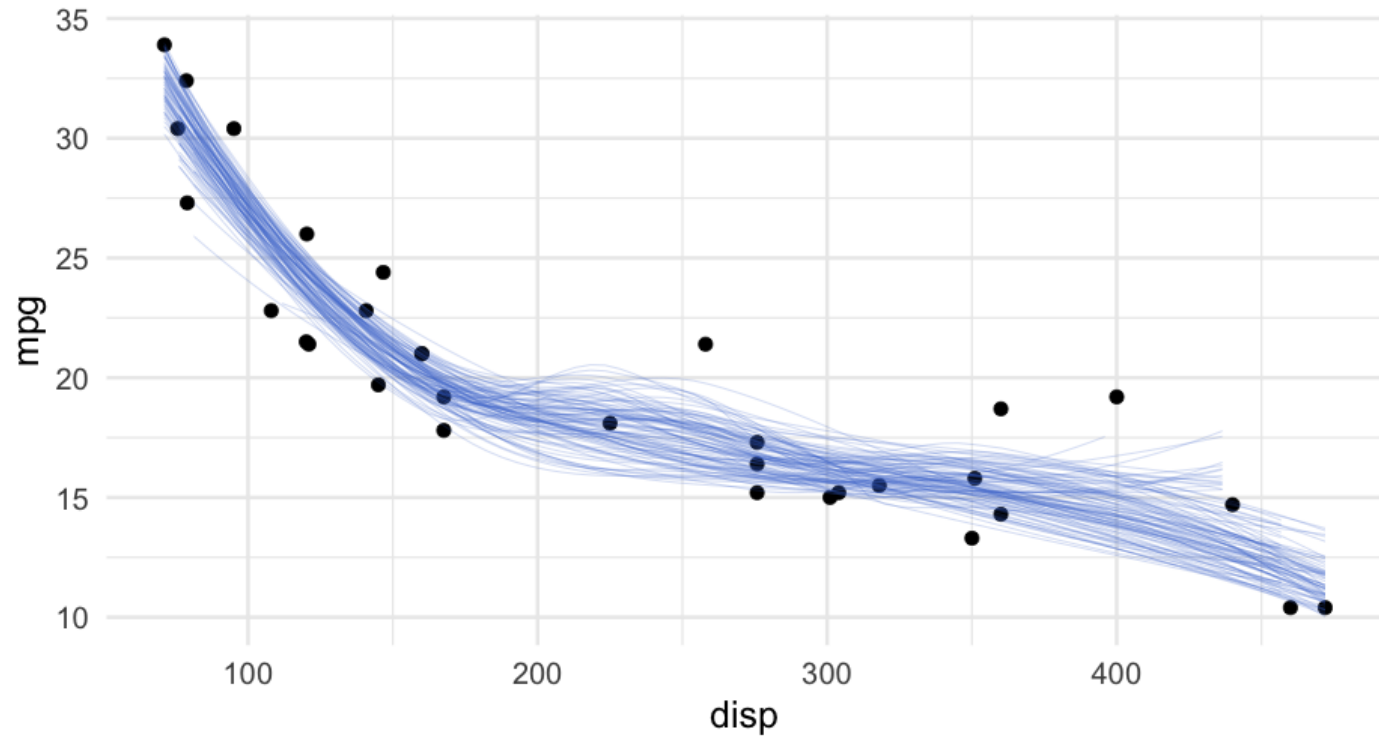
# Standard regression plot

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



# Alternative

---



# How?

---

## Bootstrapping

```
row_samps <- replicate(100,  
                        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]]  
## [1] 16 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 1 16
```

# Extract samples

---

```
d_samps <- map_df(row_samps, ~mtcars[.x, ], .id = "sample")
head(d_samps)
```

```
##           sample  mpg  cyl  disp  hp  drat    wt  qsec  vs  am  gear  car
## Maserati Bora...1      1 15.0   8   301 335  3.54  3.57 14.6   0   1     5
## Valiant...2           1 18.1   6   225 105  2.76  3.46 20.2   1   0     3
## Volvo 142E...3         1 21.4   4   121 109  4.11  2.78 18.6   1   1     4
## Merc 450SE...4         1 16.4   8   276 180  3.07  4.07 17.4   0   0     3
## Mazda RX4...5          1 21.0   6   160 110  3.90  2.62 16.5   0   1     4
## Merc 450SLC...6        1 15.2   8   276 180  3.07  3.78 18.0   0   0     3
```

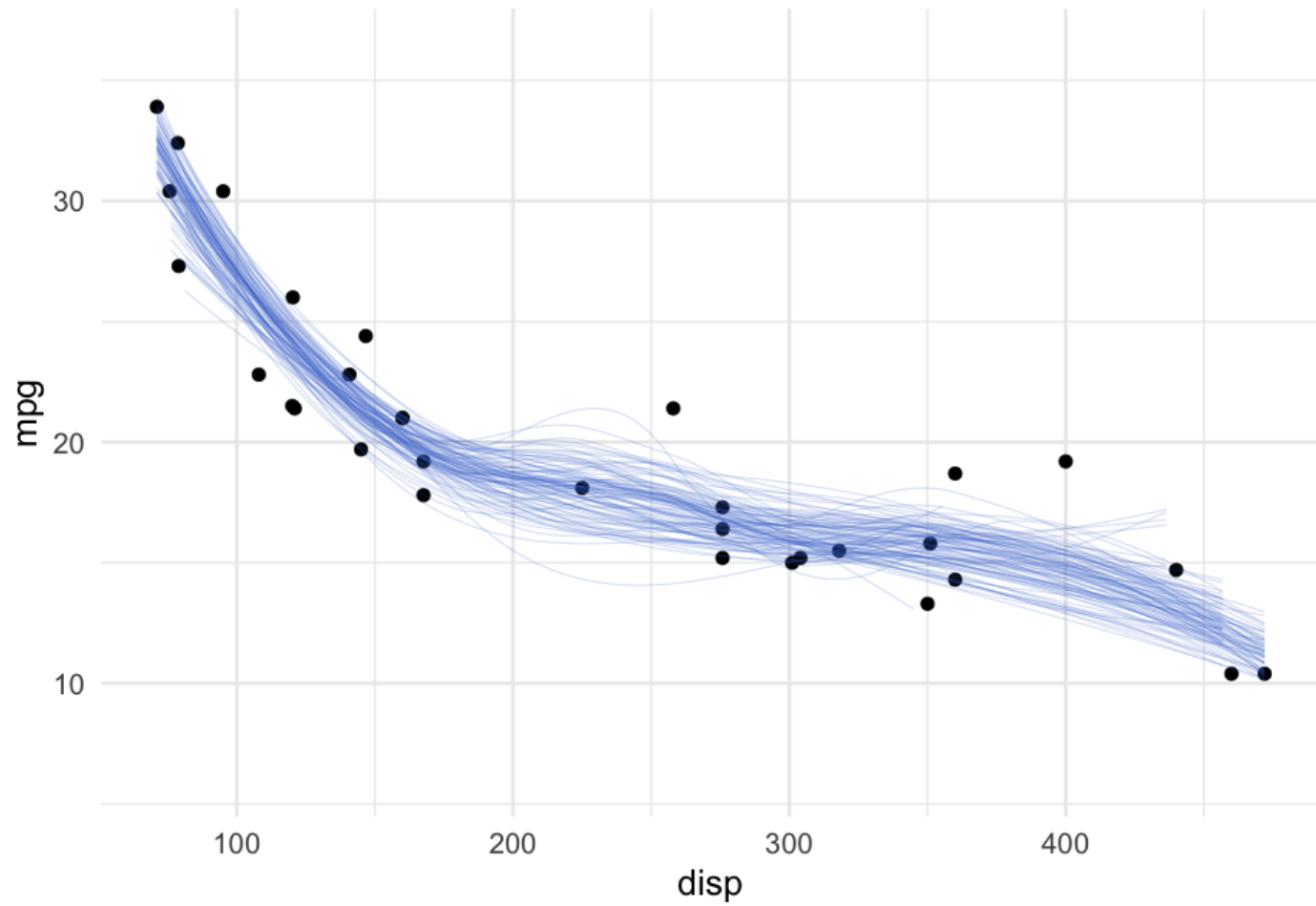
```
tail(d_samps)
```

```
##           sample  mpg  cyl  disp  hp  drat    wt  qsec  vs
## Lincoln Continental.1...3195    100 10.4   8  460.0 215  3.00  5.42 17.8
## Pontiac Firebird...3196         100 19.2   8  400.0 175  3.08  3.85 17.1
## Fiat X1-9.1...3197              100 27.3   4   79.0  66  4.08  1.94 18.9
## Mazda RX4 Wag.3...3198           100 21.0   6  160.0 110  3.90  2.88 17.0
## Hornet Sportabout...3199         100 18.7   8  360.0 175  3.15  3.44 17.0
## Lotus Europa...3200             100 30.4   4   95.1 113  3.77  1.51 16.9
```

# Plot both data sources

---

```
ggplot(mtcars, aes(displacement, mpg)) +  
  geom_point() +  
  stat_smooth(aes(group = sample),  
              data = d_samps,  
              geom = "line",  
              color = "#4375D3",  
              fullrange = TRUE,  
              size = 0.1)
```

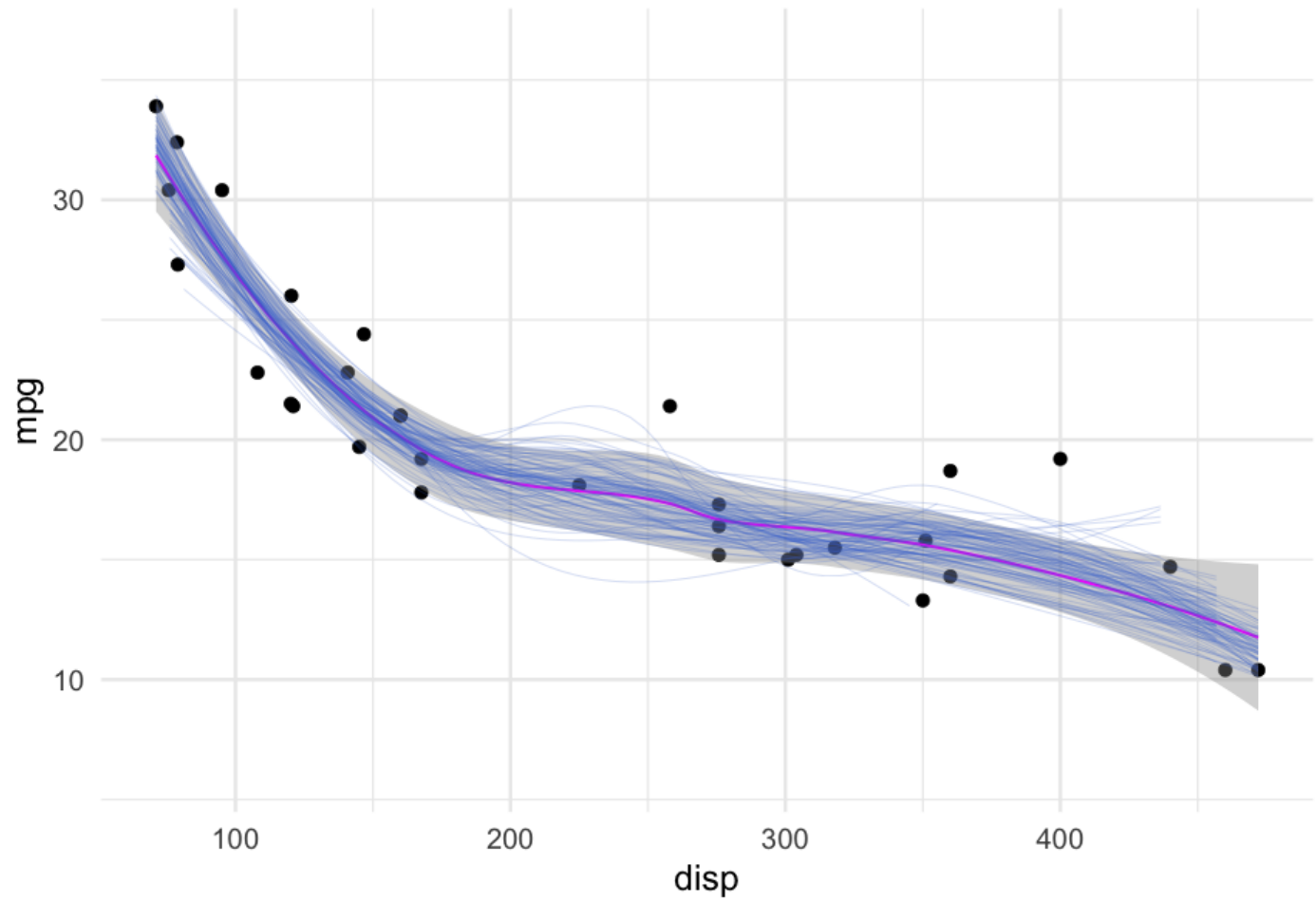


# Note, they match up

---

```
ggplot(mtcars, aes(displacement, mpg)) +  
  geom_point() +  
  geom_smooth(color = "magenta") +  
  stat_smooth(aes(group = sample),  
              data = d_samps,  
              geom = "line",  
              color = "#4375D3",  
              fullrange = TRUE,  
              size = 0.1)
```

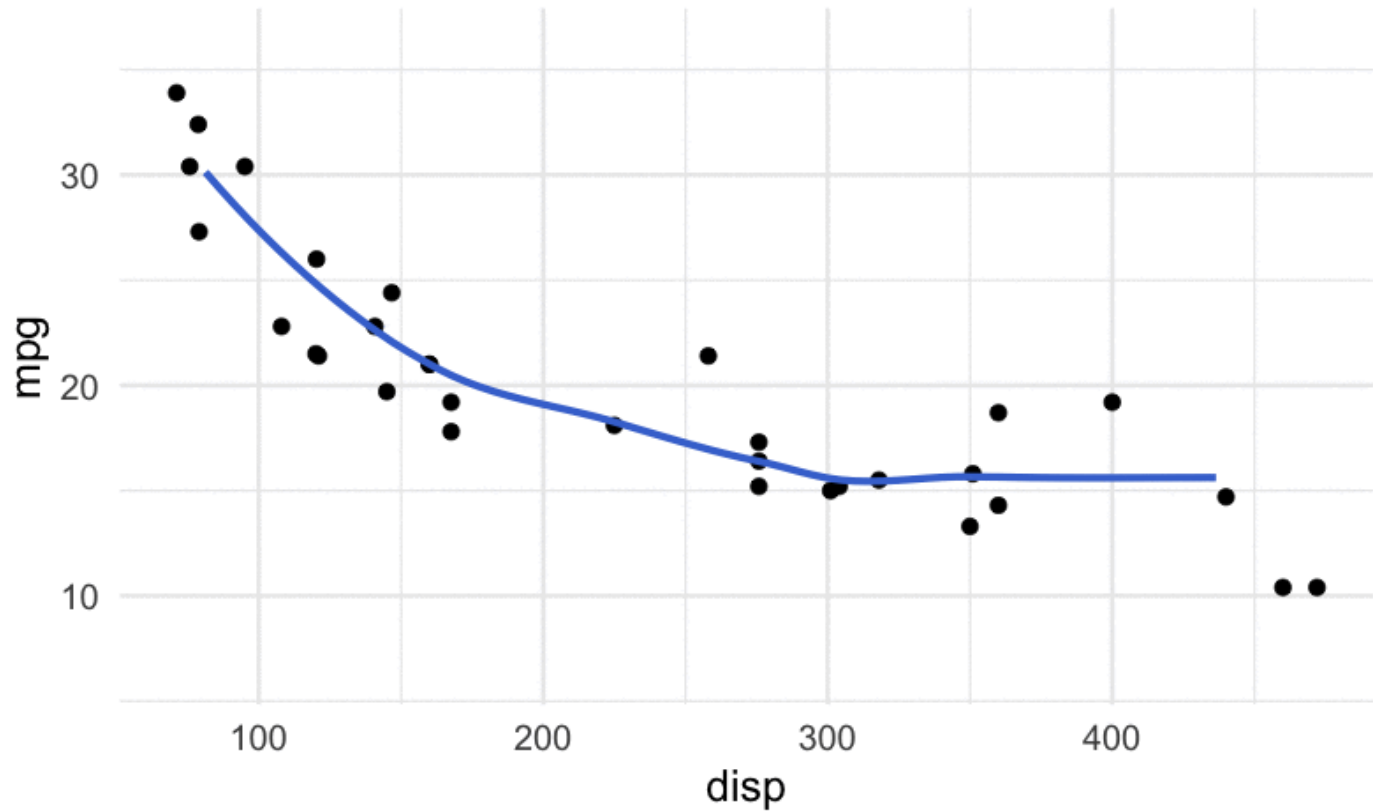




# HOPs

---

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



# How?

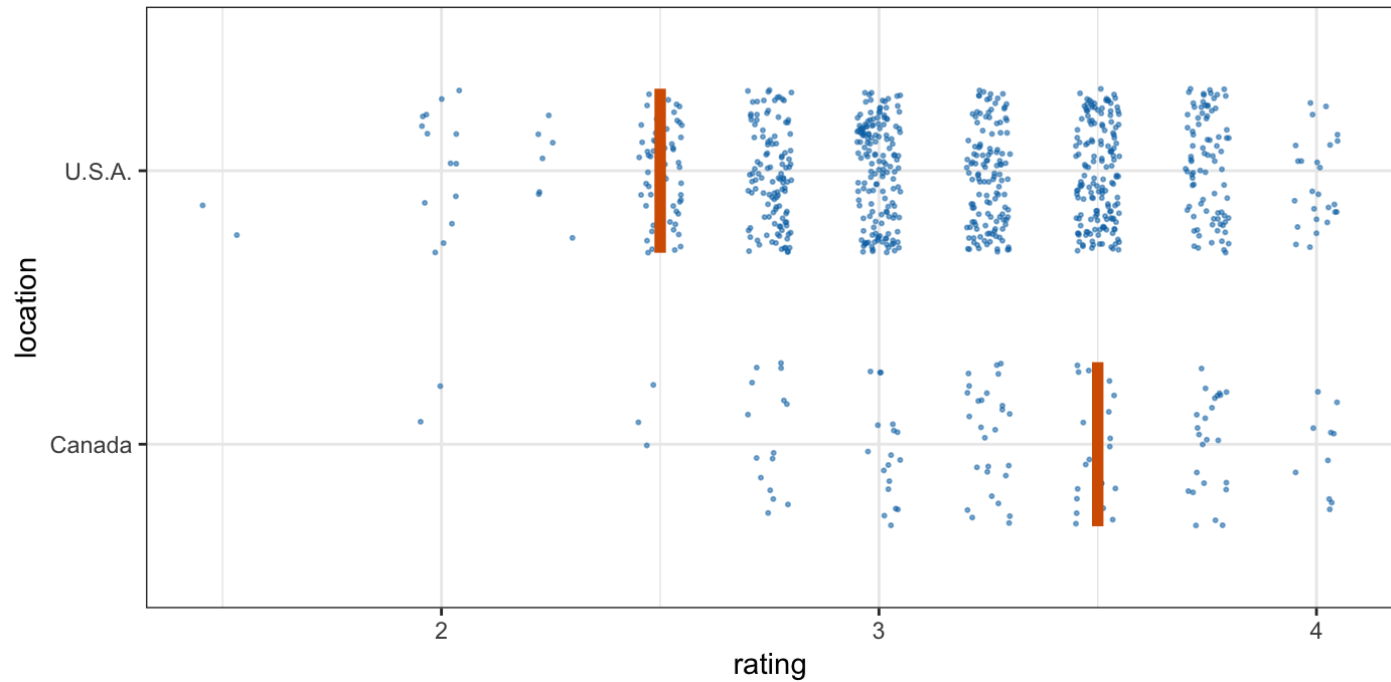
---

## gganimate::transition\_states

```
library(gganimate)
ggplot(mtcars, aes(displacement, mpg)) +
  geom_point() +
  stat_smooth(data = d_samps,
              geom = "line",
              size = 2,
              color = "#4375D3",
              fullrange = TRUE) +
  transition_states(sample,
                    transition_length = 0.5,
                    state_length = 0.5) +
  ease_aes('linear') # Smoother transitions
```

# Another example

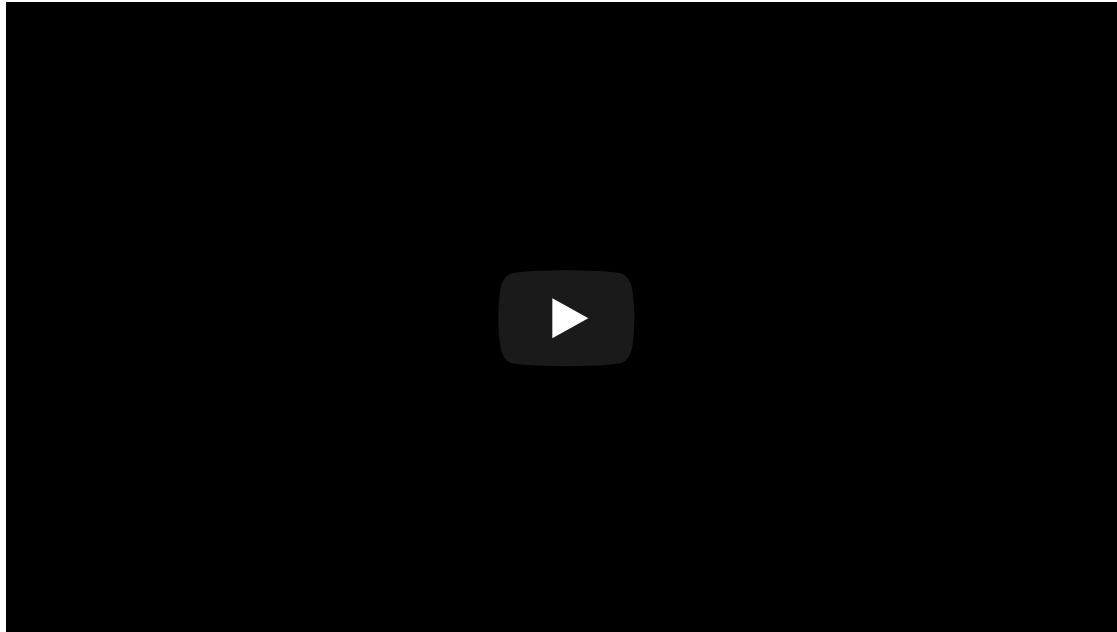
---



# 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